Technical University of Crete

School of Production Engineering and Management

Thesis Title

AUTOMATED VALUATION MODELS IN THE GREEK REAL ESTATE MARKET

Student Name: Dimitrios Andritsos

March 2021

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Real Estate Market: Evolution and Trends

Real estate is a type of real property that includes buildings, land, developments and changes on these, as well as the rights of use and indulgence of the property.

Real property examples, reflecting the real estate market, can be classified into three categories, based on their use, as follows[1]:

- Residential real estate includes undeveloped land, houses, and apartments, which may be owner-occupied or rental properties, as well as single-family or multi-family dwellings.
- Commercial real estate, either self-standing or in shopping malls, can be non-residential buildings used as offices, warehouses, or retail buildings.
- Industrial real estate consists of larger, in most cases, properties, such as factories, mines, business parks, and farms. Access to harbours, rail lines, and other transportation centres is usually needed.

House prices are one of the most critical financial issues involving all citizens, either referring to citizens that own a house and worry about its value or to citizens that aspire to own one and are worried about the evolution of the prices. In this context, for most people, buying a house is a long-term commitment considered as a safe and wise investment and is currently the most regular type of real estate investment. In many cases, homeowners have purchased their property by taking out a mortgage loan, in which the asset serves as collateral if the loan goes into default.

Some decades ago, homeownership was undoubtedly considered a synonym of stability for society and, eventually, economic development (Cerutti, Dagher, & Dell'Ariccia, 2017). This belief was, though, shaken, after the emergence of the subprime mortgage crisis in 2007, indicated by a surprisingly significant number of subprime mortgages, taken out in 2006 and 2007, defaulting or foreclosing only some months later (Demyanyk & Van Hemert, 2011).

In the following sections of this chapter, a brief presentation of the evolution and trends of the real estate market up to now, at global and European level, as well as specifically in Greece, is undertaken.

[1] https://www.investopedia.com/terms/r/realestate.asp

1.1.1 Global Real Estate Market

When referring to a review of the real estate market evolution in the modern times, every discussion should start by distinguishing the period before and after the financial crisis of 2007-2008 that affected, but it was also highly affected by and related to the real estate market. The financial crisis of 2007–08, also called the global financial crisis, was a severe worldwide economic crisis, believed by many to be the most severe financial crisis since the Great Depression of the 1930s. The peak of this financial crisis is considered to be the bankruptcy of the investment bank Lehman Brothers on the 15th of September 2008.

Given the importance of the housing market in people's everyday lives, it is not strange that the spark behind the worldwide downfall of the financial world was the outbreak of the United States housing bubble. The U.S. housing bubble was a real estate bubble that had an impact in more than half of the U.S. states and appeared when banks gave too many mortgage loans to meet the demand for mortgage-backed securities sold through the secondary market. Housing bubbles are usually defined as rapid increases in the costs of real estate properties, which turn to be unsustainable and non-affordable for people to their income, as well as other relevant economic indicators, such as price-to-rent ratios. Then, in most cases, this situation results in subsequent sharp decreases in real estate prices, which is the fact that generates the bubble, coming as a result of the negative equity, namely a debt higher than the property's value, in which homeowners find themselves[2].

Going one step back on what created the bubble, many factors contributed, both from a macroeconomic and a microeconomic viewpoint. The first important factor was a considerable drop in short-term interest rates. It was generated by the overall weakening of the bargaining power of labour unions, following the Soviet Union's collapse, the progressive expansion of the Chinese economy, as well as the fundamental innovations in the IT industry that contributed the former in the downward pressures on wages and consequently on prices and the latter in boosting productivity further reducing the pressure on price growth (Ramskogler, 2015). At the same time, Asia's focus on exports brought a considerable amount of capital into the US real estate market, by that reducing U.S. long-term interest rates as well. All these factors led to making loans low-priced.

[2] https://en.wikipedia.org/wiki/United_States_housing_bubble

Interest rates pressure on going down, as well as an aspiration to bring about higher yields, stimulated investors’ desire for uncertain, hazardous assets. On the other side, people, as it seems, attempted to outweigh a loss in relative income, leading to a critical rise in mortgages, which put the basis on the production of these risky assets on a large scale. A strong correlation between debt and inequality in the United States was identified, stemming, as it seems, by the fact that, at that time, people with low income tended to make expenses beyond their means, imitating wealthier households. On parallel to that, the increase of institutional investors gave the impression that there is an anticipating pool of possible buyers of securitised bonds, which were then wrongly regarded as an alternate of insured deposits. Just before the crisis, mortgage assets acquired by institutional investors’ flooded (Ramskogler, 2015).

Once, though, faith in the underlying assets begun to deteriorate, the delicate system that had been created fell apart. The crisis that followed this housing bubble, called the subprime mortgage crisis, was caused by a significant decrease in house prices and was generated by the reasons analysed above. When home prices started to drop, many homeowners came to realise that their homes were worth less than the amount the purchase price. This fact together with the rise in interest rates led to a massive amount of default and a consequent harsh increase in the number of subprime mortgage foreclosures in August of 2006 (Demyanyk & Van Hemert, 2011). The subprime crisis was announced in August 2007, but there was not a way of anticipating the impact it would have on the global economy. The “subprime crisis” became the “global crisis” with the collapse of Lehman Brothers.

Following the breakdown of the U.S. subprime mortgage market, the global economy suffered an unprecedented chaotic period. As the significance and effects of the crisis became increasingly apparent, belief in financial markets was seriously questioned. The remarkable intervention of government in the banking system along with the collapse or near-collapse of valuable financial institutions led to an unprecedented transformation of the global economy’s landscape (Adair, Berry, Haran, Lloyd, & McGrreal, 2009). Figure 1 depicts the progression of a weighted average of the uncertainty measure for the G7 countries plus Brazil, India, Mexico, and China from 2001 up to 2009. It can be seen that in August 2007 aggregate uncertainty in the world economy hit upwards, which is when the subprime crisis first appeared, however, it is the collapse of Lehman, in September 2008, which contributed the most in the increase of the aggregate measure. On what concerns stock market returns, a worldwide increase was noted in early August 2007 and only dropped significantly in September 2008 and the following months, indicating that the world was caught by surprise with regards to the crisis. Research work suggests that the uncertainty channel of contagion might have significantly contributed to expanding the crisis globally (Kannan & Köhler-Geib, 2009).

On what concerns the transmission of financial stress in emerging economies, in comparison with advanced ones, studies that took place over that period suggested that the transmission tended to be fast, appearing one to two months after the advanced economies' financial stress emergence. This fact indicates that not all regions were affected the same during the crisis. Latin America endured the first phase of stress well, while Emerging Europe was affected seriously. This variation is mainly attributed to the intensity of the financial connection of the region in question with advanced economies. That said, countries that relied more on foreign economies (the level of which liability is estimated by portfolio investments, bank lending, and FDI as a percentage of destination country GDP) experienced more robust transmission. It is thus suggested that the bank-lending linkages drove the U.S. crisis transmission in other countries. As depicted in Figure 2, banks of Western Europe ruled bank-lending flows. At the same time, Emerging Europe sticks out as the largest recipient of them, thus explaining why the later was the first emerging market region to be severely affected by the crisis (Danninger, Balakrishnan, Elekdag, & Tytell, 2009).

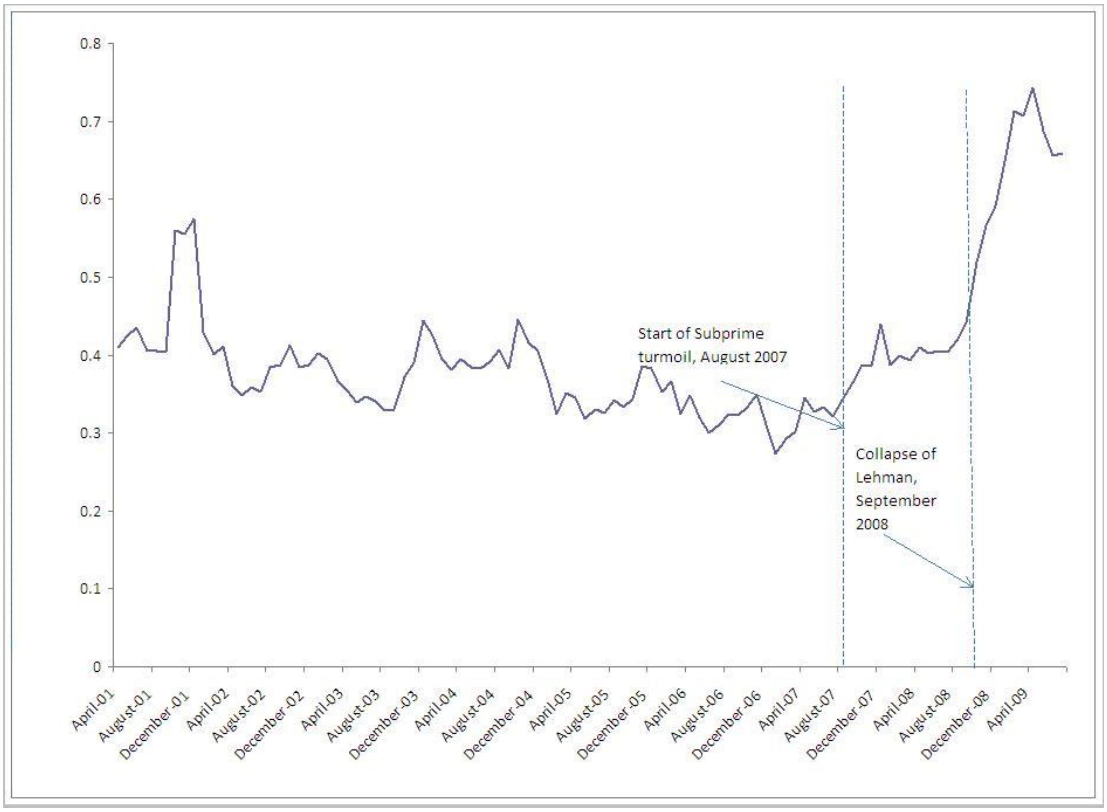


Figure 1 Standard deviation of one-year ahead forecast for GDP (weighted average G7 plus Brazil, India, Mexico, and China) (Kannan & Koehler-Geib, 2009)

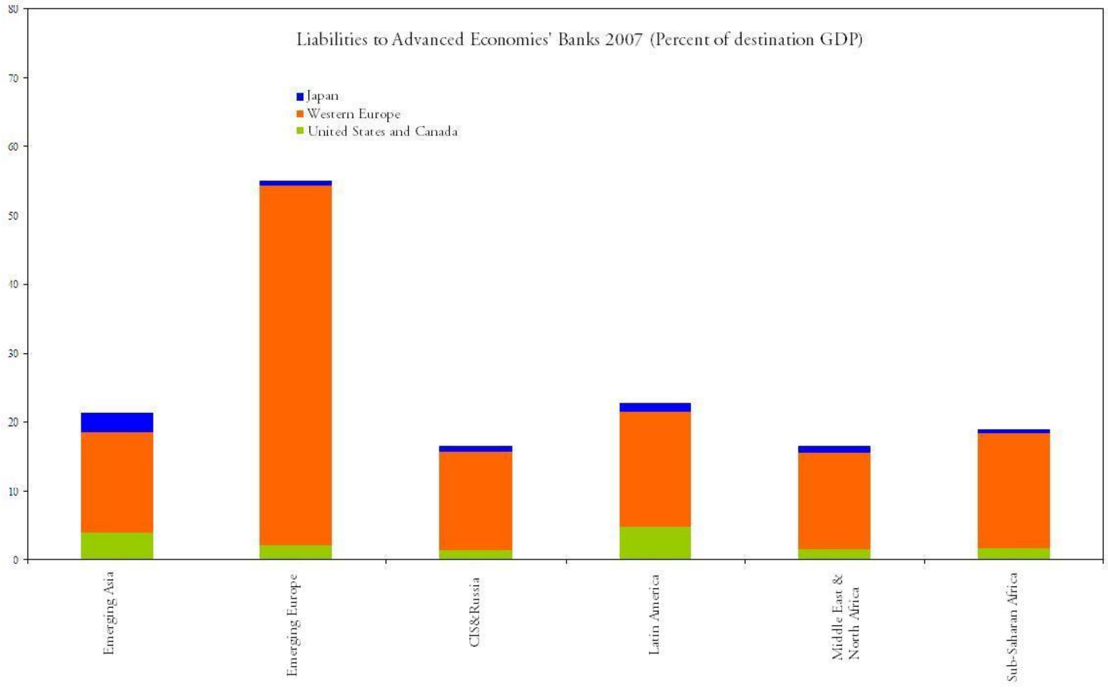


Figure 2 Liabilities to Advanced Economies' Banks 2007 (% of destination GDP)

(Danninger et al., 2009)

In this context, for the years that followed the subprime mortgage crisis, starting in 2008, real estate values dropped heavily, more than 30%. Real estate companies started to gradually get better financially, between 2010 and 2012, as the global financial system started to recover after the outburst of the crisis. That increased people's higher buying power as well as their ability to invest, thus increasing the demand for real estate, with a consequent increase in real estate prices, since the supply of real estate could not meet the demand. The years that followed, the demand for real estate assets continued to rise along with their prices.

Focusing on Europe and to better understand the evolution of the real estate market after the crisis and illustrate potential cross-border patterns and trends in European regions, the house prices indices have been grouped geographically. They are depicted in Figure 3 and Figure 4, analysing the six founding EU Members States and the countries of Southern Europe, respectively (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019). The House Price Index (HPI) estimates the changes in prices of residential properties as a percentage change from a considered start date, which has HPI of 100. In this analysis, 2007 is considered as the start date. On what concerns the six founding EU Member States, not a parallel evolution of the house prices can be detected. Instead, Germany, Luxembourg, and Belgium seem to have followed a continually growing trend since 2007, whereas in France, the Netherlands and Italy prices dropped between 2010 and 2014. Remarkably, Italy still has not recovered to its pre-crisis levels. Moving to Southern Europe, as depicted in Figure 4, the most significant increase in prices is encountered in Malta, followed by Portugal. In Greece, house prices followed a continuous, lasting decreasing trend after the crisis, which only showed the first signs of reset and gradual recovery by 2018. It needs to be noted, though, that Greece's average price index is still more than 40% below that of 2007 (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019).

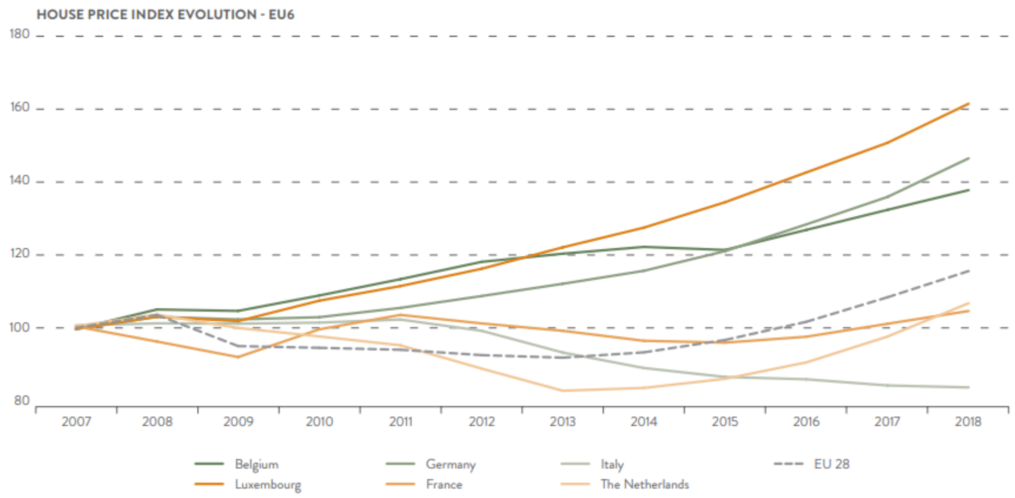


Figure 3 House Price Index Evolution - EU6 (2007=100) (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019)

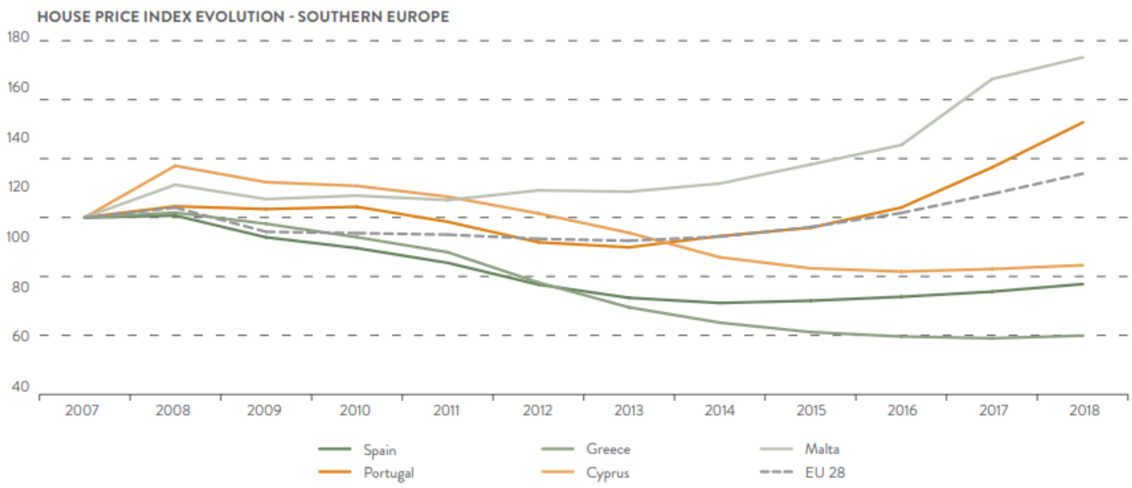


Figure 4 House Price Index Evolution - Southern Europe (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019)

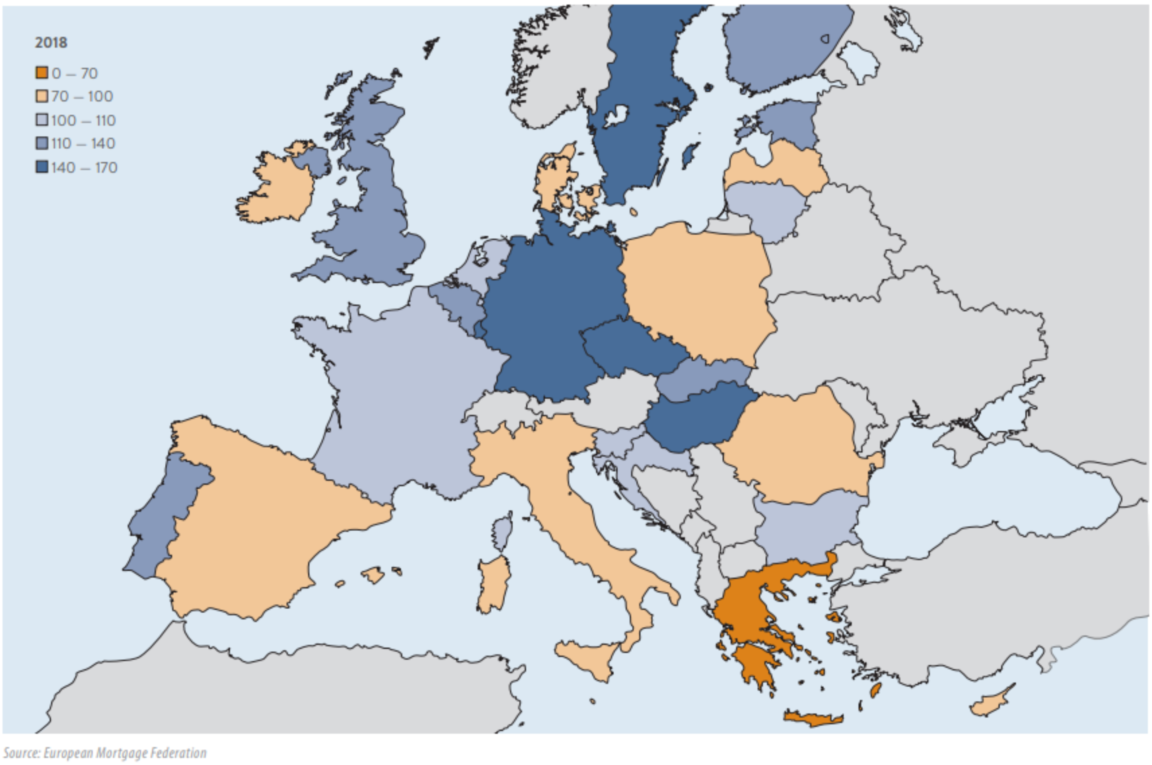


Figure 5 HPI in 2018 (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019)

In Figure 5, the House Price Index in the EU as this was formed in 2018 is depicted. 2007 is set as the start date. In aggregate terms, around 80% of the countries found themselves in pre-crisis house price levels. It was also observed that the EU28's prices increased in 2018 by 6.4% compared to 2017, while all countries examined experienced price increases, except for Italy. It is noted, though, that those dynamics are still heterogeneous among the different EU member states, and the pace of prices' increase differs significantly (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019).

Generally, macroeconomic variables, to which the status and evolution of interest rates belong, work as indicators of the economy's situation, and these tend to change, adjust differently, and evolve along with the recovery of the economy from a crisis. Economic growth should be gradual and careful, though, to avoid flipping over. In this context, the Fed (Federal Reserve) decided to raise interest rates at a slow pace, starting from 2018 and on. This fact made mortgages cost more, and as a result, credit raising became more costly too, thus making buying a house unaffordable for many people. This had a domino effect in house prices, which continued to grow, but more slowly than before, because of the reduced demand for houses and thus reduced sales[3].

Following the trend of 2018, house prices continued to grow in 2019, but again at a slower pace (3.3%) than in 2018 (5%). Mortgage interest rates, though, went down in 2019 and below 4% for standard types of loans[4].

In 2020, economists have expressed their belief that the property market is developing a bit of momentum with interest rates staying at around 3.7% for a 30-year mortgage and 3.2% for a 15-year mortgage and that housing prices will grow slightly. However, these predictions have already been questioned. Entering 2020, the contingency of the coronavirus at a global scale is already expected to significantly, though temporarily, affect the economy and consequently the real estate market. Figure 6 depicts the impact of coronavirus on stock markets since the start of the outbreak. Although governments all over the world have declared that appropriate actions will be taken to reduce, to the extent possible, the impact of the coronavirus crisis on the economy, investors continue to be reluctant. Responding to that, central banks have significantly reduced interest rates that would typically and in any other case make borrowing inexpensive and competitive, boosting consumption to keep the economy alive. These actions, however, cannot, by no means, be guaranteed they will have the expected results until the coronavirus is contained[5]. As a matter of fact, according to the Organisation for Economic Cooperation and Development (OECD), the global economy is expected to grow this year at its slowest rate since 2009 due to the coronavirus epidemic, as also seen in Figure 7. The think tank has also changed its prognostics anticipating growth of just 2.4% in 2020, down from 2.9% in November. It also highlights that a longer-lasting and more severe epidemic, that would force employees to stay home longer and factories to hold off their activity further, could dramatically reduce growth to 1.5% in 2020[6].

---

[3] https://riskmagazine.nl/article/2019-05-21-the-real-estate-market-a-decade-after-the-global-financial-crisis

[4] https://www.daveramsey.com/blog/real-estate-trends

[5] https://www.bbc.com/news/business-51706225

[6] https://www.oecd.org/economic-outlook/

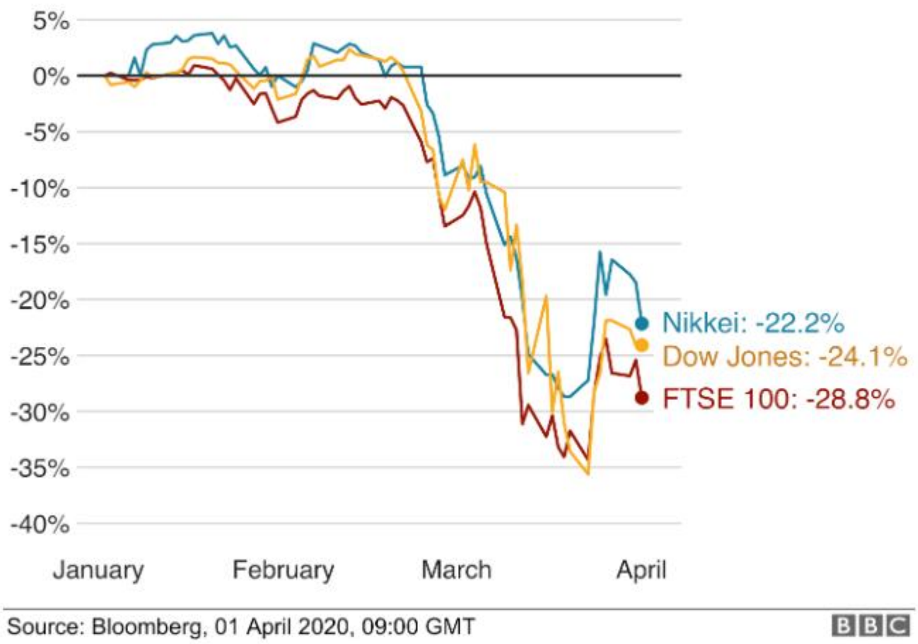


Figure 6 The impact of coronavirus on stock markets since the start of the outbreak [7]

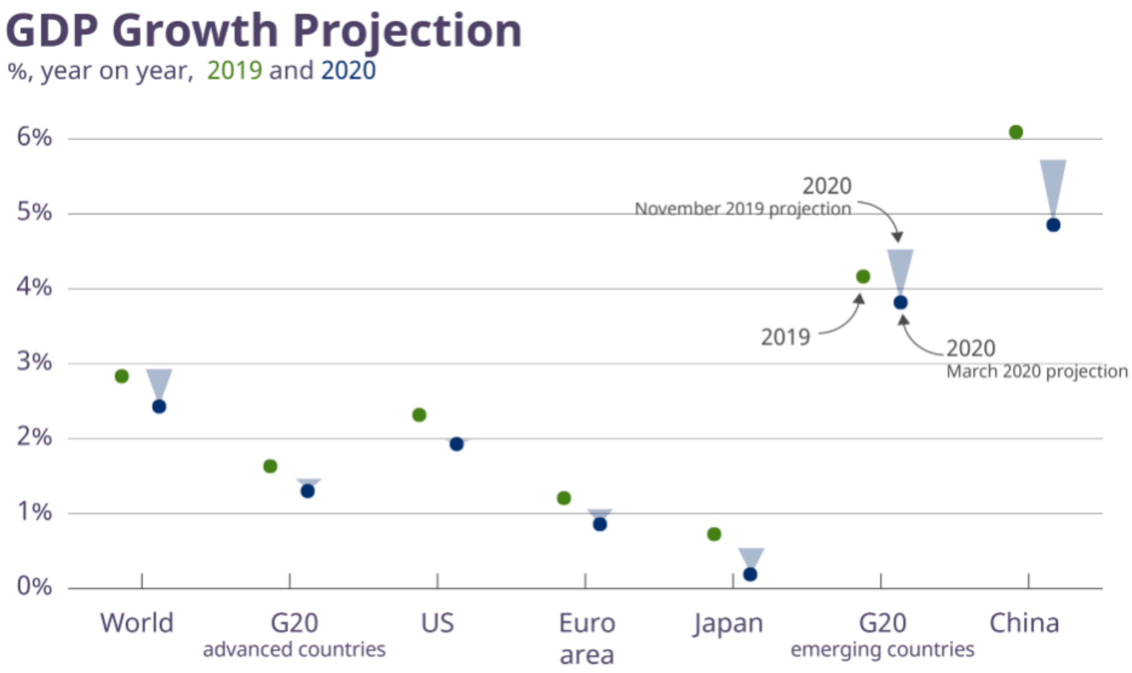


Figure 7 GDP Growth Projection (Source: OECD Economic Outlook database)[8]

On what concerns the retail market, among the many affected industries is also the short-term rental industry, with Airbnb being its largest representative. Government restrictions on travel and

[7] https://www.bbc.com/news/business-51706225

[8] https://www.oecd.org/economic-outlook/

the general fear that the coronavirus outbreak has created have led many travellers to cancel their upcoming trips. This fact left many hosts, for whom the exploitation of their properties was their primary business activity, without a source of income and with a great sense of uncertainty. Coronavirus provisions have also, at least temporarily, affected house viewings. At the same time, it is expected that many renters will encounter great difficulties in paying their rents, as an effect of business disruption. Ultimately, despite the stimulus package to be released by the EU and the governments, the economy is expected to be pushed into a recession. This recession will also impact the real estate market in terms of rents, prices, and turnover. The experience has shown, though, that, although there are times that prices fall or that the growth rate slows, dips are usually short-lived, and the upward trend soon returns. A strong rebound by 2021 can, thus, be expected according to the current situation.

1.1.2 Greek Real Estate Market

1.1.2.1 Review of the modern history of Greek Real Estate Market

The global financial crisis seriously affected Greece too and, consequently, had severe effects on the Greek Real Estate Market, as also shown before in Figure 5. The Greek sovereign debt crisis that followed the financial crisis of 2007–08 led to a sequence of unexpected reforms and austerity measures that harmed income and property values. It began in late 2009, provoked by the distress of the global Great Recession, besides the intrinsic deficiencies of the Greek economy. To address the economic difficulties, the Greek government executed 12 rounds of reforms, spending cuts, and tax increases in the years 2010 to 2016. Unemployment reached nearly 25%, and Greek salaries went down around 20% from mid-2010 to 2014. These facts reduced GDP and income, leading in a harsh recession, a considerable inability of people paying their taxes, and a substantial increase in debt-to-GDP ratio.

As mentioned above, the Greek crisis did not leave Greece's real estate market unaffected, which has not yet fully recovered. Greek real estate market fell apart after 2009, mainly pushed by the decline of residential mortgages, the decrease of GDP per capita, and the considerable increase in taxation, minimising housing prices and investments. As a result, the Greek real estate market was, until recently, an exception or else an "outlier" for the European markets. It is identified by a surplus of houses with a parallel and subsequent 41% drop in housing prices from 2008 to 2015 and a 72% decline in the number of transactions from 2008 to 2014, as depicted in Figure 8. In parallel to that, real estate taxes increased around six times, namely approximately € 3bn., in the years 2010 to 2015, further reinforcing the economic decline[9].

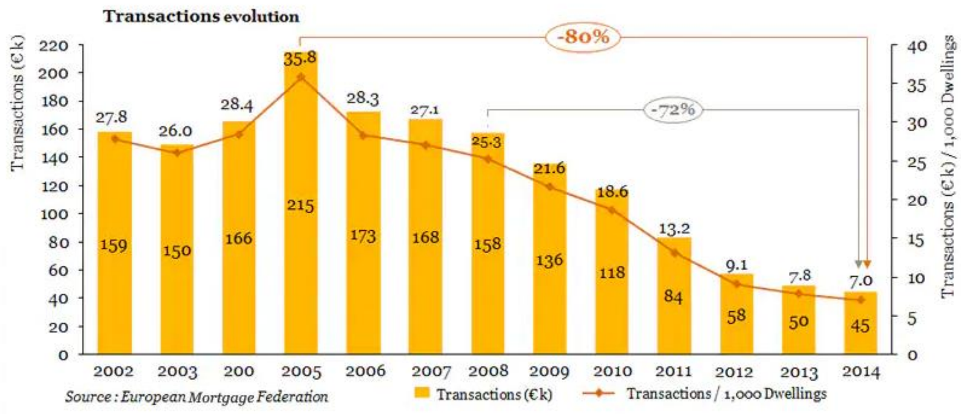


Figure 8 Transaction evolution in Greece from 2002 to 2014

Greece's economy started to show the first signs of recovery in 2017, following a stagnation in 2015-2016, where a positive GDP growth (1.5%) was recorded, being the first positive growth after two successive years of negative growth (marginal decreases in 2015: -0.4%; and 2016: -0.2%). GDP per capita grew further, by 1.9%, in 2018 and by the same rate in 2019 (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019). By 2020, Greece's economy has now regulated the most critical economic imbalances that led to the crisis and is about to find momentum towards a continuous and viable growth trajectory.

In parallel to this impression of recovery, unemployment has demonstrated a considerable drop over the past years, reaching 16.5% in November 2019. On what concerns trade balance and inflation, though, there were some soft negative indications, namely the fact that the former remained negative and the later slowed down during the year, remaining below 1% in all four quarters of 2019.

The ratio of non-performing loans to total loans, the NPL ratio, is another measure adding to the general impression of improvement for Greece, displaying a continuous negative trend in 2019 extending from 2018, as depicted in Figure 9. The NPL ratio is a common and popular statistic used to assess the financial performance of a banking institution. It is regularly used, amongst others, to evaluate and compare the quality of loan portfolios (Festić, Repina, & Kavkler, 2009), to analyse lending policies, to predict future bank failures (Jin, Kanagaretnam, & Lobo, 2011), and

[9] https://www.pwc.com/gr/en/publications/greek-thought-leadership/greek-real-estate-market-2016.html

to formulate models to timely detect and warn for potential financial imbalance (Serwa, 2013). For Greece, this ratio shows that conditions are still demanding but that there is also a clear trend towards steady improvement.

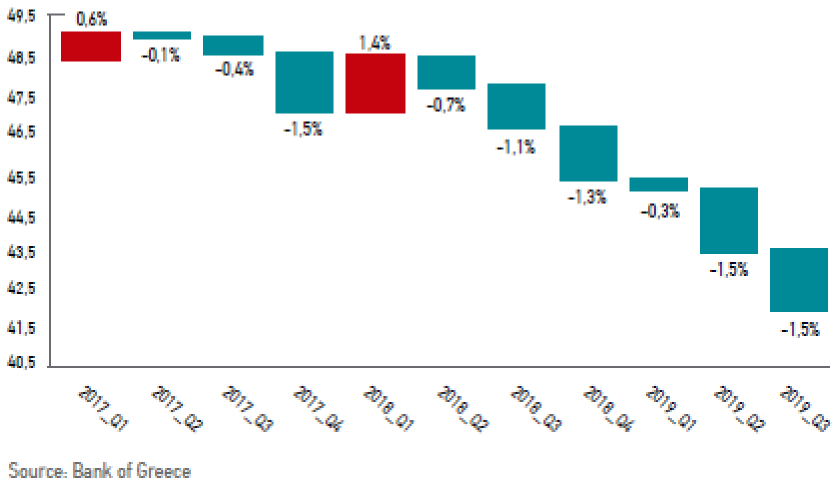


Figure 9 Overall NPL Ratio (in %) for Greece

Greek banks put specific focus on improving their health with respect to NPL and NPE[10] ratios, successfully pushing forward with NPL and REO[11] portfolio sales throughout the year, as well as securitisations. The total amount of NPLs reached €71.2bln by 2019Q3 while the NPL ratio reached 42,1%, dropping by 3,3% since 2018Q4 (Cerved Property Services, 2020). In 2019, to further support NPL portfolio sales, all types of loans were considered, in contrast with 2018, where the focus was mainly on unsecured consumer NPL portfolios. This decision was grounded on the improved market conditions that called for higher valuations of portfolios, as well as the activation of the Hercules Asset Protection Scheme (APS). The Hercules APS, voted in the second half of 2019, was devised to support banks in securitising and removing non-performing loans off their balance sheets. In this context, an independently managed, private securitisation vehicle acquires from the bank non-performing loans and then sells notes to investors. A public guarantee is provided by the State for the less uncertain notes of the securitisation vehicle, in exchange for reimbursement in line with market conditions. The main objective of this scheme is to help the banks in lowering the number of non-performing loans on their balance sheets while engaging a

[10] NPE (Non Performing Exposure) ratio is defined as the sum of outstanding nonperforming loans, advances and debt securities divided by all gross carrying amounts of loans, advances and debt securities. (Bärnthaler, Elsinger, Fessler, Woschnagg, & Jakubik, 2018)

[11] Real Estate Owned

broad group of investors (European Commission, 2019b). According to the European Commission, under this asset protection scheme, the Greek State will be compensated at market terms for its exposure to risk by allocating a guarantee on securitised non-performing loans.

The activation of Hercules APS in 2020 has led the closing securitisation transactions agreed in 2019 to be scheduled for 2020. At the same time, the pressure to achieve the targets submitted to SSM (Single Supervisory Mechanism) regarding the reduction of NPLs has also contributed to other transactions initially planned for 2021 to be rescheduled for 2020. Regarding the next period, 31.5 billion NPLs are anticipated to be assigned to Hercules APS from early 2020 to mid-2021 by the four systemic banks. In particular, Alpha bank is expected to assign €12 billion, Piraeus Bank €6 billion, Eurobank €7.5 billion and NBG €6 billion. Eurobank will be the first to join the Hercules APS making use of state guarantees of €2.5 billion and is also apt to securitise the Cairo mixed portfolio of €7.4 billion, with its subsidiary servicer FPS. Alpha Bank is anticipated to join Hercules in early 2020, with the securitisation of the Galaxy project of €12 billion and its Orion portfolio of €1.9 billion mortgage NPLs. The National Bank of Greece intends to enter Hercules APS within 2020 with portfolios of €6 billion. Finally, Piraeus Bank aims to direct to Hercules APS a mortgage NPL portfolio of €2 billion, while two securitisations of secured business NPLs portfolios are also expected within 2020.

Securitisation, generally, increases government guarantees too, as was the case with Greece, where the government guarantees coming with senior securitisation bonds increased from 9 to 12 billion euros. This fact reveals banks' increasing interest in participating in the Hercules APS, of which objective is to support them removing bad loans of around €30 billion out of their portfolios. This will, in turn, permit banks to reinforce their assets and gain liquidity and credibility, thus allowing them to concentrate their efforts in financing households and businesses and encourage growth[12]. It has to be noted, though, that the successful completion of current and future NPL portfolio securitisations and sales is based on the prospect of the consistent improvement of the financial health of the economy as well as consistent increases in NPL collateral values, contributing to more solid prospects of future NPL recoveries.

On parallel to the previously mentioned actions and measures regarding NPLs, Greece also took up new legislation regarding the protection of primary residences, following the expiry of the Household Insolvency law (or else known as Katseli law). The latter was designed to be temporary and expired, after a two-month extension, at the end of February 2019. The main problem was

---

[12] https://www.auraree.com/greece/npl-reo/greek-parliament-to-approve-hercules-asset-protection-scheme/

that, although mortgages are the best performing asset class in Greece, mortgage NPEs, accounting for around one-third of total NPEs, are the hardest to tackle. The reason is that the majority of borrowers, many of whom are considered strategic defaulters, have requested legal protection under the Katseli law, protecting their primary residence from bank foreclosure. The new law, induced by this situation, makes it more difficult for borrowers to be qualified for protection from foreclosure, by tightening the respective criteria.

This scheme, the primary legislation of which was adopted on 29 March 2019, aims, thus, to encourage the restructuring of non-performing loans. It is considered as credit positive both for the banks and the Greek economy in general. In particular, an electronic platform is built for applications to the scheme by natural persons, who are borrowers of loans that are secured with collateral on the primary residence and were unpaid on 31 December 2018. Given that the borrowers meet the specified eligibility criteria, they may apply for a restructuring and discount arrangement of their mortgage debt. This can be done by either agreeing on an extension by the creditor and standardised restructuring proposals, as these derive from the platform or by taking the matter to court. Such an arrangement will allow borrowers to protect their primary residence from foreclosure given that they will make the necessary instalment payments on the restructured debts. At the same time, state subsidy is also foreseen for part of the instalments. The new scheme is also considered by the Commission to be secure enough to hinder misuse and violation by strategic defaulters. On parallel to that, it strengthens Greek banks attempts to lower the big stock of NPEs by urging borrowers able to pay their debt to restructure their loans and start paying them off (European Commission, 2019a).

Passing on pure real estate related measures, investors appear cognisant of the steady recovery of the Greek market, resulting in a sharp rise in Foreign Direct Investment in real estate since 2016 and record-high numbers over the past quarters, as seen in Figure 10. On what concerns Fixed Capital Formation, on the other hand, investments on that respect are still lagging, especially those linked to housing, as depicted in Figure 11, representing only a minor fraction of its pre-crisis levels. On the beneficial measures, a positive trend is detected on the buildings permit numbers in 2019 (see Figure 12).

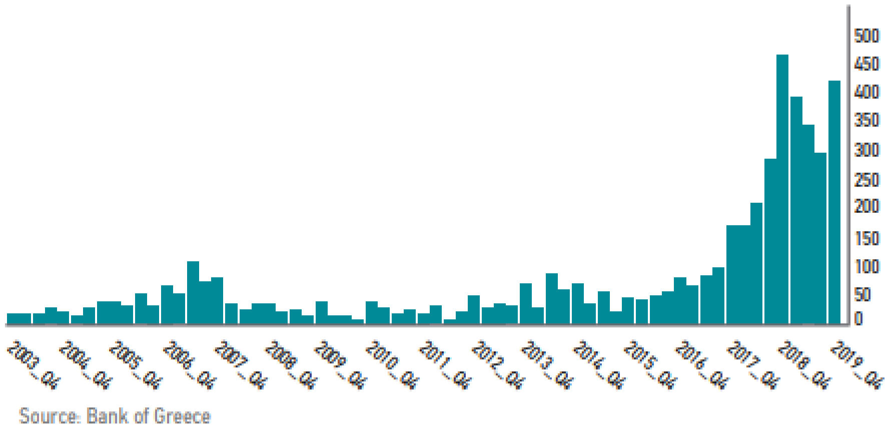


Figure 10 FDI in Real Estate - Greece (in Eur Mln) (Cerved Property Services, 2020)

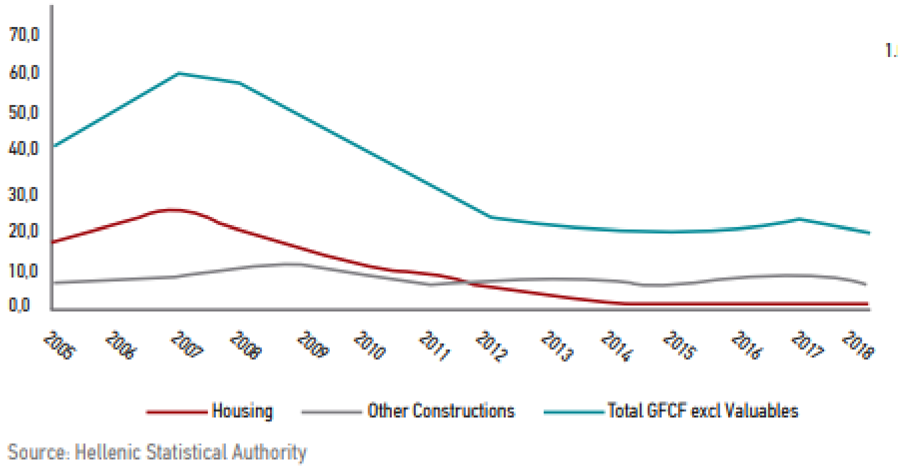


Figure 11 Gross Fixed Capital Formation - Greece (in Eur bln) (Cerved Property Services, 2020)

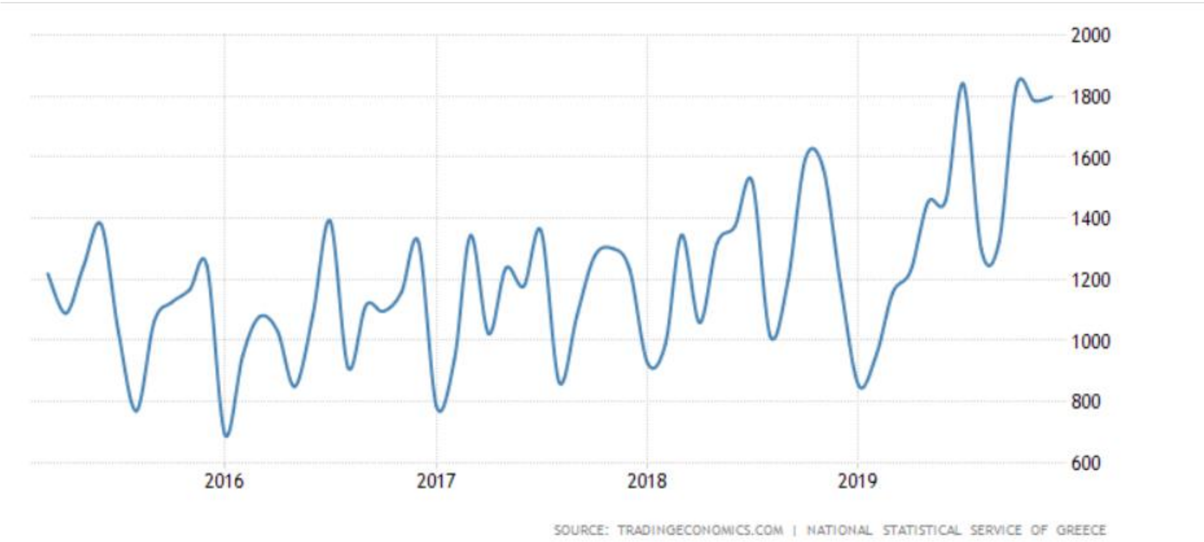


Figure 12 Number of Building Permits for Greece over the last five years[13]

Regarding house prices, they have started to recover, according to the Bank of Greece, for the first time after nine years of consequently falling prices. Regarding the residential property market, prices of apartments grew by 1.6% in 2018, against a decline of 1.0% in 2017. On what concerns commercial properties, the prices of prime offices grew substantially by 7.0% in 2018, against a rise of 1.8% in 2017. Finally, as for the retail market, prices of prime retail grew by 4.3% in 2018, against a rise of 1.7% in 2017. Residential loans continued to decrease by 2.8% in 2018 and this continued almost unaffected (-2.9%) in early 2019 (European Mortgage Federation-European Covered Bond Council (EMF-ECBC), 2019).

This actual progress was also met in the central Greek cities. Notably, in Athens, the prices of houses grew by 11.91% in the third quarter of 2019, achieving its highest increase since the second quarter of 2006. During the latest quarter of 2019, house prices increased by 2.21%. In Thessaloniki, house prices increased by 8.52% year-over-year in the third quarter of 2019, which was an acute change considering last year's annual rise of 1.32%. This was also for Thessaloniki its most significant increase since the second quarter of 2007. In other cities, house prices increased by approximately 6.87% during the year to the third quarter of 2019, a change from a year-over-year increase of 0.8% the previous year[14].

[13] https://tradingeconomics.com/greece/building-permits

[14] https://www.globalpropertyguide.com/Europe/Greece/Price-History

Before passing now on Greece's rental market, it should be noted that approximately three fourths (in particular 73.5% in early 2019) of the Greeks possess their own homes, according to Eurostat, therefore leaving for the rental market around 20% of the residences' stock.

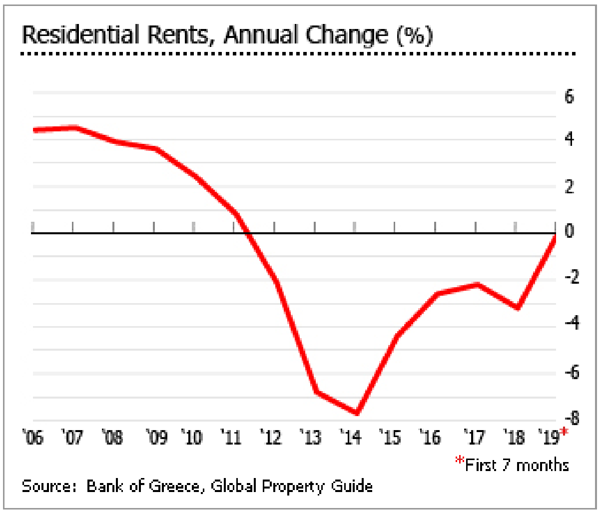


Figure 13 Annual Change, expressed in %, for residential rents in Greece

Having said that and starting from Greece's capital, Athens, and its centre, gross rental yields[15] on apartments are found to be fair and unexceptional, at approximately 4.2% for apartments of 120 square metres, but rather more for smaller apartments, as Global Property Guide research reports. For the suburbs of Athens, apartments' gross rental yield is somewhat remarkable, at around 4.5%, but this is not the case for houses, which are found to have minimal yields, at about 2.6% to 3.2%.

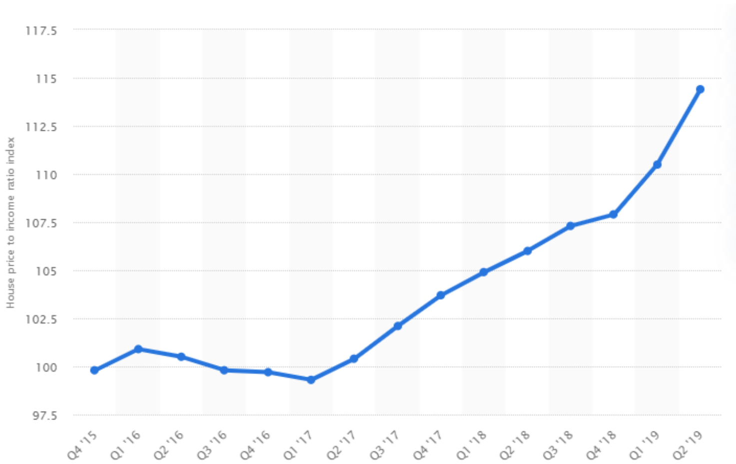


Figure 14 Quarterly house price to rent ratio in Greece 2015-2019

Source: Statista Research Department, February 2020

[15] Gross rental yield is the annual income of a property as a percentage of the property's value or purchase price.

Figure 14 showcases Greece's house price to rent ratio starting from the fourth quarter of 2015 until the second quarter of 2019. It is measured by dividing nominal house prices by rent prices. It is used to estimate whether it is cheaper to rent or own property. It can be observed that the house price to rent ratio varied slightly and irregularly around a value of 100 in the period from the fourth quarter of 2015 to the first quarter of 2017, arriving at 99.3 in the latter. Since then, though, it grew significantly, reaching a value of 114.4 in the second quarter of 2019[16].

A factor that has significantly affected the real estate market was the decision by the Greek government, introduced by Law in 2013, to offer Golden Visa, i.e. permanent residence, to non-European residents investing €250,000 and above in Greece, with purchase acquisition being the most common way for acquiring the Visa. According to data from the national E-Real Estates network, there have been more than 5,000 Golden Visa property transactions in Greece up to September 2019, with 80% of those properties being in the greater Athens area.

The outstanding growth of Airbnb is another factor putting pressure on rents as it removes properties from the long-term rental market while keeping prices high. Currently, there are over 50,000 houses in Greece that have joined short-term rental platforms that accommodate tourists.

The result of the factors mentioned above, along with Greece's economic recovery, is higher rent prices in various areas in Athens, as they were before the crisis, and even above that, particularly in its centre. If we focus on the downtown areas of Athens, which attract large numbers of tourists and investors, median rental prices per square meter have doubled compared to 2016. However, and despite Greece's modest economic recovery, citizens' purchasing power is still narrow and restricted, leading to a growing number of them in an inability to pay their expensive rents.

1.1.2.2 What to expect for the future: a challenging year for the Greek economy and real estate

In aggregate terms, following the stabilisation of the Greek economy, a consequent progressive general stabilisation of the real estate market and a growth in prices at a local level were anticipated for the next period. The prospects were that taxes on property capital value would get more reasonable and that banks' liquidity flows would be restored, leading in further reinforcement of the citizens' disposable income and as a result even better expectations for the development of Greece's economy. In this context, it was believed that the real estate market will start steadily and progressively revive, with prime properties being the first to be influenced positively.

[16] https://www.statista.com/statistics/592267/house-price-to-rent-ratio-greece/

Greece, however, is still facing significant challenges, being in a large extent a legacy of the economic crisis, in combination with other factors, including the changeable worldwide economic environment, unusual weather conditions due to climate change, geopolitical pressures in the Eastern Mediterranean area, the recent aggravation of the refugee crisis, but most of all the coronavirus disruption. The coronavirus disruption is currently the most crucial risk for the economy at a worldwide and European level and, as such, has seriously questioned the growth expectations for Greece too. There is a direct effect on Greece's economy from both supply and demand side, with a severe negative impact on shipping, transport, supply chains and on top of all tourism. The effects on domestic demand also should not be underestimated since there is a significant decrease in individuals' consumption.

The coronavirus outbreak will call for considerable expenses to confront the disease, uphold the business world, and control unemployment levels to remain low. These actions, along with the immediate, direct effects of the outbreak, mentioned above, will seriously affect economic growth and, as a result, public revenue. Up to this point, the Bank of Greece has revised its projections for GDP growth in 2020, from 2.4% which was before to 0.0% now, taking into consideration the expected effects of the coronavirus outbreak. However, as the coronavirus progresses and shows its extent and its alarming side effects, new projections are coming into light that are more discouraging than the previous ones, as is the case with the projections made public by the IMF, reporting, amongst other, for a 10% decrease of GDP for Greece for 2020 and then a 5% increase in 2021 (International Monetary Fund, 2020). Greece displays the most severe drop in GDP among the European countries, according to IMF projections, which is mostly attributed to its high dependence on tourism. In parallel to that, there is information that the Bank of Greece has estimated that the NPE ratio will increase between 4% and 11%, reaching 44% to 51%, meaning an increase in non-performing loans, between € 6.4 billion and € 18.1 billion.

The economic impact cannot, at this point, be measured accurately, but only examined based on distinct hypothetical scenarios, since the duration of the coronavirus crisis and its exact trajectory is not yet known. According to OECD, the baseline scenario assumes a controlled, limited disruption, and based on that, global economic growth is expected to be 2.4% in 2020, which is 0.5 percentage points under the November's 2019 forecast. The bad, severe scenario, though, that assumes a broader coronavirus dispersion and a consequent broad impact, suspects a drop of global economic growth to 1.5%.

The short-term impacts on economic growth and business activity are, however, undeniable and have started to appear. Real estate agencies' activity has been put on hold concerning property investments by Chinese with the Golden Visa program, rendering the target of 1 billion euros for this year through the program uncertain. Also, the attempt to attract foreign millionaires with a special tax regime, subject to an investment of 500,000 euros, is likely to be lured too, at least for the months to come. At the same time, there is almost zero mobility on the part of indigenous buyers of real estate. As they are mainly individuals who are interested in meeting their housing needs, the new conditions created by the coronavirus crisis oblige them to postpone any plans.

The biggest complication for the housing market, and especially real estate owners, is expected, though, to arise by the failure to pay rents next year on both residential and commercial leases, given the "quarantine" in which the Greek economy has recently entered. Given, also, the high dependence of the real estate market on tourism and other sub-sectors of the economy, it is expected that in the first months of 2020 property prices will remain stagnant or in some cases subject to pressures, the size of which will depend largely on the duration of the current special conditions; an issue which the Bank of Greece has already highlighted, according to its latest monetary policy report [17].

Despite the unpredictable nature of the situation, there is a joint agreement that the most crucial factor for the economy will be the time to limit the pandemic and return to normalcy.

1.2 Background and Motivation

The direct correlation of the welfare of the real estate market with economic stability and upturn was highlighted in this chapter, following the historical evolution of the real estate market within the last years and the crisis that were yielded. An overview of its progress, both abroad as well as focusing on Greece, reveals that the value of a home or property changes over time starting from the property characteristics, following trends, and influenced by external factors in a generally predictable way. Transparency and trustworthy information are the driving forces and the principal ways of ensuring the system’s flexibility and autonomy. In that sense, the future of the real estate market is directly connected with its past and the lessons learned from it. Quantitative analysis helps to capture the current trends of the market, better understand the expected behaviour of the borrowers and lenders under examination and identify a few of the influencing factors driving these markets. Therefore, upon analysis, the challenges the market in question faces can be identified and conclusions can be drawn on what is expected for the future of Europe’s real estate markets, in line with the altering socio-economic environment.

[17] https://www.bankofgreece.gr/en/news-and-media/press-office/news-list/news?announcement=49748136-1841-47d7-b5a5-e6a49bc99b6d

Appraisals are one of the core professional activities of the business of real estate, which involve an analysis of the market and a deep understanding of real estate's inherently heterogeneous nature. They are a significant element of the property buying procedure or particularly necessary when a property is about to be used as collateral. A real estate appraisal determines a property's market value, namely the expected price to be sold if this was available for sale in a free and competing housing market. It needs to be noted, though, that the transaction price is not always the most reliable measure of the latent worth of the property, since the buyer may simply have paid more due to misinformation, significant search costs or deception. Therefore, the appraisal is more than a direct analogy of the transaction price (Demiroglu & James, 2018).

While appraisals were traditionally performed manually, today software tools are developed which are designed explicitly for appraisal purposes. In that way, the process is performed quicker and more accurately. The term Automated Valuation Model (also referred to as AVM) is generally used to describe these types of services that leverage a mathematical model to provide a real estate property value. AVMs minimise the need to inspect and scrutinise each property on the market personally. In the following chapter, a literature review on the Automated Valuation Models, including, among other things, an analysis of their origins, their most prominent methodologies, and their strengths and limitations, is attempted.

2 Literature Review

Both banks but also dedicated analytics companies, as is the European AVM Alliance, have concentrated their efforts on the development of automated valuation models (AVMs), which are the main risk monitoring tools currently used in the real estate market. An AVM is any "system that provides an estimate of the value of a specified property at a specified date, using mathematical modelling techniques in an automated manner"[18]. Such evaluations are crucial to both purchasers and vendors of properties as well as banks or institutions who provide mortgages since they must verify the value of the collateral on a mortgage. The applications of AVMs are, though, not limited to these. AVMs can be used for portfolio valuation, fraud detection, and many more.

Initially, property appraisals have been handled by qualified assessors. AVMs, on the contrary, are conducting the appraisals automatically by using and applying statistical and mathematical models and methods. This is also the main distinguishing factor from traditional appraisal methods, which call for physical inspection of the property in question by an appraiser, relying on his knowledge of the real estate situation, his intuition, and his perception, to suggest an evaluation of the property's market value (International Association Of Assessing Officers, 2003). It has been proven that if AVMs are accurately produced, they may cost less, be more rapid, more unbiased, more understandable and more transparent than human appraisers. That, of course, does not mean human replacement, since, human intervention by experienced personnel is needed for the development of the model by contributing their robust experience for the necessary prior analysis as well as ensuring quality through the examination of the appraisals generated by the model.

The use of AVMs in real estate markets is growing at a global scale (Bellotti, 2017; Downie & Robson, 2008; European Mortgage Federation and European AVM Alliance, 2016). In this chapter, a literature review on AVMs is undertaken. It provides a synthesis and summary of the concentrated knowledge regarding their origins, their evolution, their theoretical framework, their technical background, concluding with their contribution in risk mitigation, as well as the current challenges and limitations AVMs are facing.

2.1 Origins of Automated Valuation Models

To undertake a housing market analysis, first, there needs to be a common understanding among people on what a reasonable, legitimate value of a specific property is, by making use of analogous

[18] From "Glossary of Terms and Definitions" by the European AVM Alliance (EAA) – http://www.europeanavmalliance.org/media/default/pdf/eaa_glossary.pdf

inferences and assumptions to come up with an estimation. Therefore, to agree upon a property's value, understandable techniques in the appraisal of single properties were needed (Ramsey, 2004).

In the urgency for legitimate, fair market value, legal disputes emerging from bankruptcies, acquisitions, and mergers came to be added. By the late 1920s, there was a fair amount of literature and many court precedents regarding the methods and approaches for the estimation of property market value. Therefore, appraisals of real estate properties started as a side activity of companies that would typically own or manage real estate properties. (Ramsey, 2004).

Early attempts towards the creation of a professional appraising organisation started within the National Association of Real Estate Boards (NAREB). In 1922, NAREB established distinct branches leaving appraising aside as being too minor to advocate an autonomous division. After the 1930s, however, and the remarkable downfall of real estate investments, NAREB created an independent division for appraising, the American Institute of Real Estate Appraisers (AIREA). It can be considered as the starting point for appraising to be regarded as a separate professional business activity.

In the late 1970s, the term "mass appraisal" appeared describing the procedure of evaluating several properties on a specific date working with the same data, uniform techniques, and statistical tests (International Association of Assessing Officers, 2017). This definition is the "Mass Appraisal 1.0", which originated from the SMARP (Standard of Mass Appraisal of Real Property).

As depicted in Table 1, by now, many institutions have been occupied with the formalisation and standardisation of real estate mass appraisal. Mass appraisal may be encountered, in the literature, with different keywords, though, serving as synonyms, with the most prominent ones being "real estate appraisal", "property valuation" and "mass valuation".

Table 1 Main Standards and institutions for the mass appraisal (Wang & Li, 2019)

Standard	Institution	Year (1st Version)	Year (latest version)
SMARP (International Association of Assessing Officers, 2017)	IAAO	1976	2017
RICS Red Book (Royal Institution of Chartered Surveyors, 2017)	RICS	1983	2017
IVS[19]	IVSC	1990's	2017
USPAP[20]	AF	1987	2018

The notion of "Automated Valuation Models" (AVMs) emerged for the first time, as a result of IT development, in the '70s for land valuation as "Computerized Assisted Assessments" and real estate property valuation as "Model for Automated Assessment" (Glumac & Des Rosiers, 2018). With the evolution of computer-assisted mass appraisal (CAMA), an automated valuation methodology for mass appraisal was progressively adopted (D'Amato, 2017).

A formal definition for AVMs was, though, only given by the International Association of Assessing Officers in 2003 (International Association Of Assessing Officers, 2003), as follows: "An automated valuation model (AVM) is a mathematically based computer software program that produces an estimate of market value based on a market analysis of location, market conditions, and real estate characteristics from information that was previously and separately collected".

There was a noteworthy parallel development of AVMs with credit scoring, which made the automation of lending decisions possible, typically made before by bank managers. However, what probably contributed the most to the evolution of AVMs was the advance of information systems, along with the appearance of decision support systems (DSS) supporting the development of new

[19] https://www.ivsc.org/standards/international-valuation-standards/consultation/IVS-review#tab-summary

[20] https://www.appraisalfoundation.org/imis/TAF/Standards/Appraisal_Standards/Uniform_Standards_of_Professional_Appraisal_Practice/TAF/USPAP.aspx?hkey=a6420a67-dbfa-41b3-9878-fac35923d2af

techniques and perspectives in automated valuation. In the context of real estate, DSS applications started developing in the 70s and relevant expert systems in the 80s. On what concerns appraisals, the first DSS for real estate valuation emerged in the early ’80s (Trippi, 1990).

Today, AVMs are being used increasingly, frequently as a precursor, or in parallel to, an appraisal (i.e., physical inspection by a licensed, certified professional). After the 2008 Global Financial Crisis, AVMs use has grown in Europe for many different reasons, though the extent of their use differentiates among EU member states. As an example, AVMs use increased in Germany as a result of cost pressure and streamlining of procedures in the banking industry, while in Italy and Netherlands as a result of compulsory risk management and quality control, and in Norway a result of increasing demand for transparency and better risk management (European Mortgage Federation and European AVM Alliance, 2016).

2.2 Theoretical Framework of AVMs (Steps in AVM development)

The development and implementation of an AVM system comprise four steps:

(a) Reliable data collection and establishment of uninterrupted access to them
(b) Development and validation of the model
(c) Provision of the service
(d) Backtesting

Every AVM system has as the first step of its development the establishment of uninterrupted access to reliable data. The data, in the majority of cases, are collected beforehand and independently from the AVM development. Some examples of these data involve data from property listings for rent or sale at property websites, actual transaction data from land title registries, and data from banks obtained as part of the mortgage underwriting process. A key challenge is that these data are proprietary, and therefore their owner might not be willing to share them, since he may instead set up an AVM on its own. It is also critical to additionally make sure that the data are trustworthy and up to date. The second step of an AVM development process involves data cleaning, variable selection, model specification, model calibration and model validation. Data cleaning should be as automatic as possible. At the same time, variable selection calls for a thorough knowledge of the market, data and their definitions, to come up with a selection of the variables that are more representative of the market value of a property. In cases where statistical significance is used for the selection of variables, there is an overlapping between variable selection and model specification and calibration steps. During the model specification and calibration steps, the appropriate function, best representing the market in question, must be determined. Once one, or several appropriate models have been set up, there needs to be a validation of the model, using out-of-sample validation. It has to do with testing or practice running of the AVM before its release. This step is also an opportunity to evaluate and weigh the different models that might have seemed equally appropriate during model development. The third step of the AVM development process concerns the employment of the model from a technical perspective and the provision of the service. Most frequently, the appraisals need to be produced in real-time on desktops and in many cases to be provided online. At this stage, it is essential to clarify who will be the anticipated users, to have realistic expectations on what information these users can or cannot provide. For instance, an average user might have difficulties comprehending what each category of the state of repair represents. This fact also applies to the output of the service, since the average user might not be able to follow what a confidence interval is. Thus alternative approaches should be identified to make the service user-friendly. The fourth and last step involves backtesting the AVM after its release, which means that the statistical model can be improved even after its release by monitoring and detecting appraisal errors and considering adjustments to the model when these errors show some pattern (R. Schulz, Wersing, & Werwatz, 2014).

In the following sections, the more pervasive, individual stages of AVM development are analysed in detail.

2.2.1 Data

Three main types of data are exploited in AVMs as price response; revealed preference data, stated preference data, and a combination of these two. Revealed preference data have to do with real market transactions. It is critical, though, to highlight that data type and data source are two different things. In this context, both sales prices, namely notary deeds, and asking prices (i.e., the price suggested by a seller on property websites) classify as revealed data type, revealing preference derived from real market conditions. On the other side, bid price as a data source is on rare occasions unveiled, only in foreclosures and governmental tendering, and is subject to bargaining. More specifically, the bid price is the price a purchaser is inclined to pay for a property and is thus considered a stated preference data type (Glumac & Des Rosiers, 2018). Stated preference data involve measurements of preferences obtained in a survey or experiment. Thus it is considered "stated" rather than "revealed". Finally, combining stated with revealed data, named combined preferences, is another, accepted way of assessing the eagerness to pay.

Most of the academic literature related to AVMs and most of the existing AVMs are making use of sales prices as a data source to estimate property values. In some situations, mainly when there is no sales’ price at one’s disposal, the asking price is employed to estimate property values. There is an apparent trade-off, though between these two data sources. Listing information, namely asking prices, have the advantage of being current and up to date, but they are "biased" since they are subject to bargaining. On the other hand, transaction data, namely sales prices, are the most credible indicators of market values, but they may only be available with a delay (R. Schulz et al., 2014). Also, other approaches depend on the cost of construction or the price of the rental of the property to estimate market value. Depending on the expected coverage of an AVM, a handful of local data providers may be needed. Of course, no matter what the data source, accurate and detailed property characteristics, and local geographic variables should be available for training the models.

2.2.2 Variable Selection

As mentioned above, the second stage of AVM development, model specification and validation, also includes the choice of the variables to be used as input in the model. Variables' selection is crucial in the quality of estimations. Property prices' growth or devaluation in a specific region is affected by a combination of legal, social-economic, and environmental aspects that regularly interact across space and time (Grigsby, 1986). Revealing all aspects that determine property prices is not easy and requires identification and potentially broadening of the mentioned dynamics. In that sense, for instance, fiscal policies, such as tax reduction incentives, which government imposes, as well as demographic changes, such as population growth, influencing supply and demand of dwellings, significantly reflect on property prices. Of course, one of the most outstanding aspects, undoubtedly influencing the estimation of property value, is the property itself, which can be further broken down into locational and structural characteristics. On the locational characteristics, property's accessibility, view, and closeness to amenities, such as school, public transport, and other local services, can be mentioned. On the structural characteristics of the property, some frequently used attributes are the number of bathrooms, the number of bedrooms, the building's age in years, square footage, overall condition, and quality of construction. The two latter variables are quantitative variables usually represented on a Likert scale of 1 to 5 (Bellotti, 2017; Bogin & Shui, 2020). In many times, indirect variables stemming from property characteristics may be used, such as the square foot of lot size or living area multiplied by a quality index (International Association Of Assessing Officers, 2003).

One of the critical parameters, though, that needs to be defined before identifying any other parameter, is the object of appraisal per se. AVMs can be applied to any property's type as long as there is enough information for the property and the market in question. Although not genuinely a variable, the type of property poses significant differentiation among AVMs. Therefore, AVMs designed at estimating land values should be discriminated from AVMs designed for real estate property values. Additionally, AVMs for real estate may concern and be broken down accordingly into residential and non-residential, such as offices and commercial buildings, real estate properties (Glumac & Des Rosiers, 2018). In particular, the first AVM systems concerned land properties since land is usually much more homogeneous than the other real estate types of property. The downside is, though, that land appraisal has also to deal with the low number of sales for analysis and modelling. Following land property type, residential real estate property tends to be more homogeneous than commercial property. This fact may also be considered to be an explanation for the popular and extensive design and use of AVMs, particularly for real estate property. Residential real estate appraisal is frequently divided into appraisal for detached and attached residential property. As detached, self-standing buildings on an individual land plot are considered, while attached considers constructions where various living components are united on distinct ownership forms. To this category, many types of property belong, such as terrace houses, condominiums, apartments, and semi-detached houses. The primary differentiation of the two categories is their land-to-building ratio, and this is the reason why they are usually mentioned independently. Another residential real estate property type with complexity in its valuation is the manufactured or prefabricated house, where a residential building is constructed in a factory under exact quality standards. This type can be appraised as any other property, as long as the market situation for them is known. In cases, though, where these prefabricated houses are constructed to be mobile, they should be evaluated and modelled differently and independently from traditional houses (Glumac & Des Rosiers, 2018; Glumac & Wissink, 2018).

Finally, when coming to commercial real estate properties, their valuation is even more complicated than in the previously mentioned cases since they are typically obtained to produce income and vary a lot into how they are used. At the same time, data availability is a frequent issue to confront. As an example of the variation in value depending on usage, the advantage of having a sea view can be mentioned. This characteristic would be an excellent advantage for a hotel, but possibly indifferent for a shopping mall. There is currently plenty of literature on the investigation of the different variables that influence non-residential properties' value, either generally or focusing on a specific type such as hotels (Wilmath & Engel, 2005; Zhang, Du, Geng, Liu, & Huang, 2015). The appraisal challenges of industrial real estate properties are quite analogous to those met with commercial properties. The involvement of income generation in both cases poses significant challenges in their valuation (Glumac & Des Rosiers, 2018).

On what concerns the selection of variables for model development, a broad amount of literature is available and, as it turns out, there is a large number of parameters/ variables that play a role in property value. At the same time, their influence may range from low to high. In the work of

(Metzner & Kindt, 2018), the authors have tried to collect, systematise and structure the different value-influencing variables, acknowledging that earlier research has demonstrated a big collection of parameters that either overlap or contradict each other. They concluded to the extraction of 407 parameters from earlier research works, focusing on hedonic valuation, which will be analysed in a following section. In the final list, five levels of parameters are identified and presented, falling into two major categorisation schemes, global or higher-level parameters, and specific or low-level parameters. (Glumac & Des Rosiers, 2018), on the other side, have identified six major categories of variables, or else named, price determinant classes; site (locational and intrinsic variables), environmental, legal (tenure structure), fiscal, socio-economic and demographic classes of variables that affect a property's value.

It is very unlikely that an AVM will have included all the above variables. The important thing is to ensure the inclusion of variables important in value determination and to capture to the best extent actual market relationships (International Association Of Assessing Officers, 2003). The better the variable selection, the most successful the design of the AVM will be, which is something that requires, though, skilled analysis. Appropriate variable selection is also giving the possibility for measuring the impact of each variable/aspect in determining property prices. By including and excluding the various variables from the model, their marginal contribution to value can be estimated with reliability. In that view, a governmental body will be able, for instance, to measure the extent to which the implementation of a specific expensive policy measure will impact land property values and decide whether it is worth proceeding with it or not. In this regard, it can be stated that making a sophisticated selection of aspects/variables that play a determinant role in property prices is challenging and not always possible (Glumac & Des Rosiers, 2018).

2.2.3 Specification and Development of AVM Models

Every appraisal, either for one property or mass appraisal, employs a model, which is, a description in words or a mathematical function depicting the relation between value and variables which represent factors of demand and supply. This description from SMARP shows the role of models in mass appraisal (International Association of Assessing Officers, 2017). Model specification is an essential process for the determination of the structure of the price estimation model. These are the core of the AVMs process, driving the accuracy and credibility of the estimation. Therefore, apart from the aforementioned necessary process of choosing the variables to use in the model, the type of model to be applied should be determined carefully by the market analyst (International Association Of Assessing Officers, 2003).

The simplest models that exist and may claim to be AVMs are probably the ones that have only a time component, just tracking changes in property values over time. These models can be useful in updating previous sale or value estimates to the target appraisal date. There is, however, an abundance of different and much more complex price estimation models and their classification is not a straightforward task. (Glumac & Des Rosiers, 2018) attempted the creation of taxonomy and classification of the various approaches. They suggested that resulting in an ideal mutually exclusive hierarchical classification, where each AVM belongs only to one method and approach, would not be realistic.

As a first-level classification of the AVM methodologies, a classification of the different approaches can be mentioned, before deepening on the various model calibration methods that are met in the literature. In the recent work of (Glumac & Des Rosiers, 2018), a classification of the different approaches was considered from two different perspectives/dimensions; the inclusion and management of uncertainty and the traditional grouping of valuation. Regarding the former, the approaches can be either probabilistic, non-probabilistic, or deterministic ones, i.e., not including the aspect of uncertainty at all. The first AVMs belonged to the deterministic approaches, with construction cost estimates being a characteristic example. When the aspect of uncertainty is, though, included and dealt with, approaches making use of probability theory are the most prevailing, firstly introduced with the hedonic models analysed below. At the same time, non-probabilistic approaches have also been considered in many cases, such as approaches relying on fuzzy set theory (Kuşan, Aytekin, & Özdemir, 2010) or artificial intelligence (Rossini, 2000).

Regarding the most traditional grouping of valuation approaches, AVM models are set up based on one or more of the three approaches to measure value: ***cost, income,*** and ***comparison approaches*** (Gloudemans, Almy, & International Association of Assessing Officers., 2011). The **cost** approach, which was the first to be introduced, depends on the existing cost tables which should be adopted to the local market and requires separation of land and building values (International Association Of Assessing Officers, 2003). The cost approach applies to both residential as well as non-residential, such as industrial, properties. According to this method, the assumption is made that the price a purchaser is willing to pay for a specific property is equal to the sum of the land's price and the construction costs, subject to depreciation. This method, when applied on new properties, which are not subject to substantial depreciation, can be accurate in its estimation of their market value and is usually exploited for the estimation of the property's insurance as well as for assets that are not expected to produce income and are single-use, such as detached single-family houses, schools, and churches. It is also applied to specific industrial buildings that are rarely put up for sale. It consists of two general methods: the most frequent one is the replacement method, which considers that the new property offers an equivalent utility with a new design and materials, and the reproduction method which assumes that an identical copy of the property is built, such as a historical building. A significant advantage of the cost approach is the fact that it applies to any property independently of its age, size, style, or condition, and its efficiency and trustworthiness are linked to the ability of the involved analyst to determine the value of the location, the land, and the depreciation. The cost approach does not depend on having an active real estate market of similar properties. On what concerns commercial and industrial cost models, they are much like residential cost models, and they are mostly used for properties of commercial/industrial use when there is little income and sales information.

Income-producing real property is usually obtained for the interest to earn future income. This concerns mainly industrial and commercial properties, as well as secondly land, rented or leased. The appraiser assesses this **income** for quality, quantity, duration, and direction and afterwards translates it using a suitable capitalisation rate into an expression of market value (International Association Of Assessing Officers, 2003). The basic overall direct capitalisation formula or formula using gross income multipliers or gross rent multipliers are the most frequent income approach methodologies. Discounted cash flow (DCF) analysis is also frequently used. According to the direct capitalisation method, a property's market value is acquired by estimating the Overall Cap Rate (OCR) and continuously capitalising on the property's yearly net operating income at this rate. The overall capitalisation rate (OCR) is defined as an income rate for the property in total, reflecting the relationship between the expectancy of a single year's net operating income and the property's value/price[21]. OCR is determined according to the property type (use, quality, management, state), the location and the time in question. It is typically calculated as the average of net-income-to-sale-price ratios for a collection of similar properties, or as a weighted average of the cost of borrowed capital and the cost of equity capital, declared as the ratio of the first year before-tax cash-flow to initial down payment. The direct capitalisation method mainly applies to properties that produce secure and foreseeable income flows through time, usually standing for commercial real estate investments. Direct capitalisation is a method mostly met in the literature in the '90s (Eppli, 1993; Martin, 1993).

In contrast with the direct capitalisation method mentioned above, which is most appropriate for properties with stable income flows, the discounted cash flow (DCF) method is mostly suggested in the cases of more complex properties. An example of such a case is the case of multi-use

[21] http://www.pmea.ca/en/938-overall-capitalization-rate-ocr.html

commercial properties, with highly varying income flows which can even alter from positive to negative from one year to another. In order to apply the method, all future cash flows are appraised and depreciated by using the cost of capital to give their present values (PVs). The sum of all future cash flows, both incoming and outgoing, is the net present value (NPV), taken as the value of the cash flows in question. The market value of a property or current investment corresponds to the debt part of the investment along with the present value (PV), over a specific investment horizon, of the annual cash flows generated by the property from both disposal and operations. The result of this is capitalised by the market discount rate for that type of property (Glumac & Des Rosiers, 2018). On the disadvantages of the DCF method compared to the direct capitalisation method, the necessity for a large amount of data to develop yield capitalisation estimates can be mentioned. Furthermore, another disadvantage is the fact that the method is based on several assumptions (e.g. anticipated yield, holding period) which do not easily result from the market and thus render the method and its results subjective. As in the case of direct capitalisation, DCF in appraisals is mostly met in the literature in the '90s.

Finally, the **comparison** approach applies either a ***direct real estate price comparison model***, using appropriate adjustment and specification techniques, or ***a process of two steps***. According to the latter, similar real estate properties along with their prices, are detected and selected, and they are then adjusted to the target property. The direct market models, also referred to as hedonic models, assume that the price of an asset at the market is linked with its characteristics or the services it offers. According to these models, in the case of a house, its price reflects its characteristics, such as location, condition, and size. Thus, we can assess the house's individual characteristics by examining the price buyers are willing to pay to obtain them. According to the direct market method, a single model is specified and calibrated to estimate properties value. These models come in three different types: the additive or linear models, the multiplicative models, and the hybrid or nonlinear ones. The differentiation of each type is related to the way the variables' contribution is introduced into the model. In the additive model, variables' contributions are added together in the model, while in the multiplicative model, they are multiplied. Finally, in the hybrid model, some variables may be added, and others multiplied into the model. The choice of the type to be used is mainly based on the experience and expertise of the analyst as well as the property's type to be evaluated. However, from the three types mentioned above, additive models are the most prevailing, for reasons of both tradition and existence of related software. On the contrary, hybrid models are the least used since they require more complex software, which is limited. However, they are the ones that could best reflect the relationship of the actual variables towards price estimation for the real estate market (International Association Of Assessing Officers, 2003).

In the ***two-step process*** (it can also be encountered as an "appraisal emulation") method, there are two models developed. The first is used to detect comparable sales and the second to make adaptations to accommodate differences between the selected comparable sold properties and the subject property. In this context, the first model needs to determine which properties are and which are not comparable. For that, it usually needs to include a weighted selection model, such as the application of regression coefficients or the measurement of a dissimilarity measure (e.g. Minkowski or Euclidean metrics), or else apply cluster analysis. Many AVMs rely on the efficient identification and summarisation of all recent sales within a specified radius of the subject. The second model has to do with the inclusion of the data items that are important for the estimation of value and is the one that makes the necessary adjustments of the identified comparable sales to the subject property for their characteristics that are different from the subject. From a mathematical viewpoint, just two sales are needed to make the adjustments; one that has the attribute in question and one that does not have it. Then, the difference in the sales price of the properties is considered to be the market value of the missing feature. It needs to be noted that sales comparison methods that use quantitative methods, such as direct market models, to make the adjustment, are much more trustworthy than simple pair analysis.

For the comparison, not only regular sales prices are considered, but also other types of real estate price data to approach real estate value, such as data from asking prices, biding prices, and real estate transferred prices (Glumac & Des Rosiers, 2018). One of the advantages of this approach is the fact that comparing a subject property with properties with similar characteristics that have been sold is an understandable notion for the consumers. On the other hand, although this method works well in areas with properties with common characteristics and frequent sales, it does not work just as well in areas where the selected comparable sales have considerable differences in their characteristics, and therefore a lot of questionable adjustments need to be made. Furthermore, especially for commercial and industrial properties, the amount of data of sales prices available is usually insufficient to identify commercial and industrial comparable sales and build the models (International Association Of Assessing Officers, 2003).

In Figure 15, the two different dimensions for classifying AVM approaches, i.e. valuation and uncertainty approach, are depicted. An AVM may belong to one AVM valuation approach and one AVM uncertainty approach, but their combination is not restrictive, as seen in Figure 15. In the following section, the most prominent methods used in the automated valuation of real estate properties are analysed. Each method can be, however, enclosed within one or more cells of the 2-tuple approach of Figure 15.

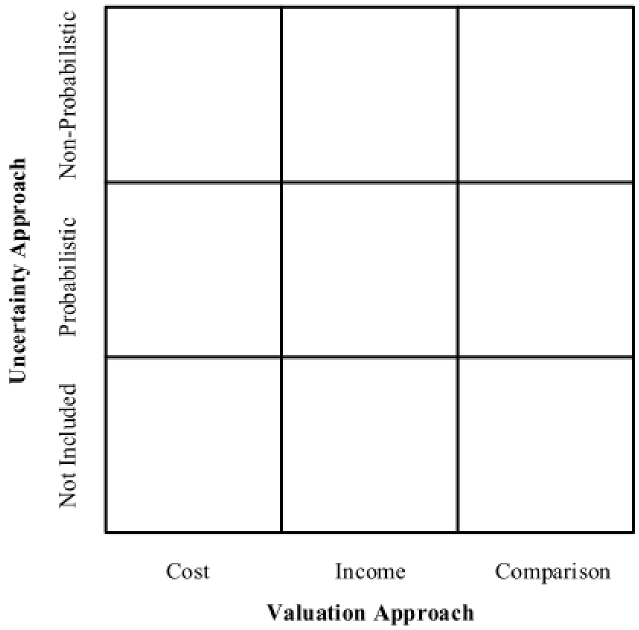


Figure 15 Nine 2-Tuple Automated Valuation Approaches (Glumac & Des Rosiers, 2018)

2.2.4 AVM Calibration Methods

After specifying the model to be used, the calibration of the model needs to follow. Calibration is the process for the determination of the coefficients of the variables in an AVM as well as which variables should be kept or removed due to statistical insignificance. It is a statistical technique, and there are a lot of different statistical tools that can be employed for calibration as well as testing its quality. Knowledge of statistical analysis and the relevant software is needed to ensure the appropriate application of these tools. Model calibration is an iterative process that stops when specified statistical diagnostics are met.

Calibration is a necessary step that ensures the accuracy and credibility of the AVM appraisals. Many methods can be used for that purpose. Under this section, the most frequent AVM calibration techniques for model development are presented and analysed. It needs to be highlighted, though, that despite the significance of the calibration technique to be employed, the analyst's expertise and skills play an equally important role, along with data quality, towards the development of a trustworthy, accurate AVM.

Hedonic Regression and Multiple Regression Analysis

The hedonic price method, also mentioned before, as a model specification technique, refers to all AVM applications that consider the property's price directly dependent on its spatial and property-specific attributes and their implicit value. Empirical applications of the hedonic price method (HPM) date back to the late 1930s (Court, 1939), but its concept officially occurred in the early

1970s (Rosen, 1974). According to the hedonic price theory, the price of a complex asset, such as a house, expresses the utility that derives from its characteristics. These correspond to a value that is implicitly provided by economic agents working in a stable market. These implicit prices are called hedonic prices and are introduced by differentiating the hedonic function towards each characteristic of the asset (Glumac & Des Rosiers, 2018). Therefore, each individual characteristic has a different influence (i.e., a partial effect) on the level of the derived price and thus the value to be requested. The hedonic price theory accepts that goods/assets are not homogeneous and do not have a uniform value, but instead that their value derives as the sum of the partial values of their various characteristics (Lancaster, 1966). In this context, properties can be seen as different combinations of advantageous, heterogeneous characteristics, differing in price and quality (Metzner & Kindt, 2018).

Therefore, the appreciable purchase price arises as to the sum of the implicit prices of the respective property's characteristics or the instinctive general gains communicated as the purchase price (Rosen, 1974). The coupling of property characteristics with the purchase price is done using the hedonic price function, as follows:

$$P = f(x_1, x_2, \dots x_n),$$

where P is the dependent variable, and x_1 to x_n are the independent or explanatory variables (Boyle, 1984). The final hedonic valuation model, which is the one that determines the values, as seen in Figure 16, comes as a result of a lot of repetitive optimisation steps (Maier & Herath, 2015). For the determination of the model, the independent variables must be linked with coefficients and data sources.

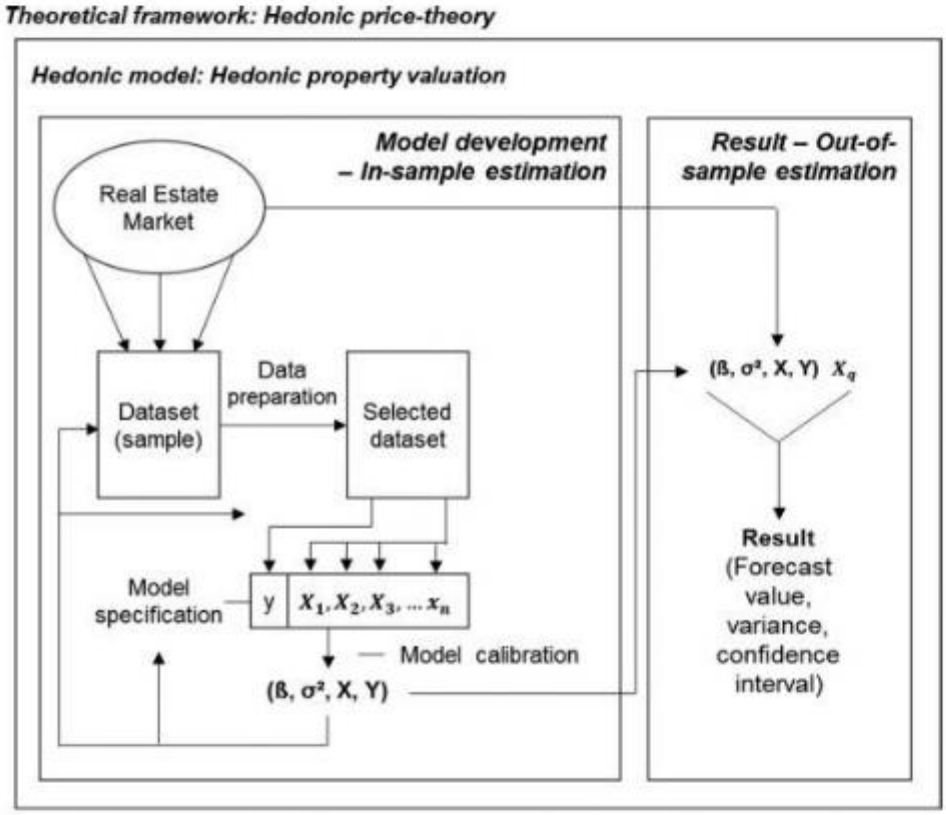


Figure 16 Development of a hedonic assessment model (Maier & Herath, 2015)

According to (Metzner & Kindt, 2018), calibration of the hedonic model is followed by measurement of its explanatory power and then always its iterative adaptation until its optimisation and the final hedonic valuation model. Then the model should be validated by using new data (out of sample). It is important to note that the hedonic valuation function is developed progressively and is the outcome of many iterations. So specific steps for the determination of the model, mainly the ones referring to tests and optimisations, will have to be repeated several times.

The calibration of the hedonic price model is done statistically. Multiple linear regression analysis (MRA) prevails as the most popular econometric method for the application of the Hedonic Price Model, where the regression coefficients that derive from MRA correspond to the hedonic prices of the characteristics of an asset. MRA is a statistical technique for the prediction of the value of a real estate property, based on two or more related features/characteristics, i.e. the independent variables (McCluskey, McCord, Davis, Haran, & McIlhatton, 2013). Since the objective of mass appraisal is to appraise many properties, being able, at the same time, to explain the valuation results to the public, user-friendly and time-saving operation and uncomplicated comprehension are needed. When the relevant data of the appraisal target are collected, the straightforward method is to investigate the relation between the appropriate features, such as the number of bedrooms, the location and the age of the building, and the associated property value (Wang & Li, 2019).

In that view, what hedonic regression does is that it fits observed transaction prices on property's characteristics. Once the model is fitted, the derived hedonic function may be used for the prediction of a property's market value based on its characteristics. To do so, hedonic regression analyses and evaluates recent sales concerning the resemblance of the target house and the transacted one. This fact is why hedonic regression is considered to be a branch of the sales comparison approach (R. Schulz et al., 2014). MRA, however, can also be utilised to adjust different parts of the income approach, along with the assessment of market rents and the extraction of income multipliers and capitalisation rates (International Association of Assessing Officers, 2017).

Since its ensuing academic recognition, the hedonic price model has expanded to several fields of the social sciences, namely housing economics and real estate. It is used for calculating various types of urban externalities (Des Rosiers, 2012) and for producing price indices (Diewert, Saeed, & Silver, 2009). Hedonic models have a formal structure, and they are a stable, trustworthy, and robust method to both explain and predict market values. This is the reason why the Hedonic Price Model growingly gained popularity over the past few decades, and current AVMs are mostly based on it (D'Amato, 2017; Downie & Robson, 2008). Therefore, hedonic prices, deriving in most cases from actual transaction prices, may well express both the willingness-to-pay of the purchaser as well as the willingness-to-accept of the vendor for each individual characteristic of the asset.

On the advantages of the hedonic price model, its reliability regarding the obtaining of estimations of the market value of the property itself as well as of its individual, respective characteristics can be mentioned. However, on its limitations, the dependence on big datasets that should be of high quality cannot be overlooked. This dependence may be a problem, mostly, when market transactions are too rare from both a time and space perspective. Furthermore, the hedonic price theory assumes that hedonic prices only indicate the influence of externalities on a given property at a given time and space, as this is perceived by economic operators, which may be proved invalid. Finally, disregarded control variables may, in a specific spatial context, cause in the model autocorrelation or heterogeneity, thus undermining the interpretation of regression coefficients. This problem can be mitigated, though, by using spatial models.

Artificial Neural Networks Methods

Artificial neural networks (ANN) are one of the most prevailing approaches in pattern recognition and machine learning, inspired by the biological neural networks that form human brains. They aim to approach human-level performance on various tasks, based on examples. A neural network is a collection of simple entities, named neurons or nodes which are connected by edges, named synapses. Each neuron uses an activation function $X = \sum_{i=1}^{n} x_i W_i$, where x_i refers to the neuron's input signal, which can be either raw data or the output of another neuron, and W_i to its associated numerical weight. Then, each neuron has an output signal Y, which can then be either the final solution of the network or input to another neuron. The neural network is typically made up of an input and an output layer and at least one more layer of neurons, known as the hidden layer. An ANN "learns" through a lot of iterations and consequent repeated adjustments of the weights (Negnevitsky, 2005). One well known and widely used type of ANN is the multilayer perceptron (MLP), a feedforward network that is trained in a supervised manner. ANNs are gaining popularity for their use, among others, as a better alternative to regression analysis when new functional forms should be modelled.

In real estate appraisal, ANNs have been considerably used for different types and applications of appraisal (Demetriou, 2017; Mimis, Rovolis, & Stamou, 2013; Rossini, 2000). In (Mimis et al., 2013), in particular, the dataset has been enhanced by the use of Geographic Information System (GIS) to better model the spatial dimension and have revealed the non-linear relationship of the property's price concerning floor space and age.

Recent research has suggested that the ANN approach is, in many cases, better than that of the hedonic price model and the traditional multiple regression analysis used (Abidoye & Chan, 2018; Mimis et al., 2013), since it can deal with non-linear relationships. Other studies also suggest that neural networks and other probabilistic approaches demonstrate a comparable accuracy in terms of predictive power (Glumac & Des Rosiers, 2018). In any case, the ANN approach's predominance is further strengthened when a big dataset is used. On the advantages of ANNs, its flexibility, its adaptation to volatile environments, and its ability to generalise unobserved situations and deal with fuzzy and noisy data should be highlighted.

On the other hand, an acknowledged disadvantage of ANNs is the lack of transparency on the ways the model's weights are related to the price. This fact also justifies the reference to them in the literature as 'black boxes'. It indicates that the resulting appraisal model is ambiguous, lacking explanatory power that would give the possibility to advocate the predicted values against any concerns (Mccluskey, Davis, Haran, Mccord, & Mcilhatton, 2012; Mimis et al., 2013). (Mccluskey et al., 2012) have also extensively examined the efficacy of the ANN methodology within the real estate sector and have raised several issues on their applicability within the mass appraisal environment, demonstrating that ANNs, though useful as tools for prediction, also have limited practicality for the evaluation of properties. They are still, though, the most popular of the AI-based models in mass appraisal (Abidoye & Chan, 2017; García, Gámez, & Alfaro, 2008; Zhou, Ji, Chen, & Zhang, 2018).

Fuzzy set theory and other rule-based models

Uncertainty inherently exists in real estate appraisal, which may affect the accuracy and stability of the resulting model. The fuzzy set theory aims to treat fuzziness and ambiguity that emerges when the human factor is introduced inevitably in valuation. Fuzzy logic, which is a subset of the fuzzy set theory, deals with degrees of membership and truth, and therefore allows any logical value in the range between “0” and “1”, in contrast with the classical Boolean logic that takes two values, either “0” as entirely false or “1” as entirely true (Negnevitsky, 2005). It comprises fuzzy sets, such as “near” and “far”, to capture human knowledge and the shape of these sets, such as “very” and “quite”, to embody language ambiguity. Rule-based approaches for assessing a property based on specific characteristics, for example, the distance to the central business district, is part of fuzzy logic (e.g. high value for the property, if the distance is near).

(Byrne, 1995) was one of the first to introduce fuzzy logic in the analysis of real estate, followed by (Bagnoli & Smith, 1998). After that and until today, fuzzy logic models have been developed and presented in the academic literature for the appraisal of residential and commercial properties, as well as land (Kuşan et al., 2010; Zhang et al., 2015). Rough set theory (RST) falls into this category as well. In real estate appraisal, RST allows for the running of the real estate appraisal model without taking into consideration the indicators that have an impact on the value of the property (Alcantud, Rambaud, & Torrecillas, 2017; D’Amato, 2007; Del Giudice, De Paola, & Cantisani, 2017; Gonzalez & Formoso, 2006; Lasota, Telec, Trawinski, & Trawinski, 2011).

What fuzzy set theory does is to introduce the human way of thinking and reasoning in real estate appraisal through simple mathematical forms. Fuzzy set theory is particularly appropriate when data available are either not a lot or imprecise. One of the main advantages of fuzzy logic is its simplicity compared to the complexity of the situation it is dealing with and compared to the other models used. Fuzzy logic is rule-based, capturing effectively and in a quantitative way, the ambiguous rule of thumb that expert appraisers are using for making their decisions on properties’ value. This has, as a result, an impact on the much looser data requirements. On many occasions, fuzzy logic is used along with other approaches for the design of the independent variables of the system (Thériault, Des Rosiers, & Joerin, 2005). However, fuzzy logic’s main disadvantage is that it usually introduces subjectivity in AVMs and consequently erroneous property appraisals. The creation of rules based on statistics and empirical evidence may limit subjectivity and thus, model’s inaccuracy.

Other AI-based models

There are many other kinds of AI-based models that have been applied in the real estate mass appraisal with good accuracy results. However, they are not as much as the previous ones referenced in academic literature. Tree-based models, such as decision, random forest and boosted trees, are well used for both classification and regression. Regarding decision trees, two are the most prominent ones; M5 and MARS (multivariate adaptive regression splines). M5 is a model trees algorithm that predicts continuous variables for regression and is then optimised by combining the decision tree with linear regression at the nodes. MARS, on the other side, is a non-parametric regression decision tree (Reyes-Bueno, García-Samaniego, & Sánchez-Rodríguez, 2018). A random forest can be considered an ensemble learning model, integrating many decision trees into a "forest", running efficiently on large datasets and dealing with input variables without deleting any. (Antipov & Pokryshevskaya, 2012) proved its value, demonstrating the best performance in comparison with other models. A boosted tree is claimed to achieving even better accuracy and running speed than the random forest alternative (William McCluskey, Zulkarnain Daud, & Kamarudin, 2014). However, the main limits of these models are the lack of transparency and difficulty of translating variables' importance into quantitative measures. Hierarchical models, called Hierarchical Linear Model (HLM) and Hierarchical Trend Model (HTM), have also been used in real estate appraisal. They are useful because they take into consideration the hierarchical structure of the data. It has been found that HTM parameters have a lower estimated variance than OLS (Arribas, García, Guijarro, Oliver, & Tamošiūnienė, 2016). Cluster analysis methods are also extensively used in real estate appraisal and the construction of valuation models as a data pre-processing step, enabling to conclude from a heterogeneous real estate market to homogeneous submarkets. Then, cluster analysis approaches can be classified in different types, such as hierarchical clustering or fuzzy-based clustering (Calka, 2019; Gabrielli, Giuffrida, & Trovato, 2017). Other AI-based models that can be met in the literature for real estate mass appraisal are also Support Vector Machine (SVM) (J. H. Chen, Ong, Zheng, & Hsu, 2017), for linear classification purposes, Genetic Algorithms (GA) that searches the best solution through simulation of natural evolution (Morano, Tajani, & Locurcio, 2018), and Data Envelopment Analysis that is used for the evaluation of the value range for real estate units (Lins, De Lyra Novaes, & Legey, 2005).

GIS-Based Models

Spatial information is directly and intrinsically linked with real estate. A property's value is formed as a result of both its spatial and non-spatial characteristics. In that view, many studies in the academic literature have examined the impact of GIS attributes on real estate appraisal and have developed models that incorporate and highlight that dimension (Bourassa, Cantoni, & Hoesli, 2007; García et al., 2008; Lake, Lovett, Bateman, & Day, 2000). These models, in most cases, build upon other traditional AI-based models and incorporate the spatial dimension concluding to new updated models. The most popular of these models is the Geographically Weighted Regression (GWR) model. According to this model, the local spatial dimension is integrated into the linear regression model, enabling to identify and expose spatial non-stationarity. GWR offers a way to examine regression analysis per location, compared to the classic MRA, which provides a global regression model. GWR is easy to use and to explain its results. It can also be used solely for parameter estimation. Its accuracy and superiority compared to other models for appraisal, have been proven by different studies (T. Dimopoulos & Moulas, 2016; Lockwood & Rossini, 2011). (T. Dimopoulos & Moulas, 2016), in particular, have applied GWR in the Greek real estate market, demonstrating its better results compared to the Ordinary Least Squares (OLS) model. (McCluskey and Borst 2011) use GWR to reveal the need for real estate market segmentation in mass appraisal. A modification of this model is also the Geographically Weighted Principal Component Analysis which introduces geographically weighting for submarket division with traditional Principal Component Analysis, enabling to take into account both spatial proximity and homogeneity and features similarity (Wu, Ye, Ren, & Du, 2018).

Another category of GIS-based models that are frequently met in the literature is the spatial auto-regressive models (SAR) which are modification and improvement of the traditional MRA model, considering spatial dependence. The spatial error model (SEM) and the spatial lag model (SLM) are the most known of these. SEM considers the spatial dependence of the error terms, according to which the error caused by a property is dependent on the error of its neighbouring ones (Uberti, Antunes, Debiasi, & Tassinari, 2018; Zhang et al., 2015). SLM, on the other side, consists of a spatially lagged dependent variable of the regression model. According to the mode, a property's price is dependent on the prices of its neighbouring ones (Anselin, 2002). (P. E. Bidanset & Lombard, 2014) have compared the performance of SLM with GWR and have found that SLM has a higher coefficient of dispersion than GWR. Finally, the Location Value Response Surface (LVRS) model can be mentioned which allows for the identification of a spatial correlation between variables and can be related to classical spatial interpolation methods (D’Amato, 2010).

Other methods and models

As mentioned before, numerous different methods and models have been applied in mass appraisal and the development of AVMs. Therefore, their complete recording, as well as their classification, is neither easy nor straightforward. (Glumac & Des Rosiers, 2018) and (Wang & Li, 2019) have recently attempted to provide a review on automated, mass appraisal systems, concluding to a different categorisation and documentation of the field and the different, available models. Here, a reporting of the most prominent ones was attempted, which is, therefore, not considered to be exhaustive. Indicatively, other models that could deserve mention at this point, since they are also well met in the literature are the Adaptive Estimation Procedure (AEP) and the Discrete Choice Method (DCM).

The first is meant at handling the issues of changeable economic phenomena across time. Most models based on long term data consider that the coefficients of the independent variables are fixed. In most cases, though, the behaviour of economic agents tends to change with time, rendering the coefficients outdated. Other methods to address this, such as market segmentation, does not consider structural changes that may arise at any point. The AEP framework considers a feedback framework according to which the predicted market response, which derives from some response model (other methods, such as the ones mentioned before, are applied to result to it) at time t-1, is compared with the actual response. Then the resulting error is fed back to the system, and the parameters of the response model are being adapted accordingly. The new model is then used for the next estimation at period t+1 (Carbone & Longini, 1977). AEP has a meaning only if applied along with MRA within a hedonic approach, on which case it offers an additional safeguard towards AVM's robustness.

The Discrete Choice Method (DCM) is applied to ensure that a choice is representative of a particular person's behaviour, while also avoiding the necessity of collecting real choice data (Breidert, Hahsler, & Reutterer, 2006). The underlying theory of DCM is the random utility theory, assuming that people will always make a choice, among alternatives, with the highest utility. For the estimation of DCM, a maximum likelihood estimation is frequently used. In real estate, it can be used to measure the willingness to pay (WTP) for each attribute of the property, which is especially useful when there are not enough real market or revealed data. DCM is, however, usually subject to hypothetical biases, resulting in an overestimation of the willingness to pay, which should be taken into account.

Hybrid models

Although the different types of models were presented separately until this point, every method can be combined to form a hybrid model for property appraisal. Three different ways to come up with a hybrid model can be identified. The first is for the model itself to adopt hybrid thinking, e.g., (Guo, Xu, & Bi, 2014) integrated elements from a sales comparison and income approach into the cost approach to better the accuracy of the estimation. The second way is to form new hybrid models based on traditional, existing models in combination with AI and GIS methods. In most cases, these combinations result in better models, such as the fuzzy clustering (Gabrielli et al., 2017), the combination of ANN and GIS (García et al., 2008), and the combination of support vector machine and decision support system (Lam, Yu, & Lam, 2009). Then, the third way is to associate traditional models with new, innovative perspectives. (Z. Chen, Hu, Zhang, & Liu, 2017), for instance, added to the traditional real estate data, additional real-time market information from the feedback they got from an online crowdsourcing initiative, enabling better, closer to the market evaluation results. In general, each hybrid model is formed to overcome a particular practical issue of the traditional model, such as the handling of missing data, the improvement of its robustness, and the enhancement of its explanatory power. However, attention should be paid on hybrid models, since propagation of errors from one model to the other may occur, making it more challenging to identify and manage them.

2.2.5 AVM Service Provision

As mentioned before, after data collection (section 2.2.1) and model development (sections 2.2.2, 2.2.3 & 2.2.4), the third stage of an AVM development refers to the technical implementation of the service. This service may either be a desktop application providing estimations in real-time or an online system, which is even more challenging to offer.

An important determinant for the provision of the service is the identification of the intended end user. Of course, this should be decided and clear before starting AVM development. However, it is a decision affecting this stage since the type of the intended end user differentiates the service offering. AVMs have been very much used in practice by various types of end users, which can be categorised into individual end users, corporate end users, and public authorities (Glumac & Des Rosiers, 2018).

Furthermore, while the primary purpose of any AVM is to offer credible property value estimations reflecting the market at the given time, it is equally important to identify the secondary purpose of valuation which clarifies the use of the AVM and consequently the service to be provided. Various uses of AVMs can be identified in the academic literature. Among these, the most prominent ones are tax assessment (Shenkel, 1970), which was one of its first uses, real estate portfolio risk assessment (Fisher, 2002), and insurance risk assessment, e.g., for monitoring mortgage insurance risk and assessing property’s exposure to floods (Bin, Kruse, & Landry, 2008). Assessing the replacement cost of a structure is also another standard requirement of the insurance market, where AVMs based on the cost approach have been employed. Another critical application field of AVMs is their use as indices for the state of the economy and consequently as a tool for public policy implementation (Hill, 2013). Additionally, minimisation of lending risk, and more specifically, mortgage lending, is one of the most frequent uses of AVM. According to this, lenders and mortgage brokers aim to accelerate the loan decision process, which would typically require weeks to conclude through inspection valuation, to days by using the immediate AVM output (Downie & Robson, 2008). In a similar context, AVM can be used as litigation support, e.g. in the case of a foreclosure, searching for validation of the lending practices (P. Bidanset, McCord, & Davis, 2016).

AVMs have also application to land-use decisions such as land consolidation which includes restructuring of space through land reallocation, taking into account ownership, and land parcel boundaries. AVMs are used here to assess the land value and ensure that all landowners will conclude with properties of nearly equal land value (Demetriou, 2017). Finally, AVMs have also been used, especially in the beginning, in support of real estate investment decisions (Trippi, 1990), as well as in the determination of the initial listing or asking price, appropriate for drawing the attention of potential buyers, which is then subject to negotiations (Demetriou, 2017).

2.3 AVMs and Risk Mitigation

The subprime mortgage crisis has dramatically changed the perception of economic agents about management and investment risks. Stakeholders in the private and institutional property sector are urged to follow strict rules and to be as transparent as possible in their lending decisions and risk management. Towards this goal, analytical tools based on statistics and econometric modelling are more and more employed as systems to contain risk (Des Rosiers, 2012).

Risk management is especially essential in the real estate sector since property transactions are usually taking place on immature, insecure markets with often imbalanced information in favour of the vendor. Property assets themselves, either individually or as part of a portfolio, also encompass many risks. Modern Portfolio Theory admits these different types of financial risks and assumes that an investor will accept more risk only if more reward is expected. The expected return of the portfolio is calculated as a weighted sum of the individual assets' returns. In contrast, the total portfolio risk is calculated as the standard deviation of total portfolio returns (Des Rosiers, 2012).

Therefore, although the financial crisis has gone by, its effects are still apparent in many impaired economies of formerly powerful countries, and valuation tools to support the minimisation of risks are more than imperative. However, the need for accurate and credible valuations should be stressed, since dependence on faulty or improper valuations may cause considerable financial instability in periods of market stress, intensifying the boom-and-bust cycle in real estate and credit prices (Duguay, 2009). Thus, in the real estate sector, investors, mortgage lenders, and other professionals are more and more seeking credibility, accuracy, and effectiveness in such tools.

Towards this goal, statistical analysis is becoming increasingly popular. It is highly employed in research to continually improve real estate appraisal for the management and minimisation of risk, while also providing information transparency. Information transparency gives the user the ability to explain the extracted results and make adjustments if needed (Des Rosiers, 2012).

In this context, AVMs emerged and gained popularity due to their appropriateness in risk mitigation. AVMs, as analysed in the previous section, are, in most cases, used for the assessment of risk, either this refers to portfolio risk, insurance risk, or lending risk. The employment of AVMs may result in advanced risk management systems since their results are continuously validated, stepping upon statistical analysis. In portfolio risk assessment, AVMs are usually applied to support investors in their decision on the price to offer an asset or group of assets of their real estate portfolio (International Association Of Assessing Officers, 2003). Property insurance companies also need AVMs to assess the risk of a property when offering new insurance.

Assessing the risk of mortgage lending is, though, the most frequently mentioned use of AVMs, saving time to lenders and mortgage brokers from the physical inspection valuation that would typically be needed. Lenders' demand for improved risk management is also believed that will be the main driving force in the evolution of real estate appraisal (Downie & Robson, 2008). Accurate and unbiased property valuation is essential for property purchasers, investors, and mortgage providers to manage credit risk. When giving a loan, mortgage providers should decide, apart from the loan amount, a loan-to-value ratio, which represents, along with the degree of homeowner equity, the credit risk of the loan. This, however, usually comes along with appraisal bias. To address this issue, several research studies have examined the inclusion of automated property valuation as an alternative and potentially unbiased measure of the underlying value of the collateral for the calculation of credit risk (Bogin & Shui, 2020; Calem, Lambie-Hanson, & Nakamura, 2017).

On top of this, another critical advantage of automated valuation is the fact that it does not come up with a single point estimate for each property. It provides a range of possible price estimates instead along with a confidence level on the final result that gives an insight on its uncertainty and consequently its quality and further facilitates credit risk assessment (Bellotti, 2017). An AVM may be used as the first step of a loan origination process to avoid a more expensive physical inspection valuation potentially. Through the use of AVMs, the mortgage provider will be also able to monitor possible changes in the property's value and assess the risk of the mortgage throughout its lifetime. This insight may be used by the lenders to then cater for better customer service facilities, such as re-mortgaging (D'Amato, 2017).

There are many other possible uses of AVMs, such as fraud or negligence detection, that also entail the concept of risk minimisation. In any case, however, any AVM should be tested, prior to its initial use, to ensure that it meets the required accuracy and uniformity standards according to the incumbent risk management policies. For this purpose, statistical diagnostics and ratio studies are required to compare the results of the models with the actual property values (International Association Of Assessing Officers, 2018).

2.4 AVMs in Practice

Given the importance of statistical diagnostics, every research study encompasses a testing phase to validate the accuracy of the proposed model and, in many cases, a comparison of it with other prevailing models in the literature. Several empirical studies have demonstrated that real estate appraisals are apt to being biased upwards, and, in particular, in more than 90% of the time, either verify or surpass the respective contract price (Bogin & Shui, 2020; Calem et al., 2017). (Bogin & Shui, 2020) have shown that appraisal bias is even more frequent in rural areas where over 25% of rural properties are appraised at more than 5% above the contract price.

Despite this fact, the credibility and accuracy of several AVMs that can be found in research studies are well documented in the literature to the extent that they have long permeated the academic sector and have emerged in the actual real estate practices. AVMs are currently and increasingly used in property markets internationally to provide estimates of market value for several public and private sector purposes. As an example, in the United Kingdom, AVMs are employed in around 30% of mortgage originations (Bellotti, 2017; Downie & Robson, 2008). Their use and application, however, vary across the EU Member States.

It is indicated that their primary use is for **portfolio valuations**. In particular, according to (European Mortgage Federation and European AVM Alliance, 2016), in Denmark, Norway, the Netherlands, Sweden, Spain, Switzerland and the United Kingdom, AVMs use for that purpose is wide. AVMs for portfolio valuation are also applied in Greece, Germany, Portugal and Romania, but to a much lesser extent. For Italy, AVMs are a recent introduction (i.e., 2014) and are increasingly used for portfolio valuations (e.g., securitisation, capital modelling, reporting to the banking regulator) and tested for inclusion by several banks. Their applications include, among others, early quality control, portfolio revaluation and risk management. In Romania, AVMs were first introduced in 2012 solely for residential apartments and afterwards for houses too. AVMs, in Romania, are used by banks for the mandatory periodical revolutions and the extent of their use is dependent on each bank and its intended clients.

The following table, Table 2, depicts the various purposes of portfolio valuation that result in AVMs use and the EU countries to which this use applies, as reported in (European Mortgage Federation and European AVM Alliance, 2016).

Table 2 Purposes of AVM use for portfolio valuation on different EU countries

COUNTRIES	PORTFOLIO VALUATION PURPOSES						
	Capital Requirements Purposes	**(a)Covered bond & (b)securitisation transactions**	**Investment Property Funds and Asset Management**	**Risk Management**	**Accounting**	**Property Portfolio Transactions**	**Other***
DENMARK	✓	✓		✓	✓		✓
GERMANY	✓	✓ *(b)*	✓	✓		✓	
GREECE	✓						
ITALY	✓			✓		✓	
THE NETHERLANDS	✓	✓	✓	✓	✓	✓	✓
NORWAY	✓	✓ *(a)*		✓			✓
ROMANIA				✓			✓
SPAIN	✓						
SWEDEN	✓	✓	✓	✓	✓	✓	
SWITZERLAND	✓	✓	✓	✓	✓	✓	✓
THE UK	✓	✓		✓		✓	✓

**Other accounts for: reporting and LTV monitoring purposes (Germany), Asset Quality Review (the Netherlands), arrears management, provisioning and reporting (Norway, the UK), quality control (Romania), promotional activities (Switzerland)*

It needs to be stressed, though, that along with AVMs, other techniques are also used for portfolio valuation, such as index-based valuations. According to (European Mortgage Federation and European AVM Alliance, 2016), in Greece, indices are used primarily for revaluation purposes. In Italy, since there were no alternatives (at least until 2016, the year of the reporting), House Price Indices (HPI) are the traditional approach.

Apart from the use of AVMs for portfolio valuation, other applications of AVMs can be mentioned, such as the provision of initial value at mortgage origination and quality control concerning different types of valuation (also referred to as “second opinion”). In many EU countries, specifically Denmark, Germany, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK, AVMs are extensively used to define property values for many purposes besides portfolio valuations. Other EU countries are also using AVMs for purposes other than portfolio valuations but to a relatively minimal extent. These countries are mainly the Czech Republic, Greece and Romania. In Roumania, though, AVMs use has enhanced lately by some small banks, but not for mortgage origination, the use of which for that purpose is forbidden.

Table 3 showcases the EU countries for which other uses of AVMs besides portfolio valuations are met. As an example, in Denmark, new mortgage loans are generally granted through physical inspection valuations. However, individual mortgage banks may allow valuations without inspection in chosen areas if the models have been validated and proven accurate. In Greece, AVMs are principally used to revalue residential properties in retrospect after a first valuation through on-site visits by bank professionals. In Italy, the first users of AVMs in 2014 were international banks with Italian branches, but after that, the top 20 banks in Italy started testing AVM models on their portfolios.

Table 3 Other Uses of AVMs besides portfolio valuations on different EU countries

COUNTRIES	OTHER USES OF AVMS (BESIDES PORTFOLIO VALUATIONS)			
	Mortgage Origination: Purchase	**Mortgage origination: Re-mortgaging and equity withdrawal**	**Quality Control in Mortgage Origination**	**Other***
CZECH REPUBLIC				✓
DENMARK	✓	✓	✓	✓
GERMANY	✓	✓	✓	✓
GREECE				✓
ITALY			✓	✓
THE NETHERLANDS	✓	✓	✓	✓
NORWAY	✓	✓	✓	✓
PORTUGAL			✓	✓
ROMANIA				
SPAIN			✓	
SWEDEN		✓	✓	✓
SWITZERLAND	✓	✓	✓	✓
THE UK	✓	✓		✓

*Other may account for (not exclusively): revaluation of properties and parts of a portfolio (Czech R., Greece), re-pricing of mortgage loans (Denmark), arrears management (the Netherlands, Norway, the UK), LTV monitoring (the Netherlands), provisioning, capital modelling, reporting to bank regulator (Norway, the UK), finance valuations for taxation (Portugal), whole loan trading (the UK)

It needs to be noted that individual EU countries (i.e., Denmark, Germany, the Netherlands, Romania and Switzerland) have settled rules and guidance on the use of AVMs. In Romania, for example, a set of Valuation Guidelines issued by the ANEVAR[22] exist, with general suggestions on AVMs use for bank valuations. On the other side, Greece, Italy, Norway, Portugal, Spain, Sweden and the UK have not yet applied such rules, although, for most of them, internal guidelines within banks and professional associations on AVM use exist. For example, in Greece, each bank applies its own internal policies and procedures concerning the use of AVM-like applications. A general, internal rule in Greece suggests that if the revaluation price obtained by an AVM is over 20% the initial property price, the new price generated by the AVM is not considered and physical inspection and valuation of the property by an expert is imperative (European Mortgage Federation and European AVM Alliance, 2016).

[22] Part of Romanian Valuation Standards, http://site2.anevar.ro/

It should be stressed that for the EU countries for which no mention was made, no information indicating AVM use has been found by the time of the study of (European Mortgage Federation and European AVM Alliance, 2016).

Early-stage users are generally restricting their use to portfolio valuation and validation of value at loan origination. The USA, Canada and Sweden, on the contrary, are some of the first countries using AVMs and are now considered established. This fact gives them the confidence needed to expand their use towards second mortgages and sometimes even first mortgages, as well as risk assessment concerning collaterals. However, while established users required many years to reach an adequate level of maturity in AVMs use (e.g., 20 years for the US), early-stage users introducing AVMs in the 2000s (e.g., the UK, Japan) needed much less time, building upon the experience of the other established users. It needs to be stressed, though, that transfer of AVMs and their accompanying knowledge, from one country to another, needs attention, since the models should indicate, and thus adapt to, the country's real estate status and factors affecting value. For example, transfer of models from the USA to the UK, although relatively easy due to their shared language, was found not appropriate since in the UK the value per bedroom is more critical in determining price than the value per square meter. So, providers and bankers looking to expand their activity from one country to another need to also take into account the need for native real estate partners to provide market knowledge, share data and support overcoming language issues if these exist (Downie & Robson, 2008).

2.5 Current Limitations

Despite the AVMs increasing use for cost-effective, dynamic and accurate property valuations, there are several limitations of the existing AVM systems that are also outlined in the literature. One of the most important of these is their dependence on the existence, timeliness and veracity of the data. If there are no sales or other value data, AVMs cannot be used. The availability of descriptive and transaction property data is vital for AVMs and is the main factor preventing their development in many countries (Downie & Robson, 2008). Even if data exist, however, their quality also plays a critical role in AVM reliability. Missing values and incomplete or irregular data may seriously affect their estimations. Therefore, AVMs are most trustworthy when appraising typical properties in solid areas for which their value is close to the median value of the properties' prices in the area. On the contrary, AVMs cannot work for distinctive properties and local markets.

Apart from their availability at the time of the AVM's training, regular data updates are also needed, so that the AVM reflects the current market conditions. AVM valuations indicate a specific time. Past sales data and market trends can be projected over a short period, but the longer the projection, the weaker the credibility of the AVM (International Association Of Assessing Officers, 2003). Furthermore, AVMs have limited ability to capture a property's internal or external condition, e.g., its bettering or deterioration. Although nowadays addition of photographs and qualitative value determinants such as orientation can alleviate this AVMs deficiency, still the need for physical inspection to ensure reliability and accuracy in value estimations cannot be overcome.

One of the main concerns towards more extensive use of AVMs is the risk of inaccuracy. In cases where accuracy is not that crucial, such as the case of a low loan-to-value ratio on a mortgage loan, or when a physical inspection has preceded (e.g., second mortgages), AVMs may be considered adequate. Lenders have, thus, to accept the risk of inaccuracy, over the rapidness and cost-effectiveness of AVMs. This, of course, does not happen in the case of mortgage loans at high loan-to-value ratios, where careful loan decisions have to be taken. Therefore, lenders are, in many cases, creating their own rules as the outcome of the combined consideration of AVM's confidence levels, loan-to-value ratios and credit and capacity assessments (Downie & Robson, 2008). In many cases, impediments in AVMs use are also imposed by each country's regulations, especially on what concerns the lending process. As AVMs mature, though, more countries are permitting their use by the banks in loan origination, at least as a first step before the physical inspection.

Commercial and industrial properties demonstrate additional difficulties in assessing their value since they usually encompass many intangible items that significantly contribute to their price during negotiations, but they are not considered as part of the properties' underlying, actual market value (International Association Of Assessing Officers, 2018). In many cases, these sales prices tend to be regarded as outliers and are left off the analysis.

Given the significance of ensuring AVMs' credibility, most studies in the academic literature have been occupied with the validation of their accuracy. The most shared practice in the literature for assessing the quality and reliability of a developed AVM is to compare the predictive accuracy of the suggested method over another one. On those cases, though, the AVM's intended use is not taken into account, leading to an inadequate validation process (Glumac & Des Rosiers, 2018). Even if, though, the intended use of a property was considered, it cannot be guaranteed that it is also its best use. An analysis of the market may indicate differently, as in the case of improved properties where the improvement does not surpass the land's value. Thus another use of the property may be more appropriate (International Association Of Assessing Officers, 2018). To conclude, it is evident that there is still room for more sophisticated and professional methodologies for AVMs development to ensure their wider use, mainly when they aim to assess risk (e.g. in loan origination) (D’Amato, 2017).

3 Applications of Machine Learning Approaches for the Development of Automated Valuation Models in the Greek Market

3.1 Real Estate valuation and forecasting in non-homogeneous markets: A case study in Greece during the financial crisis

This section introduces an actual automatic valuation model for property valuation, developed using a large dataset of historical prices of properties in Greece during the period 2012-2016. The available data cover a wide range of properties across time and include the financial crisis period in Greece, which led to tremendous changes in the dynamics of the real estate market.

In this context, this section focuses on the comparison of classical statistical tools (i.e. linear regression) and new techniques from the field of machine learning for the development of a reliable automatic valuation model. In particular, linear and non-linear models based on regression, hedonic equations and artificial neural networks are formulated and compared. The forecasting ability of each method is evaluated out-of-sample. Special care is given on measuring the success of the forecasts but also on identifying the property characteristics that lead to large forecasting errors. Finally, by examining the strengths and the performance of each method, a combined forecasting rule to improve forecasting accuracy is applied. The results of this study have been published (A. K. Alexandridis, Karlis, Papastamos, & Andritsos, 2019) and indicate that the proposed methodology constitutes an accurate tool for property valuation in a non-homogeneous, newly developed market.

3.1.1 Introduction

As shown in 2.4, nowadays, big financial institutions are increasingly interested in creating and maintaining property valuation models. Of course, the need for unbiased, objective, systematic assessment of real property has always been critical. This need is, however, urgent now as banks need the assurance that they have appraised a property on a fair value before issuing a loan and also as the government needs to know the fair market value of a property in order to determine the annual property tax accordingly[23]. Furthermore, valuations determined for real properties have

[23] In 2016, Greeks were called to pay seven times more in property taxes compared to 2009, even though they had to deal with a 25 percent drop in GDP and analogous unemployment percentages. Greece is one of the countries with the highest taxation of real estate as a percentage of GDP. According to European Commission figures for 2015, the only countries with higher property taxes are France and Britain. In particular, in Greece, property owners are required to pay taxes that exceed 2.5% of GDP, when in Germany the figure is no more than 0.5%. Citizens of neighbouring countries, such as Italy, Cyprus, Bulgaria and Turkey also enjoy less property taxes.

further significant tax implications for current and new homeowners and must be verified in the courtroom in extreme cases.

Forecasters in the real-estate sector have to take into consideration the unique characteristics of a property market (Hoesli & MacGregor, 2000) such as the heterogeneity, fixed locations, illiquidity, and the absence of a central marketplace. These characteristics make the real-estate market inefficient. For the above reasons, automatic mass appraisal approaches could assist in the science of valuation. This is especially the case in a world where there are increased availability and use of data, and where failure to achieve an opinion of value which takes proper and balanced account of such information and analysis, may result in greater exposure to expensive litigation. As already analysed, AVMs or mass appraisal systems can enhance experts' valuation with data-driven estimates. They can provide model-based valuations for properties using information about the property's location and characteristics, appropriate for risk management and big data analytics. Last but not least, AVMs can be used for the redesign of the appraisal process. The automation features of the AVM can reduce the need for manual data collection and manipulation by the appraiser, while at the same time providing an independent estimated value. The role of the appraiser would be to evaluate the findings of the AVM in light of his own physical inspection of the property, verification of comparables and knowledge of local market conditions.

Although various studies have been published on mass appraisal systems, previous studies focus on large and already developed markets. Furthermore, the analysis is usually based on small samples (less than 500 properties) at a regional level (Brasington & Hite, 2008; Kilpatrick, 2011; Kontrimas & Verikas, 2011; Kuşan et al., 2010; Landajo, Bilbao, & Bilbao, 2012; Narula, Wellington, & Lewis, 2012; Selim, 2009). An exception is the studies from (Peterson & Flanagan, 2009; Zurada, Levitan, & Guan, 2011). Furthermore, (Antipov & Pokryshevskaya, 2012) argue that the existing literature does not take into account model diagnostics. Traditionally, model quality is evaluated by the use of aggregated diagnostic indicators. (Antipov & Pokryshevskaya, 2012) propose a segmentational approach for the diagnostics of mass appraisal models quality. Without such diagnostics, model quality is questionable, since it may give a much higher than average error when objects from particular segments are under consideration (Antipov & Pokryshevskaya, 2012). In this study, presented in this section, the two issues above are addressed.

Firstly, one of the main contributions of this approach is that it builds three mass appraisal systems, and their forecasting power is compared in 4 non-overlapping out-of-sample sets. The systems are based on hedonic characteristics and professional property valuations. Very few papers have examined the accuracy of professional forecasts in real estate (Papastamos, Matysiak, & Stevenson, 2015). The **first** system is linear and is based on multiple linear regressions. The

second system is a novel valuation method that uses spatial information. It is based on similarity measures and geographical distances in order to derive the price of a property using a local regression approach. The **third** system is a non-linear automatic valuation method that is applied based on machine learning. More precisely, an optimised NN is applied in order to forecast real-estate prices based on hedonic characteristics. The NN is optimised in the sense that, in contrast to previous studies, statistical methods are applied to select the appropriate number of hidden units as well as the statistically significant variables. Furthermore, the NN is finetuned using regularisation methods to avoid overfitting.

Secondly, another contribution of this study is that the proposed automatic valuation methods are tested in a new market still at its infancy with lots of unique characteristics. The Greek market is an inefficient, non-homogeneous market governed by lack of information and declining prices due to the recession. At the same time, the properties' characteristics are diverse both at regional and country level, as, for example, differences in urban and rural areas or touristic areas of high demand.

Thirdly, the forecasting performance of the proposed methods is examined in a large data set (over 35,000 properties) in the country level. Given the large size of the data set, significant conclusions are derived about the strengths and weaknesses of each method as well as the dynamics that govern the Greek real estate property market. As this application illustrates, automatic model valuations can be applied to both case-by-case valuations and batch processing of thousands of properties. The importance of checking how well the model performs in different segments of data is also highlighted. The developed models are evaluated in different segments of data and time-periods, including the financial crisis. Finally, the forecasts from the three methods are combined in order to obtain one "overall" forecast aiming at gaining predictive power from the different aspects the three methods can capture.

The proposed AVM tool can have a significant impact on the decision-making process as well as managerial implications to different stakeholders such as government, commercial banks and decision-makers, as indicated along the following lines.

3.1.2 Methodology

3.1.2.1 Multiple regression analysis

The first method used in this study is a typical hedonic regression model. Hedonic models assume that the price of a property reflects inherent characteristics valued by some implicit prices. In empirical studies, these implicit characteristic prices are coefficients that relate prices and the underlying attributes in a regression model.

The model takes the form

$$Y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_j^i + \varepsilon_i \qquad (1)$$

where X_j^i is the value of the j-th explanatory variable/characteristic for the i-th property, Y_i is the logarithm of the value of the property translated to the value of the current period and β_j, $j = 0,\ldots,k$ are regression coefficients associated with the explanatory variables, β_0 being the intercept. The usual assumptions for the errors apply namely zero mean and constant variance.

Estimation of the model was done using standard OLS approach. The variable selection approach, however, was not standard, as explained later. There are many reasons for considering such a simple model. Regression model, while simple, can reveal useful information about the underlying structure. Being simple offers certain advantages as a) it is easy to use and interpret, b) provides easy and stable variable selection approaches, c) modification is relatively simple, the same for its update and generalisation, and finally d) inference is simple, and hence insight can be generated relatively simply. It needs to be noted that the interest of this study lies in forecasting new properties and not identifying the critical characteristics, so all the approaches are based on this.

A variable selection approach was applied to find the variables that are predictive for the value of the property. The aims were:

a) to check existing work and whether it needs simplification with simpler models to attain parsimony,
b) to formulate a meaningful model to use and
c) to be able to derive a comprehensive and simple model to see the variables that are deemed useful for the prediction.

Since the aim of the approach was to predict new unseen properties, the forward selection approach was modified in order to use it for creating a predictive model. Standard forward selection selects the new variables to add to the model among the significant ones. The reason is that the model building aims at producing a descriptive (exploratory) model that can help to identify the variables with relationship to the response. In this case, the interest lies in prediction, and hence a model that predicts well needs to be found while it is not necessarily the best for exploring the existing data.

Hence the approach is the following:

1. Start from a model with only the constant.
2. Select as the variable to enter the model the one that minimises the mean of the relative absolute prediction error for the model k, defined as

$$MAPE_k = \sum_{i=1}^{n_t} \left| \frac{y_i - \hat{y}_i}{y_i} \right. \quad (2)$$

where y_i is the observed value of the property from the validation sample and $\hat{y}_i$ is the predicted value of the model. In the above n_t is the cardinality of a validation.

3. With the selected variable in the model, go back to step 2 to find among the other candidates the one that minimises the MAPE
4. Stop when no further decrease of MAPE is possible.

The final model is used to forecast the values of the properties out-of-sample. The approach mimics typical forward approaches but uses a criterion that selects a predictive model. An interesting note is that usually the MAPE after few steps almost stabilises and further covariates create a small decrease. For predictive purposes, this needs some care because it is known that for prediction, the more covariates, the more overfitting is achieved, and hence the model may lose its value very quickly. In this study, the intention was to keep the model parsimonious, i.e. without many covariates. Finally, note that other variable screening/selection approaches like LASSO could have been used, but since mainly the covariates are categorical, particular amendments for the LASSO were needed.

3.1.2.2 Similarity measure valuation

In this section, the Similarity Measure Valuation (SMV) method is proposed and presented. The SMV method is based on spatial information and a representative asset (RA). The RA is the "average" property derived from the database. This is a standard procedure in sales comparison methods since comparables have different characteristics (Kauko & D'Amato, 2009). The value of each property is converted to a Hedonic Value (HV) based on the characteristics of the property and the Index area. The role of the HV is to convert all properties into a representative property in terms of characteristics. So, each comparable in the database used in this study has each own HV based on their characteristics compared to the RA and is given by:

$$HV_i = X_S^{RA} \exp\left[\log\left(\frac{UV_i}{X_S^i}\right) + \sum_{j=1}^{J} \beta_{kj}(X_j^{RA} - X_j^i)\right] \quad (3)$$

where β_{kj} is the hedonic coefficient of variable j for the index area k where property i is located, X_j^i is the value of variable j for the property i, X_S^i is the size of the property in square meters and X_j^{RA} is the value of variable j for the RA. Finally, UV_i, is the updated value of property i.

The database consists of historical valuations, V_i, performed by experts. The intention here is to update each property's historical value to the current time using the proposed method. Residential indices by region are used to update the values of comparables. The UV_i is given by:

$$UV_i = V_i \frac{ind_1}{ind_3}\left(\frac{ind_1}{ind_2}\right)^{\frac{m_1 - m_2}{3}} \quad (4)$$

where ind_1 is the residential index at the current quarter, ind_2 is the residential index of the previous quarter, ind_3 is the residential index of the initial quarter and m_1, and m_2 are the month of the quarter of valuation and the month of the quarter of the initial valuation respectively.

All available properties in the database are ranked based on their similarity with the property under consideration. A metric, W_{ij}, is defined to quantify the similarity:

$$W_{ij} = exp\left[w_1 log\frac{c_1}{d_{ij}+c_1} + w_2 I_{ij}(X_7) + w_3 I_{ij}(X_8)\right] \qquad (5)$$

The above formula assesses the similarity of property *i* to another property *j* from the database by considering the geographical distance between properties *i* and *j*, the administrative sector and the type of the property where:

- d_{ij} is the geographical distance between properties *i* and *j*.
- X_7, X_8 are the main characteristics of the properties as defined in section 3.1.3.
- $I_{ij}(x)$ is a $0 - 1$ indicator which equals 1 if properties *i* and *j* are identical in terms of their characteristic *x* and 0 if they differ on that characteristic.
- w_i are weighting coefficients, which sum up to 1; they indicate the relative importance of the different characteristics of the properties in defining the above similarity metric.
- c_1 is a scaling parameter for the distance; it is used to map the difference between the properties being compared on a similarity scale common to all characteristics. They are scalars used to avoid numerical problems.

The weights and the scaling parameters are adjusted differently for each administrative index area, and they have been defined based on inputs obtained from experts. The higher the similarity metric W_{ij} is, the stronger the similarity between properties *i* and *j*.

After selecting the most suitable properties, a weighted RA value, *WRAV*, is obtained based on the following formula:

$$WRAV = \frac{\sum_{i=1}^{n} w_i HV_i}{\sum_{i=1}^{n} w_i} \qquad (6)$$

Finally, the *WRAV* should be converted into the weighted value based on the property's under valuation characteristics.

$$SMV = X_8^i e^{\ln\left(\frac{WRAV}{X_S^{RA}}\right) + \sum_{j=1}^{J} \beta_{kj}\left(X_j^{RA} - X_j^i\right)} \qquad (7)$$

where, as before, β_{kj} is the hedonic coefficient of variable *j* for the index area *k* where property *i* is located and X_j^i is the value of variable *j* for the property *i*,

3.1.2.3 Neural networks

In this study, NNs are treated as the eminent expression of non-linear regression, which constitutes a compelling approach, especially for financial applications. The main characteristic of NNs is their ability to approximate any non-linear function without making a priori assumptions about the nature of the process that created the available observations. A multilayer perceptron (MLP) is a feed-forward NN that utilises a back-propagation learning algorithm in order to enhance the training of the network (Rumelhart, Hinton, & Mcclelland, 1986).

For this study, a three-layer NN is proposed. The lower layer is called the input layer and consists of the input variables. The middle layer is the hidden layer and consists of hidden units (HUs). Finally, the upper layer is called the output layer, where the approximation of the target values is estimated. Often more hidden layers can be used. Each node in one layer connects to each node in the next layer with a weight w_{ij}, where *ij* is the connection between two nodes in adjacent layers within the network. The units of each layer receive their inputs from the units of the layers immediately below. Then, they send their outputs to the units of the layers lying directly above. The flow of information is done through the connections. A sigmoid activation function is used in the hidden layer while there is a linear connection between the neurons and the output nodes.

On each pass through, the NN calculates the loss between the predicted output $\hat{}y_n$ at the output layer and the expected output y_n for the n^{th} iteration (epoch). The loss function used here is the sum of squared errors, given by:

$$L_n = \frac{1}{2}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \qquad (8)$$

where N represents the total number of training points. Once the loss has been calculated, the back-propagation step begins by tracking the output error back through the network. The errors from the loss function are then used to update the weights for each node in the network, such that the network converges. Therefore, minimising the loss function requires w_{ij} to be updated repeatedly using gradient descent, so the weights at step t + 1, $w_{ij,t+1}$, are updated by:

$$w_{ij,t+1} = w_{ij,t} - \eta \frac{\theta L}{\theta w_{ij,t}} + \mu \Delta w_{ij,t} \qquad (9)$$

3.1.2.3.1 Parameter tuning for neural network generalisation improvement

A small number of HUs will lead to underfitting of the NN to the data while a large number of HUs will lead to overfitting. In this study, the model selection and variable selection algorithms presented in (Zapranis & Refenes, 1999) and extended in (Antonios K. Alexandridis & Zapranis, 2013) were adapted[24]. One method for improving network generalisation is to use a network that is just large enough to provide a good fit. Unfortunately, it is difficult to know beforehand how

[24] Analytical presentation of the model identification framework is beyond the scope of this paper. The interested reader may be referred to (Antonios K. Alexandridis & Zapranis, 2013).

extensive a network should be for a specific application. In this study, two methods for improving generalisation are implemented: regularisation and early stopping.

The default method for improving the generalisation ability of a NN is called early stopping. In early stopping, a relatively large number of HUs is used in the construction of the network. The number of weights roughly defines the degrees of freedom of the network. If the training phase continues more than the appropriate iterations and the weights grow very large on the training phase, then the network will start to learn the noise part of the data and will become over-fitted. As a result, the generalisation ability of the network will be lost. Hence, it is not appropriate to use such a NN in predicting new unseen data. On the other hand, if the training is stopped at an appropriate point, it is possible to avoid over-fitting.

A common practice to overcome the above problems is the use of a validation sample. The in-sample data consists of property valuations in the period January 2012 - December 2015. In order to train a neural network, the in-sample data were split into two samples. The first one is called the training sample, which is used for computing the gradient and updating the network weights and biases as described in the previous section. The second subset is the validation set and is used to measure the generalisation ability of the network. The data were split randomly. The training sample consists of 85% of the in-sample data, while the validation set consists of 15% of the in-sample data. This ratio allows for a large enough sample for training for all Index areas and a large enough set for validation.

At each iteration, the NN is trained using the training sample. Then the cost function between the training data and the network output is estimated, and it is used for the adjustment of the weights. The generalisation ability of the network is measured using the validation sample. More precisely, the network is used to forecast the target values of the validation sample using the unseen input data of the validation sample. The error between the network output and the target data of the validation sample is calculated. At the beginning of the training phase, the errors of both the training and the validation sample will start to decrease as the network weights are adjusted to the training data. After a particular iteration, the network will start to learn the noise part of the data. As a result, the error of the validation sample will start to increase. This is an indication that the network is starting to lose its generalisation ability, and the training phase must be stopped (Anders & Korn, 1999; Y. Dimopoulos, Bourret, & Lek, 1995). The network weights and biases are saved at the minimum of the validation set error. The network is trained using the Levenberg-Marquardt (LM) algorithm, (Samarasinghe, 2016), which is very fast but less efficient for large networks with thousands of weights. In this study, the proposed network is minimal, and only a few parameters are used for the minimisation of the fitness function.

Another approach to avoid over-fitting is regularisation. In regularisation methods, the weights of the network are trained in order to minimise the loss function plus a penalty term. Regularisation is attempting to keep the overall growth of weights to a minimum by allowing only the important weights to grow. The rest of the weights are pulled towards zero. The regularisation method tries to minimise the sum:

$$W = L_n + \delta \sum_{j=1}^{J} w_j^2 \qquad (10)$$

where the second term is the penalty term, w_j is a weight, J is the total number of weights in the network architecture, and δ is a regularisation parameter.

It is desirable to determine the optimal regularisation parameters in an automated fashion. For that, the Bayesian framework of (MacKay, 1992) is applied. The Bayesian regularisation provides a measure of the number of weights that are effectively being used by the network. The effective number of weights should remain approximately the same, no matter how large the number of parameters in the network becomes. This assumes that the network has been trained for enough iterations to ensure convergence.

3.1.3 Data description

This study focuses on the Greek property market. The Greek property market is of special interest as it is an inefficient, non-homogeneous market, still at its infancy and governed by lack of information. In particular, the Greek market is characterised by considerable heterogeneity, as there are metropolitan areas, smaller urban regions, rural areas, popular touristic destinations in the islands and others. Most of the previous studies have focused on smaller and less diverse regions, usually covering large metropolitan areas. The heterogeneity characterising the Greek market provides a stimulating basis for testing the performance of the different settings mentioned above.

All properties have been valued by certified valuers whose price assessments are used as the dependent variable for the analysis. The use of valuers' estimates instead of actual sales prices is due to two main reasons. First, in Greece, there is no formal database with sale transactions in the real estate market. Moreover, since 2009, Greece has experienced a significant economic recession, as outlined in 1.1.2, that resulted in residential property prices falling by more than 40% (during 2009-2018), according to official data from the Bank of Greece. The analysis presented here uses data spanning the period 2012-2016, during which the decline in house prices exceeded 20%, thus posing an additional challenge for testing the performance of AVMs. Moreover, during the past decade, the Greek real estate market faced abnormal conditions due to the severe economic crisis in the country. As a result, most of the transactions were forced sales made at prices that were not representative of the properties' fair value. To address these difficulties, the valuations' database was considered. These valuations are based on the economic environment, the state of the real estate market and the characteristics of the properties. They are derived in full accordance with international valuation standards, thus ensuring that the valuation process is consistent among all valuers and the estimates represent the fair value of the properties. As a result of all these factors, modelling the Greek real estate market is a very interesting and challenging problem.

The available data cover a big range of properties across time and include the financial crisis period in Greece. The database represents the hedonic characteristics of real estate properties[25]. The dataset was enriched with new variables by transformations and interactions between the initial variables[26]. The sample consists of 36,527 properties that have been professionally evaluated in the period 2012 – 2016. The properties belong to 240 different administrative sectors covering all areas in Greece. In Figure 17, a map with all the properties used in this study is presented. Most of the properties refer to urban areas. It can also be seen that in some areas there are few properties which make the forecasting a challenging option. A novelty of the current study is the attempt to model such an inhomogeneous portfolio of properties.

[25] Only the hedonic characteristics of each property were obtained and not any personal data of the clients.

[26] Due to confidentiality reasons the new variables that have been resulted due to the transformations or the interaction between the initial variables cannot be reported. The original variables are reported in Table 4.

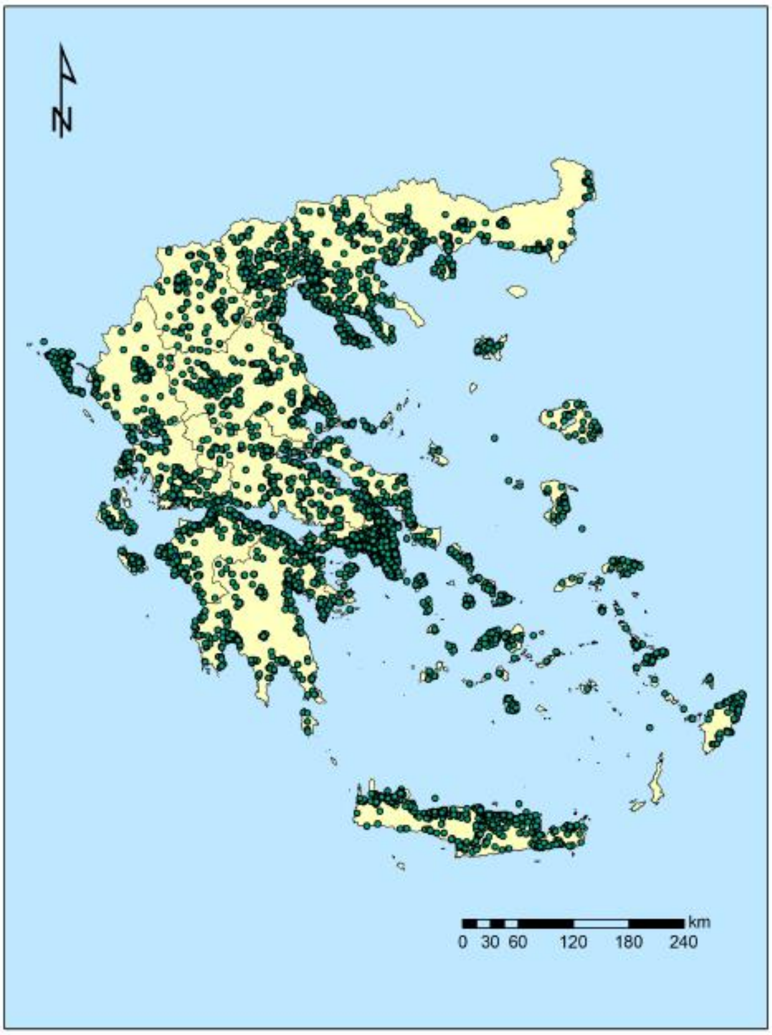


Figure 17 Geographical location of the real estate properties in Greece

Figure 18 illustrates the evolution of the mean price per square meter for the properties in the sample. For comparison, the apartment price index of the Bank of Greece (BoG) is also reported. A sharp decline is evident for the prices up to 2013q1, followed by a smaller decrease, up to the end of 2014. During the subsequent period, the prices are mostly stabilised, yet some volatility is evident.

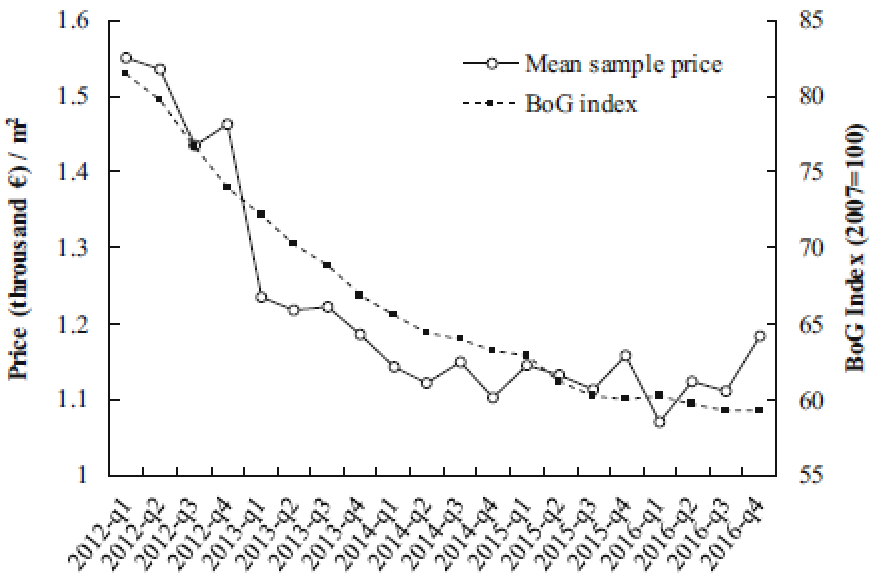


Figure 18 Mean price of the sample properties by quarter in comparison to the apartment price index of the Bank of Greece

The various characteristics of each property are presented in Table 4. The valuation price of each property (V06) should be forecasted. In Table 5, the descriptive statistics of each variable are presented. The values of the properties range from €15,000 to €1,000,000. Similarly, much variation can be identified in the year of construction (from 1800 to 2016) and the size of the properties (from $12m^2$ to $400m^2$).

Valuations in the period of 2012 to December 2015 will constitute the in-sample period that will be used for the estimation and fitting of all models. Then, property prices in the first quarter of 2016 are forecasted. Finally, a recursive procedure to forecast the property prices in the remaining quarters of 2016 is followed. Hence, the in-sample consists of 32,477 properties, while the out-of-sample contains 4,050 properties.

Some sectors contain only a few observations; hence, the data are grouped into 32 aggregated administrative areas (Index areas). The majority of the properties are located in the capital or large cities. This is expected as around 50% of the population in Greece lives in two cities, the capital – Athens – and Thessaloniki. Similarly, around 84.5% of the properties are flats, while 6.5% are houses, 5.4% maisonettes and only 3.6% of properties are of type duplex[27].

Finally, it needs to be noted that the properties are the ones existing in the bank's database for which evaluation from the bank was asked. Therefore, it is neither a random sample of any hypothetical population nor a product of some controlled experiment.

[27] In the supplementary material the number of properties per Index area, year of valuation, urban classification and type of property are presented.

Table 4 Explanation of the initial set of variables

Code	Characteristic	Code	Characteristic
V01	ID	V12	Floor
V02	Year of valuation	V13	Total number of floors
V03	Month of valuation	V14	Existence of parking space (Y/N)
V04	Administrative sector	V15	Type of parking (Indoor/Outdoor)
V05	Urban classification	V16	Type of heating (categorical)
V06	Survey value (in euros)	V17	Quality of construction (categorical)
V07	Type of residence (categorical)	V18	Number of bedrooms
V08	Usable residence area (in sq. m.)	V19	Touristic hotspot (Y/N)
V09	Land area (in sq.m)	V20	Elevator (Y/N)
V10	Year of construction	V21	View (Y/N)
V11	Distance from the centre (in km)	V22	Number of bathrooms

Table 5 Descriptive statistics

Numerical	Mean	St.Dev	Max	Min
V06	123,592	112,403	1,000,000	15,000
V08	97.64	52.42	400	12
V09	79.87	882.82	86000	0
V10	1988	16.88	2016	1800
V11	28.33	45.38	321.20	0
V12	1.81	1.59	14	-1
V13	3.44	1.75	25	0
V18	2.10	0.87	6	0
V22	1.46	0.68	6	0
Categorical	**Mode**	**Value**		
V07	Flat	2		
V16	Low efficiency	1		
V17	Good	2		
Binary	**Proportion 0**	**Proportion 1**		
V14	87%	13%		
V15	97%	3%		
V19	87%	13%		
V20	69%	31%		
V21	92%	8%		

3.1.4 Empirical results

3.1.4.1 Out-of-sample real estate valuation

In this section, an out-of-sample validation of the proposed methodologies is provided. The three models are evaluated to four non-overlapping samples corresponding to the four quarters of 2016. A recursive window forecasting scheme is applied. Initially, the in-sample data consists of the property's valuations between the 1st quarter of 2012 and the 4th quarter of 2015 ($2012q1 - 2015q4$). The out-of-sample data consists of the property's valuations that took place during the 1st quarter of 2016 ($2016q1$). In the next step, $2016q1$ is included in the in-sample data set, and the 2nd quarter of 2016 ($2016q2$) is forecasted. Similarly, for the remaining quarters. The entire out-of-sample set consists of 4,050 observations.

Three criteria are used for the evaluation of the forecasting ability of each method. The first one is the Mean Absolute Percentage Error (MAPE), and it is given by

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \qquad (11)$$

The second error criterion, denoted by $P20$, measures the percentage of the cases where the MAPE is less than 20%. This is a standard metric used in real-estate valuations, (see, e.g. (Rossini & Kershaw, 2008)) and it is given by

$$P20 = \frac{100}{N}\sum_{i=1}^{N} 1_{|PE_i|\leq 0.2} \quad (12)$$

where PE is the percentage error, and it is given by

$$PE = \frac{y_i - \hat{y}_i}{y_i} \quad (13)$$

and $1_{|PEi|\leq 0.2}$ is an indicator function where

$$1_{|PEi|\leq 0.2} = \begin{cases} 1 \ \ if \ |PEi| \leq 0.2 \\ 0 \ if \ |PEi| > 0.2 \end{cases} \quad (14)$$

Finally, the squared correlation coefficient, R^2, is calculated between the predicted and the real prices. In this definition of R^2, the value is not directly a measure of how good the modelled values are, but rather a measure of how good a predictor might be constructed from the modelled values In Table 6, a summary of the results is presented. More precisely, the Average PE, the standard deviation of the PE, the average MAPE, the average P20 and the R^2 are presented for each of the four quarters of 2016.

A closer inspection of Table 6 reveals that NN always outperforms the alternative methodologies. Interestingly, there is an indication that the results from NNs are stable. They produce similar forecasting errors for all quarters. The MAPE ranges from 15.05% in the first quarter to 17.67% in the last. The MRA produce similar but slightly worse results for the 1*st* quarter, but the MAPE increases significantly for the remaining quarters. More precisely, the MAPE increases from 15.34% to 20.72%. Finally, SMV seems to produce the most significant out-of-sample forecasting errors ranging from 18.15% in the third quarter to 22.64% in the fourth.

Similarly, the P20 is always higher when NN is used, followed by MRA while SMV ranks last. Except for the last quarter, the P20 is always above 70% for the NN, while for the MRA is above 70% for the first two quarters. Finally, it is always below 70% for the SMV. The R^2 is always higher when the NN is used. The MRA has a higher R^2 for the first and fourth quarter, but it is lower for the second. Finally, MRA and SMV have the same R^2 in the third quarter.

In general, the MAPE increases in the third and fourth quarter, indicating a change in the dynamics of the Greek housing market. However, one must be careful in the interpretation of the results since in each quarter a different set of properties is included. For example, in the 4th quarter, the number of properties with a land area is doubled, and they have a significantly larger land area on average[28].

[28] As an example, a property with $86{,}000m^2$ land area is reported while in the historical data set the average land area was around $1{,}200m^2$. Properties with zero land area where excluded from the calculation of the mean.

As it is shown in the next section, for all methods the MAPE is higher when properties with land area are considered. This is because only 6.5% of the properties have a land area.

Next, the focus is on combining the results. Two simple averaging methods are used. The first method is to take the average of the two best methods, NN and MRA since SMV produces significantly higher errors. The second method is to compute the average of all three methods.

In general, both averaging schemes improve the results. Surprisingly, the inclusion of the SMV method further reduces the MAPE. More precisely, the NN+MRA produce the best results, outperforming the NN, in the first quarter with a MAPE of only 14.54% and a P20 of 77.00%. For quarters 2 and 3, the best results are given by the SMV+NN+MRA approach with a MAPE of 15.70% and 15.89% respectively, while the P20 is 71.76% and 71.33%. Finally, for the last quarter, neither averaging technique can outperform the NN concerning the MAPE. However, the P20 was increased to 69.03% when all three methods are used compared to 68.28% in the case of NN[29].

Table 7 shows the number of the best predictive performance of the three main methods with (bot) and without (top) averaging methods, i.e. in how many index areas each method ooutperformsall the other in each quarter. In summary, the NN outperformed the alternative methods in 63 cases out of the 126. The MRA method produced the most accurate forecasts 39 times while the SMV only 24. A closer inspection of Table 7 reveals that the NN outperforms the other methods in all quarters while MRA and SMV always rank second and third, respectively. Taking into consideration the two averaging techniques, SMV+NN+MRA produces the lower MAPE in 40 cases while NN in 38. The MRA outperforms all the other methods in 25 methods while the SMV in 16. Finally, the NN+MRA give the best forecasts only in 9 index areas. Breaking down the results by quarter, it can be observed that in the first quarter the NN method ranks first and the NN+MRA+SMV ranks second, while it is the opposite in the fourth quarter. In the second and third quarter, both methods rank first.

Recently, artificial intelligence-based methods have been proposed as an alternative to mass assessment. However, there are mixed results. (Guan, Zurada, & Levitan, 2009) find no improvement when advance machine learning techniques are used while (Worzala, Lenk, & Silva, 1995) find that NNs-based methods are inferior to traditional regression methods. More precisely, (Worzala et al., 1995) find that NN-based methods do not produce results that are notably better than those of MRA, except when more homogeneous data are used. In contrast, in this study, where NNs are fine-tuned, and extra care is taken to avoid overfitting, the results indicate that NNs can significantly outperform traditional valuation methods. They indicate the importance of

[29] Analytically results of the MAPE and the P20 for each index for all 5 approaches are presented in Supplementary Material that accompany the online version of this paper.

constructing the architecture of the NNs based on statistical methods. Finally, they are in line with (McCluskey et al., 2013; Nguyen & Cripps, 2001; Peterson & Flanagan, 2009), where NNs proved to be effective in the case of large heterogeneous datasets.

Table 6 Out-of-sample performance for the four quarters of 2016

	SMV	NN	MRA	NN + MRA	SMV+NN+MRA
2016q1					
Av. PE	6.93%	2.05%	1.25%	1.65%	3.41%
Std. PE	0.1400	0.0423	0.0452	0.0392	0.0510
MAPE	19.73%	**15.05%**	15.34%	**14.54%**	14.86%
P20	66.63%	**75.54%**	75.42%	**77.00%**	75.99%
R_2	81.13%	**86.98%**	86.85%	**88.31%**	88.11%
2016q2					
Av. PE	0.67%	1.86%	1.01%	1.43%	1.18%
Std. PE	0.0722	0.0532	0.0581	0.0500	0.0474
MAPE	18.30%	**16.22%**	17.46%	16.19%	**15.70%**
P20	67.27%	**72.06%**	68.06%	71.06%	71.76%
R_2	81.71%	**85.71%**	78.18%	84.14%	85.62%
2016q3					
Av. PE	3.20%	1.61%	0.10%	0.85%	1.63%
Std. PE	0.0661	0.0511	0.0604	0.0502	0.0487
MAPE	18.15%	**16.67%**	18.13%	16.48%	**15.89%**
P20	66.19%	**70.97%**	65.95%	69.65%	**71.33%**
R_2	84.44%	**85.64%**	84.44%	87.03%	**87.70%**
2016q4					
Av. PE	10.18%	3.91%	2.45%	3.18%	5.51%
Std. PE	0.7240	0.2448	0.2807	0.2390	0.3227
MAPE	22.64%	**17.67%**	20.72%	17.80%	18.10%
P20	65.33%	**68.28%**	60.80%	67.15%	**69.03%**
R_2	78.65%	**88.25%**	80.08%	87.75%	**88.29%**

Table 7 Number of the best predictive performance of the three main methods with (right) and without (left) averaging methods

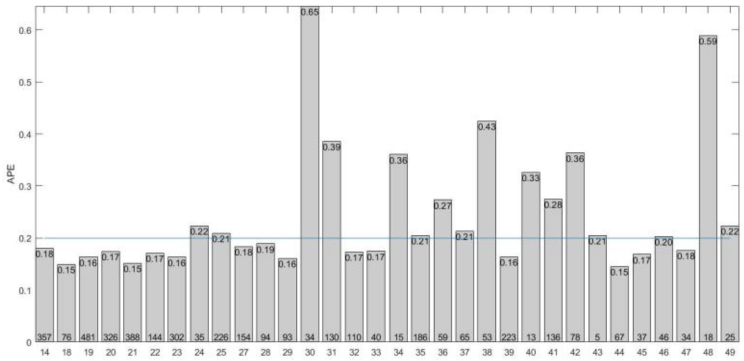
	Main Methods			All Methods				
Quarter	SMV	NN	MRA	SMV	NN	MRA	NN + MRA	SMV+NN+MRA
Q1	2	18	11	2	11	8	1	9
Q2	8	15	9	3	9	8	3	9
Q3	8	15	8	6	10	3	2	10
Q4	6	15	11	2	8	7	3	12

3.1.4.2 Analysis of the forecasting errors

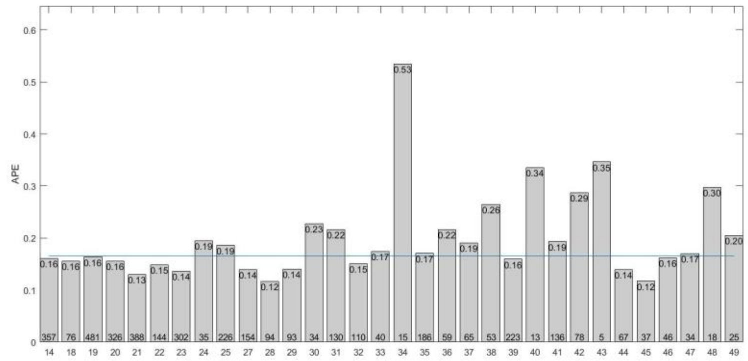
In this section, the forecasting errors of each methodology are analysed. More precisely, it is examined how the forecasting error changes when the characteristics of the properties change[30]. Due to space limitations, the focus is on the characteristics where the analysis is most insightful. The analysis is based on the complete out-of-sample period (2016q1-2016q4) and consists of 4,050 properties.

In Figure 19, the MAPE for each Index area is presented. Also, the number of observations for each Index area is depicted in Figure 19. A closer inspection of Figure 19 reveals that the variation of the MAPE is more significant in the case of SMV compared to the other methods. For all methods, the MAPE is greater when only a few observations are present while the lower MAPE for all indices is obtained when the average of the three methods is considered. Finally, the MAPE is similar across all indices for the NN, the MRA and the averaging method while is quite different for the SMV method. Note also that all methods perform poorly for some indices just because they refer to few properties and rather inhomogeneous areas. For example, index 30 refers to islands in the Aegean Sea, which contain both some very touristic islands but also some other islands with no tourism.

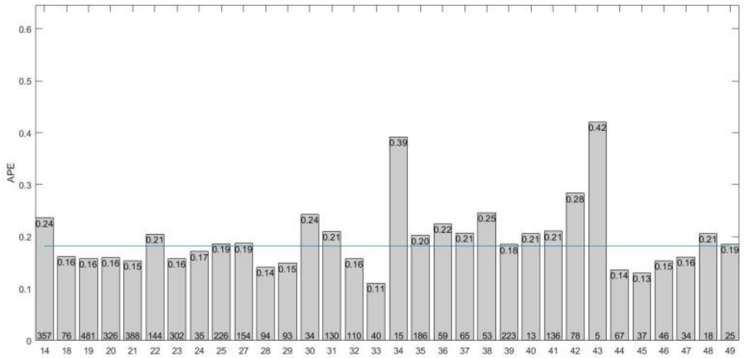
[30] Due to space limitation the results for all the characteristics cannot be presented, however the results are available from the authors upon request.



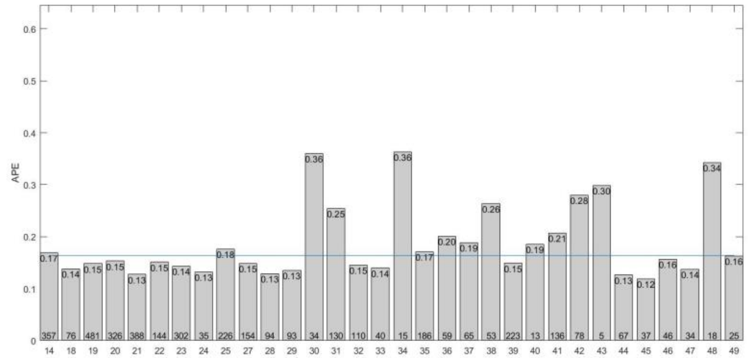
(a) SMV



(b) NN



(c) MRA



(d) SMV+NN+MRA

Figure 19 Mean absolute percentage error per index area. The horizontal lines are the average error across all index areas.

Next, the contribution to the error of the following characteristics is examined: urban classification, property type, usable residence area, land area, age and number of bedrooms[31]. The MAPE per urban classification is similar for all methods. The MAPE is higher for rural areas and small towns while it is significantly lower for small, medium and large cities and the capital. While the number of observations per urban classification is the same in the out-of-sample set (except the capital) this is not the case in the in-sample. Most of the properties are in the capital (18,123) while there are 3,483 and 2,571 for large and medium-sized cities. On the other hand, there are only 1,615 properties in rural areas in the in-sample where the out-of-sample MAPE is greater. Similar results are obtained when the MAPE per type of property is examined. More precisely, the MAPE is lower for flats while it is large for houses. Most of the properties are flats, 3,181, while only 356, 256 and 304 properties are of type house, duplex and maisonette, respectively.

Regarding the usable residence area, the error is minimised for properties between $50m^2$ and $80m^2$ when the SVM method is used, while it is significantly larger for any other category. For the NN and the MRA, the results are similar. The MAPE is lower for properties up to $120m^{2,}$ and then it increases as the area increases. Finally, the MAPE for the NN is smaller for every category. When the land area is considered, all methods produce significantly higher errors when the land area is included in the property. However, SMV produces significantly higher errors. More precisely, when the land area is included, the MAPE for the SMV is 0.40 while it is only 0.29 for the remaining methods. When the properties do not have any land, the MAPE falls to 0.18 and 0.17 for the SMV and the MRA respectively, while it is only 0.15 for the NN and the averaging method. Again, the lower errors for each category are obtained by the NN and the averaging method.

Next, the effect of the age of the property to the forecasting ability of the models is examined. The MAPE is higher for properties constructed before 1970. Also, the variation for the SMV is higher compared to the other methods while it is relatively stable for the remaining methods. Again, the lower MAPE per category is obtained by the NNs. Finally, the MAPE per number of bedrooms is examined. The MAPE is high for the SMV, MRA and the averaging method when properties with 0 or 5 bedrooms are considered. On the other hand, for the NNs the MAPE increases for properties with 5 or 6 bedrooms. A closer inspection reveals that the majority of the properties have 1–3 bedrooms. Again, the best results for all categories are obtained for the NN and the averaging methods.

[31] Due to space limitation these figures are presented in the supplementary material. Analytical results for all characteristics are available from the authors upon request.

A final noticeable remark arises from Figure 20 where the smoothed (using LOESS smoother) average predicted value over all the properties predicted at 2016 is presented for the property size (a) and the age at the time of valuation (b). Each line corresponds to one of the methods, but their combination is also depicted. The different methods model a different effect, while their combination, since it compromises the different effects, improves prediction. From Figure 20b, one can see a very steep decline in the price after the age of 30 years. As for the size of the property, one can see that there is an increasing trend up to 300 square meters. The SVM method based on a linear (in the logarithmic scale) trend leads to much larger predicted values. The plots reveal the different dynamics of the different approaches.

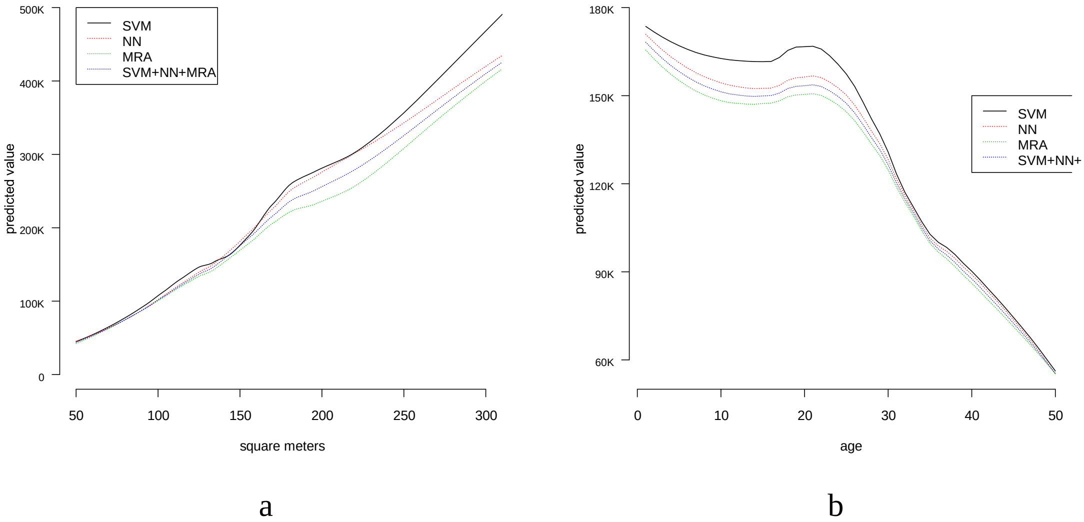


Figure 20 Smoothed average predicted value for the entire 2016, based on all methods

3.1.5 Conclusions

In this study, three mass appraisal systems for the automated valuation of real estate properties in Greece were developed. As mentioned before, the Greek property market, being a new market with lots of unique characteristics, is a challenging one. Linear and non-linear models based on regression, hedonic equations, spatial analysis and artificial NNs were formulated and compared.

An extensive out-of-sample analysis in four non-overlapping data sets was performed. In contrast to previous studies, the results indicate that NNs continually outperform traditional valuation methods. In this study, the proposed NN was fine-tuned, and extra care was taken to avoid overfitting. The MRA method ranks second while the SMV method ranks third. Forecasting accuracy can be further improved by employing averaging techniques. A simple average of the three methods performs as well as, and in some cases outperforms, the NN.

Finally, a focus was given on identifying the property characteristics that lead to large forecasting errors. The results indicate that the forecasting error increases when the residence area is above $120m^2$ or the property is a house or large land area is included. Similarly, very old properties (built before 1950) lead to larger forecasting errors. However, it is worth to mention that the analysis revealed that NNs are less sensitive to the changes in these characteristics compared to the SMV or the MRA.

The results indicate that the proposed methodology constitutes an accurate tool for property valuation in non-homogeneous, newly developed markets. The results of this study can potentially have significant policy and fiscal implications. The proposed methodology can help both the government and the public sectors like commercial banks.

3.2 Developing Automated Valuation Models for Estimating Property Values: A Comparison of Global and Locally Weighted Approaches

Following the comparison in the previous section (Section 3.1) of different techniques, traditional and new ones, for the development of a reliable automated valuation model, this section presents a published work (Doumpos, Papastamos, Andritsos, & Zopounidis, 2020), which specialises in the development of models that focus on local effects and the investigation of their effectiveness against simple AVM techniques (i.e. statistical and machine learning ones). In particular, it introduces a **benchmarking** comparison of regression approaches focusing on residential properties and distinguishing **parametric** and **non-parametric regression** techniques for the development of reliable automated valuation models. Different approaches are explored to incorporate spatial effects into the valuation process, covering both global and locally weighted models. The analysis is based on the same dataset as section 3.1, namely a large sample of properties from Greece during the period 2012-2016. The results demonstrate that linear regression models developed with a weighted spatial (local) scheme provide the best results, outperforming machine learning approaches and models that do not consider spatial effects.

3.2.1 Introduction

The importance of proper valuation tools for risk management in real estate, given the latter's significant interest for various stakeholders, including investors, financial institutions, and policymakers, was also highlighted before. In that respect, AVMs and mass appraisal systems are widely used in this field and are the main focus of this section. The development of AVMs is a data-intensive process that is grounded on standards set by various professional organisations, such as the International Association of Assessing Officers, the Royal Institution of Chartered Surveyors and the International Valuation Standards Council.

Several empirical studies have shown that hedonic models that consider (implicitly or explicitly) spatial heterogeneity provide improved results. For instance, (Bourassa, Hoesli, & Peng, 2003) compared models developed on data segmented based on geographical criteria and statistical techniques and found that the former perform better, whereas the addition of spatial dependence further improves the results. (Fik, Ling, & Mulligan, 2003) compared various specifications of an OLS model and found that the use of regional dummy variables and geographical coordinates improves the accuracy of the results. (Bitter, Mulligan, & Dall'erba, 2007) found that GWR outperforms OLS models and models that consider spatial expansion terms. (Helbich & Griffith, 2016) used data from Vienna and found that GWR performs similarly to a spatial expansion method and a local regression model. (W. McCluskey et al., 2013) compared an OLS model with a neural network, a spatial expansion model, and GWR, concluding that the latter provides superior results, while the neural network performed worst.

Regarding studies that focused on machine learning approaches, (Antipov & Pokryshevskaya, 2012) found that ensembles, such as boosting and random forests, outperformed tree-based models, neural networks, and OLS. Similar results were also reported by (Kontrimas & Verikas, 2011) who further found support vectors to perform well. On the other hand, more positive results about the predictive power of neural networks have been reported by other studies (A. K. Alexandridis et al., 2019; Lin & Mohan, 2011; Mimis et al., 2013).

Motivated by prior studies on the superiority of approaches that consider spatial effects, the objective of this section is to compare the performance of linear and nonlinear regression models in different settings for introducing spatial effects. In contrast to GWR, which is computationally very intensive for large data sets, the focus here is on approaches that scale up well with the size of the data and are easy to implement. More specifically, three linear regression approaches are considered, namely ***OLS, least absolute deviation regression***, and ***the least absolute shrinkage and selection operator (LASSO).*** Also, two non-linear machine learning techniques are used, namely ***random forests*** and ***Gaussian process regression***. Using these regression techniques, global and local models are tested. The former are first constructed in a simple hedonic regression framework, which is further enhanced with spatial terms. Local models are fitted on a sample of properties selected according to their location to the subject properties being valued. Both weighted and unweighted local models are considered.

This study allows for the combined examination of different schemes, which has not been explored before, as follows:

- linear/non-linear models,
- global/local schemes,
- geographically weighted/unweighted approaches.

Therefore, valuable insights can be drawn into how established approaches can be applied successfully in a real estate pricing context for residential properties. The results show that simple linear models implemented with a locally weighted approach perform very well, providing superior results compared to non-linear machine learning approaches, which are not benefitted from local schemes.

3.2.2 Data and Empirical Setting

3.2.2.1 Data Description

The data used in the analysis are the same us the one used in the previous section, section 3.1, and presented in further analysis in section 3.1.3.

The list of independent (predictor) variables covers various information about the properties. As shown in Table 8, a mix of numerical and categorical (qualitative) attributes is considered. Regarding the numerical variables, first, the properties' size was considered in logarithmic form to eliminate the effect of outliers. Besides, a squared size indicator is used to account for possible non-linearities in the relationship between property values and size. Other numerical attributes include the age and floor of the properties, as well as the number of bedrooms and bathrooms. The categorical attributes include the type of the property, the quality of construction and maintenance (evaluated in a four-level scale by the valuers), indicator (dummy variables) for basements and properties with high-efficiency heating, as well as a variable indicating the region of the property. The regions (240 overall) are defined by the financial institution providing the data, considering geographical data and the prices of the properties in each area. Finally, the (X, Y) geographical coordinates are also used to describe in detail the location of each property in the sample.

Table 8 Predictor Attributes (independent variables)

Attribute	Description
SIZE	Logarithm of property size (in m^2)
SIZE2	Squared logarithm of property size
AGE	Age of the property
FLOOR	Floor of the property
NBED	Number of bedrooms
NBATH	Number of bathrooms
TYPE	Type of property (House-H, flat-apartment-FLA, apartment maisonette-AM, maisonette-M)
QCONSTR	Quality of construction (Bad-B, medium-M, good-G, very good-VG)
MAINT	Condition of maintenance (Bad-B, medium-M, good-G, very good-VG)
HQHEAT	Indicator variable for high efficiency heating or natural gas
BASEMNT	Indicator variable for basements
TOUR	Indicator variable for properties in touristic areas
REGION	Region in which the property is located
Location	(X, Y) coordinates of the property's location

Table 9 Descriptive statistics

	Mean	Median	Mode	Std
SIZE (m^2)	97.63	87.3	80	52.40
AGE	25.31	26	44	14.54
FLOOR	1.81	1	1	1.59
NBED	2.10	2	2	0.87
NBATH	1.46	1	1	0.68
QCONSTR*	1.71	2	2	0.59
MAINT*	2.05	2	2	0.78
HQHEAT	0.02	0	0	0.15
BASEMNT	0.02	0	0	0.12
TOUR	0.14	0	0	0.34

*For QCONSTR and MAINT the numerical scale ranges from 1 for “bad” to 4 for “very good”

Table 10 Correlation of numerical attributes

	SIZE	SIZE2	AGE	FLOOR	NBED	NBATH
SIZE2	-0.018					
AGE	-0.129	-0.125				
FLOOR	0.028	-0.076	-0.108			
NBED	0.714	0.024	-0.114	0.052		
NBATH	0.617	0.239	-0.187	0.024	0.590	
ln(price)	0.804	0.047	-0.393	0.151	0.595	0.587

Table 11 Mean logarithmic property price by categorical factors

Type		QCONSTR		MAINT	
H	11.97	B	10.77	B	11.08
FLA	11.22	M	11.06	M	11.01
AM	11.97	G	11.44	G	11.37
M	11.89	VG	11.87	VG	11.52
BASEMNT		HQHEAT		TOUR	
No	11.33	No	11.32	No	11.29
Yes	11.06	Yes	11.58	Yes	11.56

Table 9 presents some descriptive statistics for the sample. On average, the data set involves houses with a size of around 100m^2, 25 years of age, two bedrooms, and medium construction quality/maintenance condition. Table 10 presents the correlations of the numerical attributes with the logarithmic price of the properties. The logarithmic price is used as the dependent variable in the analysis. For the categorical attributes, Table 11 shows the mean (logarithmic) property prices for each level of the attributes.

Regarding the numerical attributes, the properties' size has the strongest association with the properties' price, together with the number of bedrooms and bathrooms, and the properties' age. The floor and the squared size variables have lower associations, yet significant at the 1% level. Concerning the categorical attributes, prices are higher for houses and apartment maisonettes, for properties with good quality of construction and maintenance, equipped with high-efficiency heating, located in touristic areas. Moreover, the price of basements is significantly lower. Both parametric and non-parametric tests (ANOVA and Kruskal-Wallis) confirmed the statistical significance (at the 1% level) of the categorical attributes for modelling property prices.

3.2.2.2 Empirical setting

In order to apply and test models for estimating the values of the properties in the data set, a moving window approach is employed, using a period of three years for fitting the estimation models and testing their performance on the data for the subsequent quarter. This process starts by using the period 2012q1-2014q4 for model fitting and testing the obtained models in the first quarter of 2015 (i.e., 2015q1). Then, the time window is moved one quarter ahead, and the process is repeated by fitting the estimation models on the 2012q2-2015q1 data and testing them on

2015q2. In the same manner, six more tests are performed until the last quarter of 2016 (i.e., 2016q4).

In this moving window process, given that the valuers' assessments have been performed over different periods, all properties' values are time-adjusted to the mid of each test quarter, thus making all input values comparable by eliminating time trends. The adjustment is made using price indices maintained at the regional level by the financial institution providing the data. In particular, given the value Pt of a property i, as assessed by a certified valuer at quarter t, the value P_i^T of the property at future quarter $T > t$ is adjusted as follows:

$$P_i^T = P_i^t \left(\frac{I_T}{I_t}\right)\left(\frac{I_T}{I_{T-1}}\right)^{(2-\tau)/3} \qquad (1)$$

where I denotes the index value used for the adjustment, τ is the month of quarter t where the valuation was done by the valuer (τ = 1, 2, 3).

With the data described in the previous subsection, the most basic setting is based on developing models for estimating the values of the properties through the following regression equation:

$$\ln \hat{y} = \alpha + \boldsymbol{x}^{\mathsf{T}}\boldsymbol{\beta} + \gamma R \qquad (2)$$

where y is the estimated property value, x is the vector of the property characteristics (cf. Table 8), whereas R denotes the property's region (modelled as a categorical attribute through the introduction of appropriate dummy variables).

To incorporate explicit spatial effects into this simple model, first, the third-degree polynomial expansion of the properties' geographical coordinates was considered, under (Bitter et al., 2007). Thus, the above regression equation is augmented with additional predictors for the *(X,Y)* coordinates, as well as for X^2, Y^2, XY , X^3, Y^3, X^2Y and XY^2.

As an alternative way to incorporate spatial effects into the estimation process, a local regression modelling scheme was followed. Under this setting, the regression model (equation (2)) is estimated separately for each property, only using a subset of properties from the full sample. The sample used for this local estimation consists of the 1000 properties that are closest to the subject property being valued, in terms of their geographical distance. Finally, this local regression scheme was extended by introducing weights for the subset of properties used for model fitting. These weights are defined according to their distance from the subject property, as follows: $w_j = 1/(\varepsilon + d_j)$, where d_j is the distance between property j and the property being valued and ε is a small positive constant (ε = 0.001 was used).

Table 12 summarises the four modelling schemes described above, namely the two global regression variants of the regression model (equation (2)) and the two local regression schemes.

Table 12 Modelling schemes

Abbreviation	Description
GM	Global model fitted on the full sample with no explicit spatial effects
GMSE	Global model fitted on the full sample with polynomial expansion of geographical coordinates
LM	Local model fitted on a subset of properties
LWM	Local model fitted on a subset of properties, weighted by their distance to the subject property

3.2.3 Methodologies

For the development of models for predicting the value of the sample properties, five regression techniques are compared. The most straightforward approach involves the estimation of all regression models with ordinary least squares (OLS). Except for OLS, four other regression techniques are also considered. The approaches selected for the analysis have been chosen to cover various popular methodological paradigms. In that regard, first, different approaches for fitting linear models were considered, including regularisation and linear programming, which allows the analysis of how different model fitting criteria affect the performance of simple linear AVM prediction systems. Moreover, given that linear models may not be able to describe the values of the properties accurately, the performance of powerful non-linear regression modelling techniques was investigated, such as kernel methods and ensemble machine learning. Below the regression approaches and their selection for the analysis are briefly described.

Least absolute shrinkage and selection operator (LASSO) regression: LASSO (Tibshirani, 1996) estimates the regression equation $y = \alpha + \mathbf{x}^T\boldsymbol{\beta}$ by minimising the regularised least squares function:

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - a - \mathbf{x}_i^T\boldsymbol{\beta})^2 + \lambda|\mathbf{1}^T\boldsymbol{\beta}| \quad (3)$$

where n is the number of training cases, 1 is a column vector of ones, and $\lambda > 0$ is a parameter that controls the trade-off between the model's mean squared error and the regularisation term $|\mathbf{1}^T\boldsymbol{\beta}|$, which shrinks the regression coefficients $\boldsymbol{\beta}$. For this analysis, this regularisation parameter was specified through a 5-fold cross validation procedure. The regularisation term introduced by LASSO is an implicit model selection mechanism because the coefficients of irrelevant are shrunk down to zero, thus leading to more sparse models. This also ameliorates multicollinearity issues, which often arise in AVMs, especially under localised model specifications (Helbich & Griffith, 2016; Wheeler & Tiefelsdorf, 2005). Thus, the use of LASSO in the present analysis allows the examination of how such features affect the predictions compared to the basic OLS approach.

Least absolute deviation (LAD) regression: In contrast to the minimisation of the L2 norm of the residuals in OLS, LAD regression uses the L1 norm, thus minimising the absolute errors $|y - \alpha - \mathbf{x}^\top \boldsymbol{\beta}|$ for the training cases. With this modification, the constant term and regression coefficients are obtained through the solution of a linear program. Compared to OLS, LAD is non-parametric linear regression approach that is more resilient to outliers and relaxes the OLS assumptions regarding the normal distribution of the error terms. Moreover, LAD is a particular case of quantile regression, which has recently become a popular approach for descriptive and predictive statistical modelling.

Gaussian process regression (GPR): GPR a non-parametric machine learning approach for regression and classification (Rasmussen & Williams, 2006). In a regression context, a GPR model can be expressed in the following general form:

$$y = f(\mathbf{x}) + \varepsilon \qquad (4)$$

where ε is a normally distributed error term with zero mean and $f(\mathbf{x})$ is the model to be inferred from the data, which follows Gaussian process with mean function m(x) and covariance defined by a kernel function $K(\mathbf{x}, \mathbf{x}^\top)$, which models the dependence between the outputs of the function at different points x and $\mathbf{x}^\top$. The most common specification for the kernel function is the squared exponential form (E. Schulz, Speekenbrink, & Krause, 2018):

$$K(x, x') = \sigma_f^2 \exp\left(-\frac{\|x - x'\|^2}{2\gamma^2}\right) \qquad (5)$$

The hyperparameters of the kernel function (σ_f^2 andγ) and the mean function are estimated from a set of training data, by maximising a marginal log-likelihood function, under (Rasmussen & Williams, 2006). GPR is used in this study as representative of kernel methods for regression. Kernel approaches are powerful non-parametric approaches that enable the modelling of complex non-linear relationships among the predictors. Compared to other popular kernel methods, such as support vector machines, GPR enables the specification of the kernel function parameters directly from the data, and also enable the consideration of the uncertainty regarding the prediction model.

Random forests (RF): RF is a popular machine learning technique for classification and regression modelling, which is based on the combination of multiple base models into an ensemble prediction system (Breiman, 2001). RF is a tree-based ensemble, which uses bootstrap aggregation (bagging) to construct the base models (regression trees) from random bootstrap samples of the training set (Breiman, 1996). The final output is determined by averaging the estimates of all individual regression models. A critical factor for the success of ensemble schemes involves the combination of independent base models. In RF, this is achieved through a random feature selection step, which enables the development of independent individual models at each bootstrap run. Thus, the combination of bagging with feature selection leads to improved prediction results that are robust to noise and outliers. RF is a popular ensemble machine learning approach. Ensemble systems have been shown to provide superior prediction results in various regression and classification tasks. Thus, the consideration of RF in this study enables the examination of the performance of standalone linear and non-linear prediction models compared to an ensemble approach.

OLS and the four above mentioned regression approaches are implemented in combination with the four modelling schemes described in 3.2.2.2 (cf. Table 12). The only exception is that the LWM scheme is not applicable for GPR, as the latter does not employ user-defined weights for the sample observations. All models were implemented in MATLAB R2019a. LASSO, RF, and GPR were applied with the default parameters in MATLAB's built-in functions.

3.2.4 Results

This section presents and discusses the obtained results from the application of the regression approaches described above to the data sample. An analysis of the estimates regarding the contribution of the predictor attributes is first introduced. It is followed by the examination of the predictive power of the models, and some sensitivity analysis results.

3.2.4.1 The contribution of the predictor attributes

The regression methodologies presented in the previous section were applied using the moving window approach described in 3.2.2.2.

Table 13 & Table 14 summarise the estimates from the OLS, LASSO, and LAD regressions, as well as the estimates for the importance of the attributes from RF, for both the global (GM, GMSE) and the local (LM, LWM) schemes. For all numerical attributes, the standardised coefficients are reported, which allow comparisons of the relative magnitude of the estimates. It should be noted that the RF variable importance results have a different interpretation compared to standard regression models, indicating the impact of each attribute on the mean squared error of the model. The reported results are averages over all eight moving window runs.

Regarding the numerical attributes, size and age are consistently the most significant predictors having larger regression coefficients and RF importance estimates than other variables. These are followed by the floor and the squared size variable. The latter is found to have a similar effect to the number of bedrooms and bathrooms, in the global linear models (GM, GMSE; cf. Table 13). On the contrary, its relative importance is higher in the RF model and the locally weighted linear models (LM, LWM; cf. Table 14).

The categorical attributes have weaker explanatory and predictive power compared to numerical variables. The quality of construction and maintenance are the two most critical qualitative factors. Regarding the coordinates' spatial expansion attributes, it is interesting to observe that even though their coefficients in OLS and LAD are large, in LASSO, most of them are assigned zero coefficients. In RF, their importance is generally greater than several of the properties' attributes. Finally, it is worth noting that the regression coefficients in the local models are greater than the ones in the global models, which indicates that in a local setting the properties' attributes in the regression models have stronger explanatory power.

Table 13 Regression estimates for global models (regression coefficients and RF attributes' importance)

	GM				GMSE			
	OLS	LASSO	LAD	RF	OLS	LASSO	LAD	RF
Constant	7.098	7.110	7.105	-	6.846	7.080	6.811	-
SIZE	0.673	0.678	0.678	5.733	0.675	0.680	0.681	5.819
SIZE2	-0.019	-0.003	-0.018	2.478	-0.018	-0.002	-0.018	2.514
AGE	-0.250	-0.239	-0.279	9.376	-0.250	-0.243	-0.280	9.720
FLOOR	0.093	0.096	0.090	4.579	0.093	0.095	0.090	3.868
NBED	0.017	0.009	0.014	0.825	0.017	0.010	0.014	0.812
NBATH	0.020	0.030	0.014	0.929	0.019	0.029	0.013	0.883
TYPE=FLA	−0.001	0.000	0.013	0.738	0.000	0.000	0.014	0.584
TYPE=AM	0.031	0.025	0.028	-	0.032	0.024	0.028	-
TYPE=M	0.033	0.000	0.032	-	0.033	0.000	0.030	-
QCONSTR=M	0.129	−0.016	0.084	1.881	0.130	−0.016	0.084	1.586
QCONSTR=G	0.181	0.038	0.122	-	0.182	0.034	0.122	-
QCONSTR=VG	0.271	0.118	0.184	-	0.270	0.112	0.182	-
MAINT=M	0.002	-0.036	0.000	2.131	0.002	-0.037	0.003	1.791
MAINT=G	0.053	0.000	0.044	-	0.053	0.000	0.046	-
MAINT=VG	0.100	0.044	0.080	-	0.099	0.042	0.081	-
BASEMNT	-0.155	-0.101	-0.131	0.996	-0.157	-0.093	-0.135	0.922
HQHEAT	0.024	0.005	0.011	0.078	0.024	0.012	0.010	0.052
X	-	-	-	-	94.675	0.056	128.832	1.086
Y	-	-	-	-	89.680	0.000	128.746	1.828
X^2	-	-	-	-	- 86.109	0.000	- 105.165	1.146
Y^2	-	-	-	-	- 93.311	0.000	- 133.901	1.583
XY	-	-	-	-	- 99.510	0.000	- 147.136	2.434
X^3	-	-	-	-	11.650	0.000	7.597	1.130
Y^3	-	-	-	-	28.751	-0.093	40.575	1.973

	GM				GMSE			
	OLS	LASSO	LAD	RF	OLS	LASSO	LAD	RF
X^2Y	-	-	-	-	58.138	0.000	82.634	1.526
XY^2	-	-	-	-	25.354	0.000	40.493	2.326

Standardised coefficients are reported for the numerical attributes and the (X, Y) coordinates

Table 14 Regression estimates for local models (regression coefficients and RF attributes' importance)

	LM				LWM			
	OLS	LASSO	LAD	RF	OLS	LASSO	LAD	RF
Constant	6.234	6.412	6.478	-	6.301	6.428	6.618	-
SIZE	0.803	0.791	0.771	2.442	0.803	0.786	0.766	2.189
SIZE2	0.055	0.043	0.044	1.700	0.057	0.043	0.046	1.548
AGE	−0.298	−0.293	−0.337	3.764	−0.306	−0.301	−0.335	2.853
FLOOR	0.080	0.079	0.088	1.054	0.089	0.088	0.105	0.930
NBED	0.001	0.004	0.007	0.679	-0.003	0.003	0.012	0.723
NBATH	0.025	0.025	0.006	0.623	0.028	0.029	0.000	0.650
TYPE=FLA	−0.086	−0.008	−0.098	0.381	−0.125	−0.020	−0.182	0.411
TYPE=AM	−0.125	−0.013	−0.126	-	-0.155	−0.020	−0.137	-
TYPE=M	-0.091	-0.013	-0.134	-	-0.106	0.004	-0.105	-
QCONSTR=M	0.187	0.035	0.223	0.791	0.115	0.022	0.097	0.734
QCONSTR=G	0.275	0.124	0.280	-	0.215	0.122	0.160	-
QCONSTR=VG	0.394	0.230	0.328	-	0.330	0.223	0.222	-
MAINT=M	0.051	0.004	0.064	0.769	0.073	0.016	0.089	0.730
MAINT=G	0.101	0.050	0.103	-	0.086	0.028	0.113	-
MAINT=VG	0.172	0.117	0.143	-	0.164	0.102	0.156	-
BASEMNT	-0.225	-0.200	-0.253	0.152	-0.173	-0.162	-0.175	0.124
HQHEAT	-0.002	0.014	-0.023	0.038	0.008	0.015	0.026	0.108

Standardised coefficients are reported for numerical attributes

3.2.4.2 Analysis of predictive performance

In order to assess the predictive power and accuracy of the models on the future (out-of-sample) data for each test run of the adopted moving window approach, various performance metrics are used, namely:

- The coefficient of determination between the estimates ($\hat{y}$) derived from the prediction models and the values (y) of the properties as defined by the valuers:

$$R^2 = 100\left(\frac{COV(\hat{y},y)}{s_{\hat{y}}s_y}\right)^2 \quad (6)$$

  where $COV(\hat{y},y)$ is the covariance between $\hat{y}$ and y, whereas $s_{\hat{y}}, s_y$ represent the corresponding standard deviations.

- Mean (MAPE) and median (MDAPE) of the absolute relative prediction error $|\hat{y}_i - y_i|/y_i$.
- The k% trimmed mean absolute relative prediction error, calculated by excluding the $(k/2)$\% smallest and the $(k/2)$% largest error values. In the current analysis, $k = 1, 5$ (henceforth denoted by TMAPE1 and TMAPE5) is set.
- Percentage of test properties with absolute relative prediction error lower than a threshold ε, i.e. $|\hat{y}_i - y_i|/y_i < \varepsilon$. For the current analysis, the cases ε=0.1, 0.15, 0.2$ (henceforth denoted as P10, P15, P20) were considered.

Table 15 Predictive performance metrics (averages over all time periods and rankings of the models according to the Tukey's honest significance test)

Scheme	Model	R2	MAPE	MDAPE	TMAPE1	TMAPE5	P10	P15	P20
GM	OLS	79.71 (3)	19.07 (3)	18.55 (4)	17.55 (4)	13.51 (3)	38.67 (3)	54.50 (3)	65.89 (4)
	LASSO	78.63 (4)	20.15 (4)	19.61 (5)	18.49 (5)	14.46 (4)	36.29 (4)	51.63 (5)	63.92 (5)
	LAD	78.51 (4)	18.99 (2)	18.46 (3)	17.45 (3)	13.38 (2)	39.07 (2)	55.45 (2)	66.83 (2)
	RF	82.97 (2)	18.93 (2)	18.38 (2)	17.28 (2)	13.53 (3)	39.00 (2)	54.30 (4)	66.12 (3)
	GPR	85.16 (1)	17.49 (1)	16.97 (1)	16.03 (1)	12.52 (1)	41.44 (1)	57.89 (1)	69.20 (1)
GMSE	OLS	79.79 (3)	19.08 (4)	18.55 (4)	17.57 (4)	13.55 (4)	38.29 (4)	54.37 (4)	65.98 (4)
	LASSO	78.76 (4)	19.94 (5)	19.38 (5)	18.29 (5)	14.17 (5)	36.96 (5)	52.30 (5)	64.75 (5)
	LAD	78.49 (5)	19.00 (3)	18.47 (3)	17.47 (3)	13.37 (3)	38.94 (3)	55.10 (3)	66.85 (3)
	RF	84.04 (2)	18.24 (2)	17.66 (2)	16.56 (2)	12.95 (2)	40.96 (1)	56.16 (2)	68.15 (2)
	GPR	84.75 (1)	17.64 (1)	17.11 (1)	16.19 (1)	12.76 (1)	40.75 (2)	56.98 (1)	69.03 (1)
LM	OLS	83.95 (2)	18.05 (2)	17.52 (2)	16.56 (2)	13.05 (3)	40.38 (3)	55.79 (3)	67.96 (2)
	LASSO	83.75 (2)	18.12 (3)	17.60 (3)	16.62 (3)	13.01 (2)	39.82 (4)	55.81 (2–3)	67.88 (2)
	LAD	83.15 (3)	18.28 (4)	17.74 (4)	16.71 (4)	13.07 (3)	40.49 (2)	55.90 (2)	67.76 (3)
	RF	82.52 (4)	19.14 (5)	18.53 (5)	17.38 (5)	13.60 (4)	38.56 (5)	54.42 (4)	65.86 (4)
	GPR*	85.28 (1)	17.61 (1)	17.03 (1)	16.06 (1)	12.57 (1)	41.51 (1)	57.35 (1)	68.87 (1)
LWM	OLS	87.67 (2)	16.68 (2)	16.07 (2)	15.11 (2)	11.55 (2)	44.77 (2)	60.92 (2)	71.89 (2)
	LASSO	87.94 (1)	16.47 (1)	15.85 (1)	14.89 (1)	11.38 (1)	45.36 (1)	61.17 (1)	72.40 (1)
	LAD	86.32 (3)	17.46 (3)	16.71 (3)	15.64 (3)	11.77 (3)	44.44 (3)	59.26 (3)	70.52 (3)
	RF	84.31 (5)	18.36 (5)	17.73 (5)	16.57 (4)	12.51 (4)	41.80 (4)	57.34 (4)	68.02 (5)
	GPR*	85.28 (4)	17.61 (4)	17.03 (4)	16.06 (5)	12.57 (5)	41.51 (5)	57.35 (4)	68.87 (4)

*GPR-LWM and GPR-LM have the same results, because case weights are not applicable in GPR

Table 15 summarises the results for all modelling schemes and regression approaches in terms of the above performance metrics. The presented results refer to the average performance of the different approaches over all test quarters (i.e., out-of-sample results). Moreover, the same table shows the ranking of the different regression approaches under each scheme, according to the Tukey's honest significance test, with rank 1 corresponding to the best result.

For the two global schemes (GM, GMSE), the non-linear models developed with RF and GPR perform significantly better than linear regression (OLS, LASSO, LAD), with GPR almost consistently providing the best results. On the other hand, LASSO yields inferior results in almost all metrics. Comparing the GM setting to GMSE, it is evident that the addition of the additional spatial terms in GMSE does not improve the results. The only exception is RF, for which there is a noticeable improvement under the GMSE setting over the base GM scenario. This could be attributed to the feature selection scheme used in RF to inject randomness into the base models and increase their diversity, which works best when the number of predictor attributes is increased. For the rest of the methods, however, the spatial terms do no yield an improvement. (Bitter et al., 2007) note that the complexity of spatial patterns may not be accounted for by a spatial expansion of location coordinates. The presented results seem to confirm this finding.

The two local schemes (LM and LWM) provide significant improvements as far as the linear regression models are concerned. Under this setting, the results of OLS, LASSO, and LAD are significantly improved compared to the two global schemes. These results are following the findings from the literature. For instance, (Füss & Koller, 2016) used data from Zürich-Switzerland and noticed that hedonic models relying solely on physical attributes of the properties without controlling for spatial heterogeneity provide inferior results compared to models that use location dummy variables or models developed on sub-market segments defined considering spatial heterogeneity.

For the two non-linear regression approaches, however, the local schemes do not lead to improved results. RF and GPR perform very similarly under both the global and the local settings. For instance, RF with the LM scheme performs slightly worse than the base GM setting, whereas the results with the locally weighted scheme (LWM) are very close to those of GMSE, which considers spatial effects. Similarly, the differences between GPR under the local settings and the global ones are barely noticeable. Even though non-linear regression approaches have been extensively used for modelling house prices, we are not aware of prior results on the performance of such methods in a context that explicitly considers spatial effects, such as the local schemes used in this analysis.

The above results imply that non-linear models can capture (to some extend) spatial effects from the full data set that covers regional areas in Greece with very different characteristics. This is particularly true for GPR, which even under the base GM setting, performs very well. Adopting a local regression setting enables linear regression models to identify strong spatial effects that are missed by the global models.

Moreover, it is worth noting the improvements that the locally weighted scheme (LWM) brings over the unweighted setting (LM). Indeed, all approaches (OLS, LASSO, LAD, RF) that enable the introduction of weights for the training properties in terms of their distance from each test observation provide significantly better results. The improvements are larger for the linear regression models (OLS, LASSO, LAD). The results of the weighted linear models are also significantly better than those of GPR. Among the linear models, LASSO consistently outperforms all other approaches, even though it performed poorly under the global schemes. The combination of LASSO with a local estimation approach has also been considered by (Wheeler, 2009), who presented simulation results as well as an application on data involving crimes prediction and found that such an approach allows local model selection and the reduction of the prediction error. OLS follows LASSO as the second-best approach and LAD as the third one. These results indicate that there are strong spatial effects in the Greek market, which cannot be fully captured by non-linear models. Properly designed local linear models with geographically defined weights seem to provide superior results.

Figure 21 provides additional results for the predictive (out-of-sample) performance of LASSO, OLS, and LAD, under the LWM scheme, as well as for local GPR, which provides the best regards among the other models. Results are reported for R^2 and MAPE in each one of the eight quarters used in the comparative analysis (i.e., the moving window tests). It is evident that LASSO and OLS provide very similar results in all quarters, but LASSO is consistently slightly better than OLS. These two regression approaches are followed by LAD, whereas the results of GPR are almost consistently inferior to the locally weighted models. Compared to the study of (A. K. Alexandridis et al., 2019) who used the same data but with a different empirical setting (i.e., attributes, fitting procedure, and methods), the results obtained with the local models in this study are improved.

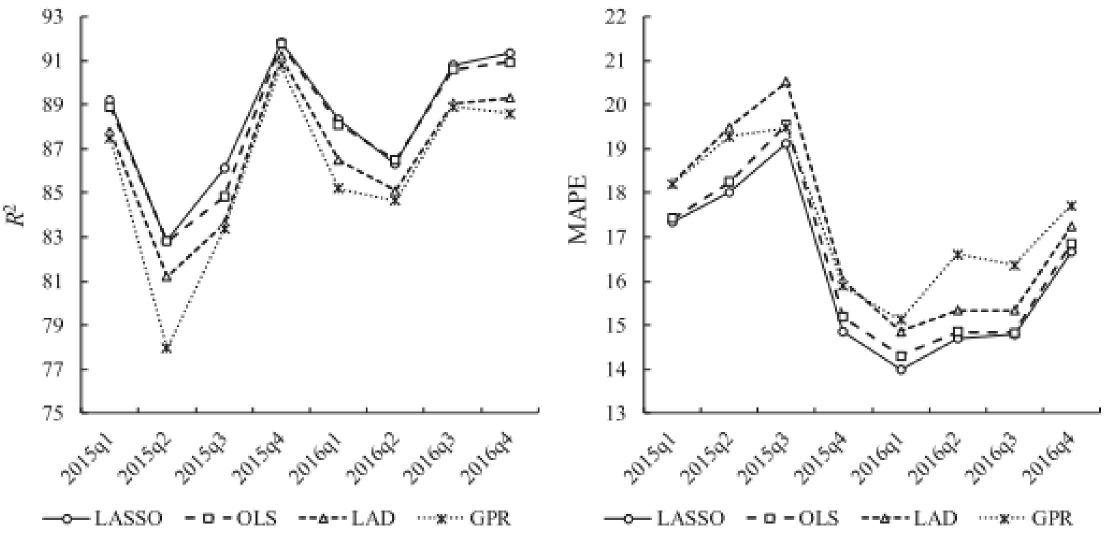


Figure 21 R^2 and MAPE by quarter for selected locally weighted models and comparison with local GPR results

Table 16 Differences in MAPE between weighted and unweighted local regression models by area type

Area type	N	OLS	LASSO	LAD
Other areas (population<100k)	11,562	−1.09**	−1.60**	−0.05
Major cities (100k< population<300k)	2738	−0.55	−0.64*	0.58
Metropolitan areas	22,229	−1.63**	−1.81**	−1.47**

N is the number of properties in the full sample, **significant differences at the 1% level, *significant differences at the 10% level

Table 16 compares the performance of the three best locally weighted models (OLS, LASSO, LAD) against the same regression approaches without the weighting scheme. The comparison focuses on three categories of the properties' area type, namely cities and areas with population less than 100,000, major cities with population up to 300,000, and the two metropolitan areas of Athens and Thessaloniki. Negative entries in this table correspond to improved results for the weighted scheme against the unweighted one. The most noticeable improvements involve predictions for properties in metropolitan areas (significant at the 1% level according to a paired-samples t-test). OLS and LASSO also show improvements in smaller areas and major cities, but these improvements are lower than the ones for the two metropolitan areas in Greece. The results of LAD under the LWM scheme are almost identical to the LM scheme for areas with a small population while being worse for major cities. However, these differences are not found statistically significant. Overall, given the weak benefits that the weighted scheme brings for properties located in major cities, it should be noted that the number of properties in this category is much smaller than those in smaller and metropolitan areas. Thus, it seems that the weighting scheme does not work well in such cases. The reason is that the market properties used in the LWM scheme are more heterogeneous, with some being in rural areas close to the subject properties being valued and other being more geographically dispersed (even belonging in urban areas). Similar results were also reported by (Gröbel & Thomschke, 2018). They compared OLS models with spatial fixed effects to local models using housing data from Berlin and found the local models to perform better when spatial density is high.

3.2.4.3 Sensitivity analysis

To provide further insights into the performance and robustness of the locally weighted scheme, the sensitivity of the results for various specifications of the number of properties used in the local regressions (market size) was examined. Table 17 summarises the results for different market sizes, ranging between 500 and 5000 properties, with 1000 being the base scenario that corresponds to the results reported in the previous subsection (cf. Table 15). For this analysis, the focus was on OLS, LASSO, and LAD, which were found to provide the best results under the LWM scheme and benefit the most from adopting a locally weighted approach.

For all three regression models, the use of a small local market size (500 instances) leads to inferior results compared to the base scenario of 1000 properties. Regarding the use of larger market samples (2000 and 5000), LASSO provides very robust results. Except for a minor decrease in R^2 when using larger markets, the rest of the metrics only show very minor differences, but with no noticeable trend (improving or worsening). The OLS results are also robust, even though in most metrics (except R^2) there are marginal improvements with the number of properties used for fitting the local models. Similar, but higher improvements are also observed for LAD (again except for the R^2 measure), which is the approach that benefits the most from using larger market sizes. Nevertheless, despite these improvements, LAD still appears to be inferior compared to OLS and LAD. Overall, these results indicate that even a relatively small subset of properties (e.g., 1000) can provide quite good results in a local regression context for predicting property prices.

Table 17 Performance metrics by market size

Method	Market	R2	MAPE	MEDAPE	TMAPE1	TMAPE5	P10	P15	P20
OLS	500	87.30	17.01	16.39	15.38	11.67	44.38	60.04	71.06

	1000	87.67	16.68	16.07	15.11	11.55	44.77	60.92	71.89
	2000	87.41	16.61	15.98	15.03	11.40	45.23	60.86	71.84
	5000	87.06	16.59	15.95	15.00	11.36	45.63	61.09	72.26
LASSO	500	88.06	16.57	15.96	15.01	11.41	45.20	60.59	72.08
	1000	87.94	16.47	15.85	14.89	11.38	45.36	61.17	72.40
	2000	87.61	16.52	15.89	14.92	11.31	45.50	61.25	72.43
	5000	87.07	16.62	15.97	14.98	11.29	45.31	61.13	72.35
LAD	500	85.91	17.84	17.12	16.02	11.99	43.92	58.68	69.49
	1000	86.32	17.46	16.71	15.64	11.77	44.44	59.26	70.52
	2000	86.21	17.20	16.52	15.48	11.65	44.77	59.76	70.89
	5000	86.09	16.92	16.30	15.28	11.54	45.14	60.41	71.86

3.2.5 Conclusions

This study presented an extensive empirical comparison of statistical and machine learning approaches for constructing AVMs for residential properties. The analysis focused on how different settings for incorporating spatial effects, affect the predictive performance of the models. To this end, linear and non-linear regression models were tested under global, local, and locally weighted schemes using a large database from Greece, which is characterised by heterogeneity and recessionary conditions throughout the study.

The results showed that locally weighted linear models perform very well, as they can capture spatial variation in prices more accurately than global and unweighted local approaches. Non-linear models developed with machine learning approaches like random forests and GPR performed well in a global setting. However, they did not benefit much from an implementation in a local context. Moreover, it was found that the introduction of spatial expansion terms has little impact on most of the approaches.

These results indicate that even simple linear models can be handy tools for building accurate AVM systems if they are fitted in a way that implicitly or explicitly takes spatial effects into account. Such spatial effects appear to be a decisive factor in the Greek market.

3.3 AVM & Value at Risk (VaR) Analysis: An Application for the Greek Real Estate Market

3.3.1 Introduction

As seen before, risk management in real estate is an issue of significant interest for various stakeholders, including investors, real estate developers, financial institutions, and policymakers, since there is a direct and undeniable two-way relationship between real estate's conditions and economic growth. This relationship's most characteristic example is, of course, the significant drop in property values in many countries due to the credit crunch of 2007-2008 and its negative effects on many other sectors, including the general economy. Despite the stabilising, upward trends recorded in several countries after that, volatility and risks remain.

Greece, especially, is still facing significant challenges, being to a large extent a legacy of the severe economic crisis faced until 2018. On top of this, other factors, including the changeable worldwide economic environment and climate change with its resulting unusual weather conditions, threaten Greece's stability and prosperity. Additionally, the current coronavirus crisis highlights in the hardest way how a severe, unpredictable phenomenon may disrupt every prospect and stability.

It becomes evident that predicting real estate values for the near future is not a straightforward task. On the contrary, it results from many conflicting factors and, of course, the country's general economy, as represented by specific macroeconomic variables, such as the interest and unemployment rates. At the same time, it is of particular interest since credible predictions can lead to appropriate proactive measures for risk mitigation.

Stress tests have been used extensively in the banking sector, especially as systemic control tools. In most cases, these involve analysis scenarios for the impact of macroeconomic variables on the quality of loan portfolios, credit risk, and financial institutions' capital adequacy. These scenarios are mostly based on econometric models and simulation. Scenarios for the impact of a downturn in the real estate market are also often considered. However, the opposite analysis, namely, the prediction of real estate values based on stress tests and simulation analysis, are less common.

In this context, this simulation exercise's aim is the detailed examination of scenarios for real estate values in Greece in the Cerved Property Services (CPS) portfolio in the short-term horizon of 1-3 years. The simulation calculates statistical measures for the volatility of real estate values and the expected losses in extreme scenarios in the coming period.

The implementation of the simulations is based on the LASSO locally weighted model that was found to provide good results in the analysis presented earlier. The training data for fitting the AVM model cover the period 2015q1-2020q1, whereas the valuation data involve the properties of 2020q2 over a period of 1-3 years (from 2021q2 to 2023q2). The analysis takes into account three key macroeconomic variables:

1. The short-term interest rate (STIR, source: OECD)
2. The consumer price index (CPI, source: OECD)
3. Unemployment rate (UNR, source: Eurostat)

The simulation process is implemented in the following three steps:

1. Development of an econometric model for modelling the effect of macroeconomic variables on CPS value indices
2. Development of random scenarios for the indices, based on the econometric model, through Monte Carlo simulation
3. Calculation of real estate values through the AVM model in each scenario and statistical processing of results

The CPS value indices are Greece's administrative sectors, as these are grouped and encoded by CPS. The names of the administrative sectors represented by the index codes of the analysis can be found in Table 18, below.

Table 18 CPS value indices and their related administrative sector

Index	Administrative sector	Index	Administrative sector
14	Central Athens	34	Ipeiros
18	Middle - North. Athens	35	Sterea Ellada
19	North. Suburbs. of Athens	36	Thesalia
20	West. Suburbs of Athens	37	Western Greece
21	South. Suburbs of Athens	38	Eptanisa
22	Pireas	39	Peloponnisos
23	Suburbs of Pireas	40	Aegean
24	West Attica	41	Crete
25	East Attica	42	Cyclades
27	Central & East Thessaloniki	43	Dodecanisa
28	Western Thessaloniki	44	Patra

Index	Administrative sector	Index	Administrative sector
29	Suburbs of Thessaloniki	45	Iraklio
30	Rest of Thessaloniki	46	Larisa
31	Central Macedonia	47	Volos
32	East Macedonia & Thraki	48	Ioannina
33	Western Macedonia	49	Rodes

The following sections describe the above steps and the corresponding results.

3.3.2 Methodology

3.3.2.1 Econometric model

In the first stage of the analysis, an econometric model was developed to link macroeconomic data with indices by region. The analysis at this stage was based on a model of the following form:

$$\ln\frac{I_{it}}{I_{it-1}} = \alpha + \beta_1 \ln\frac{I_{i,t-1}}{I_{i,t-2}} + \beta_2 \ln\frac{I_{i,t-2}}{I_{i,t-3}} + \beta_3 SIR_t + \beta_4 \ln\frac{CPI_t}{CPI_{t-1}} + \beta_5 \Delta_{t-1}(UNR) + \gamma IND + \delta YR + \zeta QR + \varepsilon_{it}$$

where:

- I_{it} is the value of index i in time period t,
- $\Delta_{t-1}(UNR)$ is the change of the unemployment rate between time periods t-1 and t-2,
- IND are pseudo-variables for the coding of individual indices,
- YR are pseudo-variables for the coding of years,
- QR are pseudo-variables for the coding of quarters.

The model was estimated using Ordinary Least Squares (OLS), as the Breusch-Pagan Lagrange multiplier test showed that this estimation should be preferred over a random effects model.

The econometric analysis was based on all available data for the indices from the beginning of 2007 to 2020q2. The results of the estimation are presented in

Table 19. The R^2 coefficient of the model is 0.4818 and the RMSE 0.024. It can be observed that the macroeconomic variables have all the expected signs and are also statistically significant at the level of 5% (excluding CPI). The pseudo-variables corresponding to the sub-indices are also very significant (all at 1% level), indicating that there are strong differences among the indices. Finally, most of the pseudo-variables concerning the years are also significant.

Table 19 Estimation results of the econometric model

	Coefficient	p-value
$\ln(I_{i,t\text{-}1} / I_{i,t\text{-}2})$	0.4926	0.000
$\ln(I_{i,t\text{-}2} / I_{i,t\text{-}3})$	-0.5781	0.000
STIR	-0.0053	0.036
$\ln(CPI_t / CPI_{t\text{-}1})$	0.1145	0.396
$\Delta_{t-1}(UNR)$	-0.0037	0.049
YR		
2008	-0.0068	0.024
2009	-0.0262	0.010
2010	-0.0334	0.003
2011	-0.0289	0.004
2012	-0.0488	0.000
2013	-0.0500	0.000
2014	-0.0401	0.004
2015	-0.0475	0.001
2016	-0.0356	0.016
2017	-0.0408	0.009
2018	-0.0244	0.090
2019	-0.0165	0.253
2020	-0.0199	0.222
QR		
Q2	-0.0025	0.496
Q3	-0.0013	0.562
Q4	-0.0045	0.106
IND		
Index 18	0.0008	0.000
Index 19	-0.0019	0.000
Index 20	-0.0012	0.000
Index 21	0.0003	0.000
Index 22	-0.0022	0.000
Index 23	-0.0017	0.000
Index 24	-0.0030	0.000
Index 25	-0.0041	0.000
Index 27	-0.0022	0.000
Index 28	-0.0041	0.000
Index 29	-0.0055	0.000
Index 30	-0.0038	0.000
Index 31	0.0029	0.000
Index 32	-0.0007	0.000
Index 33	0.0015	0.000
Index 34	-0.0028	0.000
Index 35	-0.0015	0.000
Index 36	0.0024	0.000
Index 37	-0.0009	0.000

Index 38	0.0004	0.000
Index 39	-0.0025	0.000
Index 40	-0.0009	0.000
Index 41	0.0017	0.000
Index 42	-0.0012	0.000
Index 43	-0.0019	0.000
Index 44	-0.0014	0.000
Index 45	0.0009	0.000
Index 46	-0.0001	0.000
Index 47	-0.0005	0.000
Index 48	-0.0027	0.000
Index 49	-0.0017	0.000
Constant	0.0318	0.021
N	1632	

3.3.2.2 Simulation process

The scenario analysis for 2020q2 real estate values (1101 properties) is based on a Monte Carlo simulation on the basis of the econometric model presented above.

The simulation is performed for a period of T years based on (annual) forecasts for the economic indicator, which are the inputs used in the simulation. The analysis was based on estimates / forecasts of the macroeconomic variables derived from Oxford Economics. The available annual forecasts are reduced to quarterly for the implementation of the simulations based on a quarterly time step.

The simulation process is based on the methodology used by (Follain & Giertz, 2011). In this analysis, 1000 scenarios (simulations) were examined for three different horizons of one, two and three years, having in each case as a starting point 2020q2. Thus, one-year simulations relate to the period up to 2021q2, two-year simulations relate to the period up to 2022q2, and finally three-year simulations relate to the period up to 2023q2. For each period of T years, the simulation is performed as follows:

1. For each year in the simulation period, a random effect from the years 2007-2020 is used in the econometric model of the previous section. The selection of the year is made by giving a greater probability of selection to the years that are more similar (in terms of the macroeconomic variables examined) in relation to each year of the simulation. The similarities between the years are defined using the Euclidean distance, in terms of the differences between the years on the three macroeconomic indicators (i.e., similar years are the ones with similar macroeconomic conditions). By denoting as $D_{tt'}$ the distance

between the years t and t', the similarity of the two years is calculated as $s_{tt'} = 1/D_{tt'}$. According to this degree of similarity, the probability of selecting year t' to simulate year t is given by the following relation:

$$\pi_{tt'} = \frac{s_{tt'}}{\sum_{i=2007}^{2020} s_{ti}}$$

The following table shows the similarities of the years 2021-2023 (the years of the simulation) with the years 2007-2020, as well as the probabilities of selection:

Table 20 Similarities with and probability of selection of the years 2007-2020 for the years of the simulation, 2021-2023

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
								Similarity						
2021	0.22	0.24	0.40	0.71	0.80	0.75	0.66	0.79	0.99	1.17	2.37	12.72	3.12	3.16
2022	0.21	0.23	0.38	0.73	0.85	0.68	0.55	0.60	0.64	0.68	0.98	1.52	2.28	1.21
2023	0.20	0.22	0.35	0.62	0.75	0.61	0.49	0.50	0.51	0.52	0.68	0.89	1.10	0.77
								Probability of selection						
2021	0.01	0.01	0.01	0.03	0.03	0.03	0.02	0.03	0.04	0.04	0.08	0.45	0.11	0.11
2022	0.02	0.02	0.03	0.06	0.07	0.06	0.05	0.05	0.06	0.06	0.08	0.13	0.20	0.10
2023	0.02	0.03	0.04	0.08	0.09	0.07	0.06	0.06	0.06	0.06	0.08	0.11	0.13	0.09

2. For each quarter within one year and for each index, a random error factor (the error ε in the econometric model) is generated from the normal distribution with zero mean and standard deviation equal to the RMSE of the econometric model. This random disturbance is introduced in the econometric model together with the macroeconomic data of this quarter, the selected annual random effect and the historical data of each index for the previous two quarters, in order to form the estimation / forecast of the indices in the current quarter.
3. The above two steps are repeated for the next quarter within the examined time period, this time using as a starting point the estimates / forecasts of the indices resulting from the above second step.
4. Upon completion of steps 1-3 for all quarters within the period of T years, the final (simulated) values of the indices are used for the valuation of the properties in the portfolio, with the valuation date being the end of the examined period.

3.3.3 Results

The results of the process described in 3.3.2.2 can be found in Tables 21-26 and Figures 22-24. The results concern the real estate portfolio of 2020q2. In Table 21, Table 23 & Table 25, the forecasted values of the properties in total and per index for a one-, two- and three-year forecast horizon are presented, including summary statistics for these values. In Table 22, Table 24 & Table 26, the differences between the forecasted values for a one-, two- and three-year horizon, respectively, with the values of the properties at 2020q2, in total and per index, are shown. These differences are presented both in absolute terms and as percentage changes of the forecasted values compared to the 2020q2 values. Finally, in Figure 22Figure 23Figure 24, the frequency distribution of the percentage of profit/loss for a one-,two- and a three-year horizon is depicted. The 99% VaR is also included in these figures. This means that the probability of a loss greater than VaR is at most 1% while the probability of a loss less than VaR (which may result in a profit) is at least 99%.

All three forecast horizons - one-, two, and three-year forecast horizon - predict a progressive increase in the properties' values in total, despite the differentiation in the individual indices.

By 2021q2, a 0.39% increase in Greece’s property values is expected on average compared to the 2020q2 values, as seen in Table 22, while the probability of a loss greater than 3.67% will be at most 1%, as the results of the analysis indicate (cf. Figure 22). In 2022, the increase in Greece’s property values is expected to continue reaching a 0.94% increase on average in 2022q2 compared to the values of 2020q2 (Table 24), with a 99% VaR estimated at 5.84% (Figure 23). A three-year forecast horizon showcases that the rise in property values will continue in 2023 as well. According to the results, there will be an on average 1.22% increase from the current values of 2020q2 (Table 26). This forecast involves, though, greater risk since the 99% VaR value is 6.65% (Figure 24).

This progressive increase at Greece’s property values for a one-, two- and three-year forecast horizon does not evenly apply to all indices, i.e., administrative sectors. In contrast, there are regions for which a decrease in their real estate values is expected, as is the case of middle north Athens (i.e., index 18) and the suburbs of Piraeus (i.e., index 23) where an on average 4.28% and 8.16% decrease by 2021q2 has been predicted respectively. For some cases, the increase is expected to be greater than the forecasted total average, as in the case of central Macedonia (i.e., 31) and central Greece (i.e., 35), where the one-year horizon forecast suggests an on average 11.19% and 13.37% increase in their property values respectively. In a two- and three-year horizon forecast, these trends either become stronger in some regions *(e.g., for a three-year horizon, 14.37% increase for index 31, which was 11.19% for a one-year forecast horizon, and 9.16% decrease for index 44, which was 8.25% for a one-year forecast horizon)* or less intense *(e.g., for a three-year horizon, 1.95% decrease for index 18, which was 4.28% for a one-year forecast horizon, and 6.01% increase for index 46, which was 6.18% for a one-year forecast horizon).*

Despite these differentiations, in all cases, the greater the forecast horizon, the more significant the uncertainty and, therefore, the VaR value.

The methodology presented in this chapter is a simulation methodology for analysing uncertainty in real estate valuations. Therefore, it can be of great value for investors, financial institutions and anyone interested in understanding the uncertainty enclosed in real estate. For example, an investor may orient his/her investments towards the regions (i.e., indices) that showcase the smaller loss risk, namely the smaller 99% loss VaR values and the greater percentage increase in their real estate values in a short-term investment horizon. Although the process followed refers to an automated valuation system, it can also be used by supervisors to support applying new policy measures.

Table 21 Forecasted values for a one-year horizon

Indices	Total current value	Mean	Median	Std	99% CI	
All	120890926	121358909	121437017	1941197	116131347	126160807
14	3028650	3026434	3022716	152387	2599905	3484730
18	1623396	1553948	1553935	76337	1351078	1755299
19	20372457	20294443	20233301	976837	17793040	22857947
20	11679965	11261962	11243078	558140	9815547	12676507
21	8243000	8498248	8487664	429428	7424683	9749896
22	3490206	3588527	3573144	174494	3205279	4096434
23	6392584	5870886	5866468	299560	5124747	6678828
24	938100	983057	983346	48952	855528	1121199
25	11900948	12152622	12140137	608563	10611861	13797237
27	7634251	6946504	6939268	359909	5975182	7916291
28	2579204	2551768	2546256	125896	2240957	2939835
29	5387000	5157634	5159345	250554	4513465	5756013
30	1474500	1466794	1466106	73487	1286937	1651449
31	4970536	5526513	5514883	277925	4766592	6318729
32	3387077	3420722	3419066	175394	2982470	3917304
33	749000	753115	751916	36326	661722	852557
34	535850	572296	572055	28596	499788	649175
35	4482850	5082308	5076964	269040	4400952	5913142
36	3129000	3108328	3103011	154398	2666232	3540342
37	1886296	1958232	1959390	99747	1720524	2223023
38	826600	885298	884878	44506	778755	1020772
39	2954970	3117076	3110146	161069	2735397	3545641
40	475500	459256	458552	23530	407265	530411
41	5654195	5813978	5804082	293034	5126135	6597920
42	912000	942857	942078	47040	833313	1053671
44	598400	549054	547372	28213	481286	625856
45	2033591	2142681	2137757	104773	1881000	2434153
46	1603100	1702210	1699972	87413	1501171	1953994
47	531000	569580	569843	28455	493535	650127
48	777300	747787	747039	36137	664424	849761
49	639400	654791	653401	31695	573057	740813

Table 22 Differences between forecasts for a one-year horizon and current values (i.e., 2020q2) for all indices (numbers and percentages)

	Differences (Forecasts - Current values)				% differences from current values			
Indices	**Mean**	**Median**	**Std**	**99% Loss VaR**	**Mean**	**Median**	**Std**	**99% Loss VaR**
All	467983	546091	1941197	4441739	0.39	0.45	1.61	3.67
14	-2216	-5934	152387	385493	-0.07	-0.20	5.03	12.73
18	-69448	-69461	76337	247207	-4.28	-4.28	4.70	15.23
19	-78014	-139156	976837	2213270	-0.38	-0.68	4.79	10.86
20	-418003	-436887	558140	1637948	-3.58	-3.74	4.78	14.02
21	255248	244664	429428	687354	3.10	2.97	5.21	8.34
22	98321	82938	174494	268041	2.82	2.38	5.00	7.68
23	-521698	-526116	299560	1173756	-8.16	-8.23	4.69	18.36
24	44957	45246	48952	62324	4.79	4.82	5.22	6.64
25	251674	239189	608563	1112070	2.11	2.01	5.11	9.34
27	-687747	-694983	359909	1538066	-9.01	-9.10	4.71	20.15
28	-27436	-32948	125896	318179	-1.06	-1.28	4.88	12.34
29	-229366	-227655	250554	841833	-4.26	-4.23	4.65	15.63
30	-7706	-8394	73487	176547	-0.52	-0.57	4.98	11.97
31	555977	544347	277925	111511	11.19	10.95	5.59	2.24
32	33645	31989	175394	384560	0.99	0.94	5.18	11.35
33	4115	2916	36326	79111	0.55	0.39	4.85	10.56
34	36446	36205	28596	29409	6.80	6.76	5.34	5.49
35	599458	594114	269040	-22218	13.37	13.25	6.00	-0.50
36	-20672	-25989	154398	390142	-0.66	-0.83	4.93	12.47
37	71936	73094	99747	142751	3.81	3.87	5.29	7.57
38	58698	58278	44506	40256	7.10	7.05	5.38	4.87
39	162106	155176	161069	180354	5.49	5.25	5.45	6.10
40	-16244	-16948	23530	65256	-3.42	-3.56	4.95	13.72
41	159783	149887	293034	471193	2.83	2.65	5.18	8.33
42	30857	30078	47040	69916	3.38	3.30	5.16	7.67
44	-49346	-51028	28213	111197	-8.25	-8.53	4.71	18.58
45	109090	104166	104773	110063	5.36	5.12	5.15	5.41
46	99110	96872	87413	93782	6.18	6.04	5.45	5.85
47	38580	38843	28455	28574	7.27	7.32	5.36	5.38
48	-29513	-30261	36137	107490	-3.80	-3.89	4.65	13.83
49	15391	14001	31695	59069	2.41	2.19	4.96	9.24

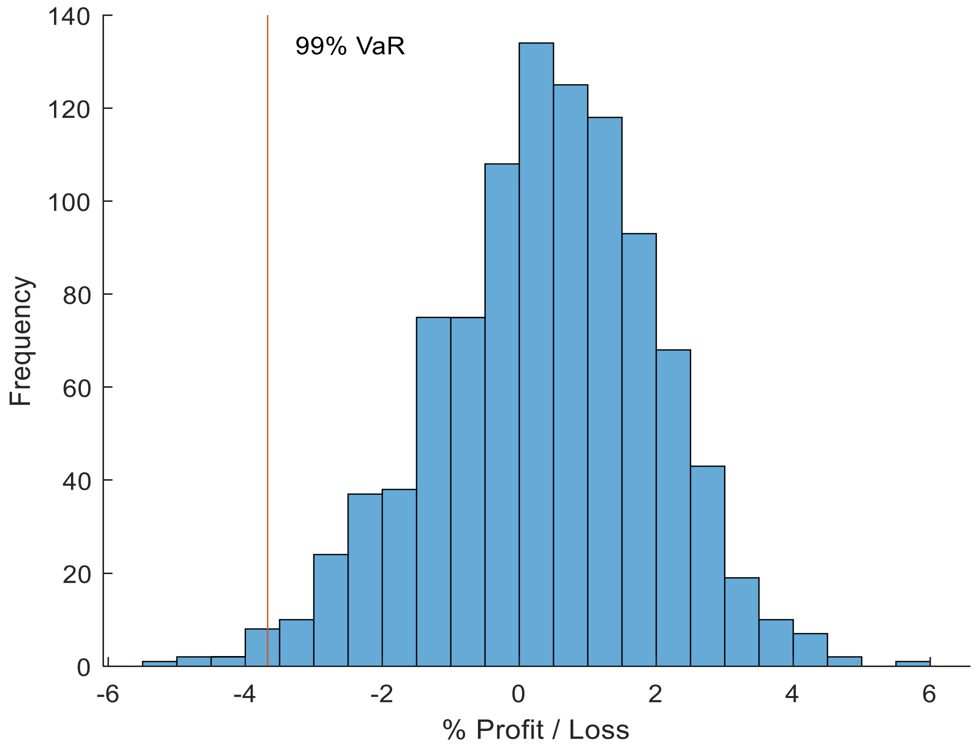


Figure 22 Frequency distribution of % profit / loss, including VaR for a one-year horizon

Table 23 Forecasted values for a two-years horizon

Indices	Total current value	Mean	Median	Std	99% CI	
All	120890936	122026856	122132720	3498772	112842672	130871632
14	3028650	3048558	3039719	204281	2560533	3600034
18	1623396	1538176	1538097	100049	1295185	1798245
19	20372456	20421008	20387576	1374285	17022752	24022016
20	11679965	11409636	11386496	720776	9775650	13473771
21	8243000	8541393	8553173	562390	7204715	9958338
22	3490206	3685550	3678919	236710	3129111	4313466
23	6392584	5937818	5936081	388291	4950435	6967122
24	938100	969052	967669	62433	816098	1131470
25	11900948	12124004	12116810	785220	10186604	14554537
27	7634251	6961622	6973538	460968	5899561	8264360
28	2579204	2568149	2559798	170728	2158239	3033380
29	5387000	5092750	5093398	339320	4280509	6011662
30	1474500	1457263	1456505	97680	1223063	1731735
31	4970536	5526905	5526754	352093	4702165	6453324
32	3387077	3431768	3428618	222149	2885616	4061837
33	749000	790803	788237	50445	670811	940965
34	535850	573107	572591	37599	481121	677158
35	4482850	5052665	5053131	336429	4228915	5815962
36	3129000	3159536	3159067	203061	2683040	3713247
37	1886296	2005989	2001965	132653	1709499	2401160
38	826600	889235	885710	59131	746167	1056030
39	2954970	3170746	3175595	213522	2643404	3707045
40	475500	463644	463149	32613	381509	567258
41	5654195	5884633	5880984	395081	4889735	6840367
42	912000	945221	943225	62094	806101	1113084
44	598400	554123	552239	35751	467432	654320
45	2033591	2130932	2127331	141326	1808569	2552210
46	1603100	1708583	1703542	114625	1432674	2023046
47	531000	592564	590843	39235	499449	696857
48	777300	744928	744274	48613	622197	872411
49	639400	646478	645570	41635	541616	759499

Table 24 Differences between forecasts for a two-years horizon and current values (i.e., 2020q2) for all indices (numbers and percentages)

	Differences (Forecasts - Current values)				% differences from current values			
Indices	**Mean**	**Median**	**Std**	**99% Loss VaR**	**Mean**	**Median**	**Std**	**99% Loss VaR**
All	1135908	1241784	3498771	7058444	0.94	1.03	2.89	5.84
14	19908	11069	204281	415588	0.66	0.37	6.74	13.72
18	-85220	-85299	100049	299590	-5.25	-5.25	6.16	18.45
19	48554	15120	1374285	3028312	0.24	0.07	6.75	14.86
20	-270328	-293469	720776	1848932	-2.31	-2.51	6.17	15.83
21	298393	310173	562390	939801	3.62	3.76	6.82	11.40
22	195344	188713	236710	330439	5.60	5.41	6.78	9.47
23	-454766	-456503	388291	1295262	-7.11	-7.14	6.07	20.26
24	30952	29569	62433	100772	3.30	3.15	6.66	10.74
25	223057	215863	785220	1572101	1.87	1.81	6.60	13.21
27	-672628	-660713	460968	1698268	-8.81	-8.65	6.04	22.25
28	-11056	-19406	170728	396783	-0.43	-0.75	6.62	15.38
29	-294250	-293602	339320	1041034	-5.46	-5.45	6.30	19.32
30	-17237	-17996	97680	229033	-1.17	-1.22	6.62	15.53
31	556368	556218	352093	201037	11.19	11.19	7.08	4.04
32	44691	41541	222149	474060	1.32	1.23	6.56	14.00
33	41803	39237	50445	72161	5.58	5.24	6.73	9.63
34	37257	36741	37599	46404	6.95	6.86	7.02	8.66
35	569815	570281	336429	180136	12.71	12.72	7.50	4.02
36	30536	30067	203061	417603	0.98	0.96	6.49	13.35
37	119693	115669	132653	162147	6.35	6.13	7.03	8.60
38	62635	59110	59131	66799	7.58	7.15	7.15	8.08
39	215777	220625	213522	267295	7.30	7.47	7.23	9.05
40	-11856	-12351	32613	87960	-2.49	-2.60	6.86	18.50
41	230439	226789	395081	675629	4.08	4.01	6.99	11.95
42	33221	31225	62094	98641	3.64	3.42	6.81	10.82
44	-44277	-46161	35751	122401	-7.40	-7.71	5.97	20.45
45	97341	93740	141326	199924	4.79	4.61	6.95	9.83
46	105483	100442	114625	136460	6.58	6.27	7.15	8.51
47	61564	59843	39235	27735	11.59	11.27	7.39	5.22
48	-32372	-33026	48613	143857	-4.16	-4.25	6.25	18.51
49	7078	6170	41635	81496	1.11	0.96	6.51	12.75

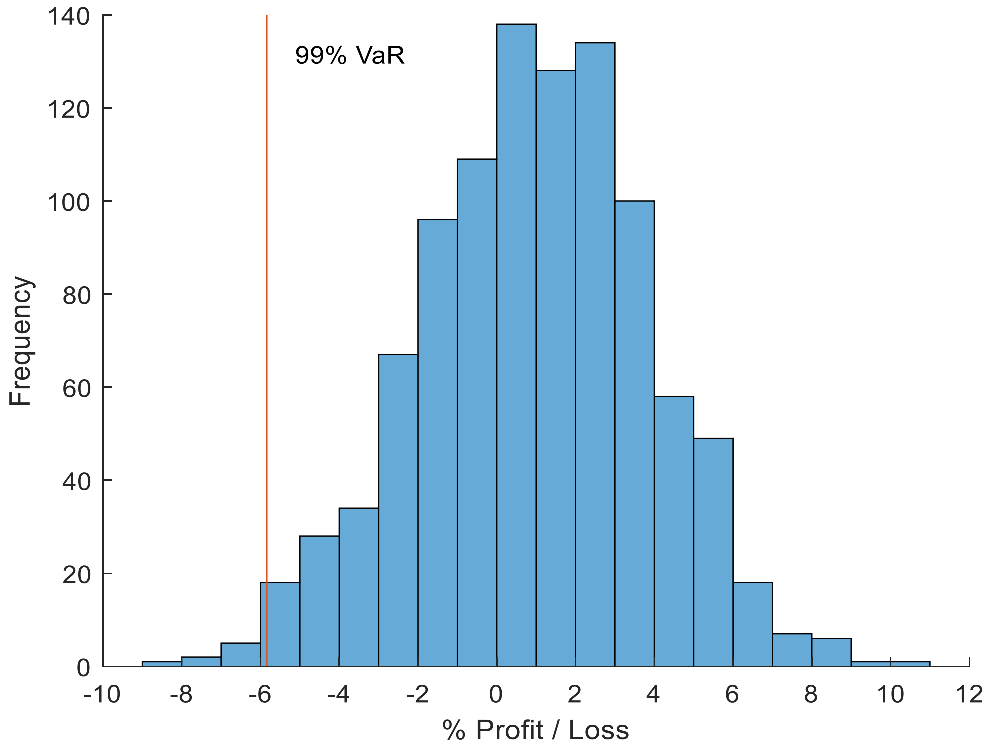


Figure 23 Frequency distribution of % profit / loss, including VaR for a two-years horizon

Table 25 Forecasted values for a three-year horizon

Indices	Total current value	Mean	Median	Std	99% CI	
All	120890936	122363296	122289536	4436203	111791648	134705408
14	3028650	3075069	3060161	227976	2537527	3736906
18	1623396	1591744	1581978	130502	1309090	1991558
19	20372456	20382532	20364410	1581121	16532576	24938604
20	11679965	11387939	11322874	888640	9374853	13640630
21	8243000	8670926	8668428	680174	7044829	10423458
22	3490206	3631630	3631447	292967	2941287	4471953
23	6392584	5958384	5940949	484630	4712275	7392997
24	938100	978907	978844	73293	813133	1170762
25	11900948	12059839	12009792	955484	9875310	14597436
27	7634251	6987626	6958503	569023	5655427	8466504
28	2579204	2521905	2513359	200029	2059400	3086496
29	5387000	5079767	5059852	399700	4137488	6176167
30	1474500	1447544	1442152	111962	1162977	1732566
31	4970536	5685002	5666570	459831	4622930	6941898
32	3387077	3467994	3457933	293186	2802562	4292414
33	749000	780756	777451	67092	632255	978453
34	535850	577497	575580	47270	466911	701174
35	4482850	5105177	5082278	421108	4073635	6278371
36	3129000	3200547	3184891	254596	2618008	3900566
37	1886296	1966385	1964510	156545	1566866	2392587
38	826600	898295	894816	70573	730755	1092150
39	2954970	3131768	3120339	251246	2505563	3837859
40	475500	464668	462910	38790	373048	568630
41	5654195	5927809	5897588	467794	4803490	7323753
42	912000	947162	944326	74717	761440	1153571
44	598400	543573	540883	43207	441536	668860
45	2033591	2195829	2191413	176548	1749886	2663850
46	1603100	1699414	1699287	138714	1359113	2126568
47	531000	586335	585814	44663	474874	713806
48	777300	747577	743861	59758	606521	914870
49	639400	663725	663324	53399	531295	818583

Table 26 Differences between forecasts for a three-years horizon and current values (i.e., 2020q2) for all indices (numbers and percentages)

	Differences (Forecasts - Current values)				% differences from current values			
Indices	**Mean**	**Median**	**Std**	**99% Loss VaR**	**Mean**	**Median**	**Std**	**99% Loss VaR**
All	1472386	1398600	4436203	8040024	1.22	1.16	3.67	6.65
14	46418	31511	227976	438221	1.53	1.04	7.53	14.47
18	-31652	-41418	130502	297817	-1.95	-2.55	8.04	18.35
19	10077	-8046	1581121	3363601	0.05	-0.04	7.76	16.51
20	-292029	-357091	888641	2189325	-2.50	-3.06	7.61	18.74
21	427926	425429	680174	1042227	5.19	5.16	8.25	12.64
22	141424	141241	292967	496846	4.05	4.05	8.39	14.24
23	-434201	-451635	484630	1441048	-6.79	-7.06	7.58	22.54
24	40807	40744	73293	120662	4.35	4.34	7.81	12.86
25	158892	108844	955484	1793288	1.34	0.91	8.03	15.07
27	-646626	-675749	569023	1917967	-8.47	-8.85	7.45	25.12
28	-57298	-65845	200029	467555	-2.22	-2.55	7.76	18.13
29	-307234	-327148	399700	1147004	-5.70	-6.07	7.42	21.29
30	-26956	-32348	111962	265383	-1.83	-2.19	7.59	18.00
31	714466	696034	459831	298299	14.37	14.00	9.25	6.00
32	80917	70856	293186	546886	2.39	2.09	8.66	16.15
33	31756	28451	67092	102798	4.24	3.80	8.96	13.72
34	41647	39730	47270	58644	7.77	7.41	8.82	10.94
35	622327	599428	421108	331812	13.88	13.37	9.39	7.40
36	71547	55891	254596	458442	2.29	1.79	8.14	14.65
37	80089	78214	156545	273356	4.25	4.15	8.30	14.49
38	71695	68216	70573	76482	8.67	8.25	8.54	9.25
39	176798	165369	251246	391482	5.98	5.60	8.50	13.25
40	-10832	-12590	38790	95921	-2.28	-2.65	8.16	20.17
41	273614	243393	467794	718926	4.84	4.30	8.27	12.71
42	35162	32326	74717	125970	3.86	3.54	8.19	13.81
44	-54827	-57517	43207	148629	-9.16	-9.61	7.22	24.84
45	162238	157822	176548	234520	7.98	7.76	8.68	11.53
46	96314	96187	138714	204502	6.01	6.00	8.65	12.76
47	55335	54814	44663	42547	10.42	10.32	8.41	8.01
48	-29723	-33440	59758	160887	-3.82	-4.30	7.69	20.70
49	24325	23924	53399	95856	3.80	3.74	8.35	14.99

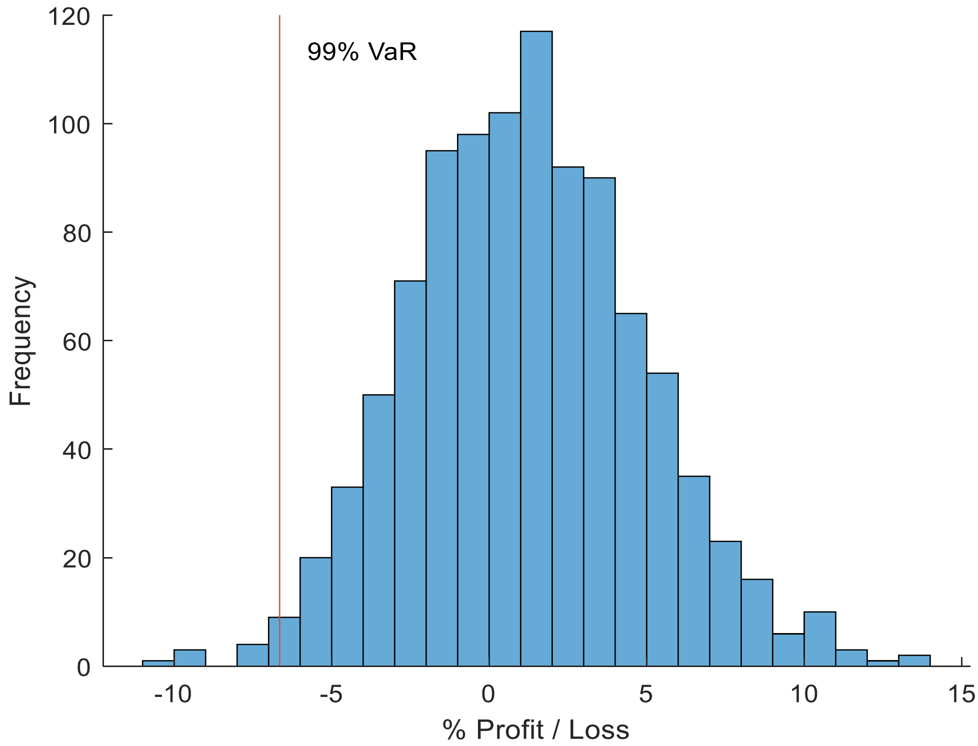


Figure 24 Frequency distribution of % profit / loss, including VaR for a three-years horizon

4 Conclusion: The Future of AVMs

Real estate is a sector that substantially contributes to economic activity and growth. Due to that, after the credit crunch of 2007-2008, when the sector encountered a significant turmoil in many countries, there was also a direct negative impact on many other sectors and the general economy. The banking sector was one of the most affected ones, due to its considerable liability in real estate, mainly through mortgage loans.

Therefore, risk management in real estate is an issue of significant interest for various stakeholders, including investors, real estate developers, financial institutions, and policymakers. However, no risk management policy can be realised without appropriate valuation tools.

In this context, AVMs have emerged. They are used at least for the last 50 years in both the academic community and in practice. A large body of literature has been occupied with the development of statistical models of appraisal in the real estate sector. Therefore, by now, many AVMs have been developed serving different valuation purposes, business applications and end-users. AVMs is, thus, a mature field that is continuously evolving, stepping upon the evolution and acceleration of digital infrastructure and consequently the access to information.

In this document, three different works, two of them published, were presented based on a large dataset of historical prices of properties in Greece during the period 2012-2016. Concerning their potential positive effects, the proposed methodologies can help the central and local governments in planning and implementing their fiscal policies, both at the micro and macro level and can promote economic and development sustainability. For example, governments can set the fair market value of a property accurately and determine accordingly fair property taxes (see, e.g., (McCluskey, Dyson, McFall, & Anand, 1996)). In Greece, the properties taxation system is based on objective values set by experts, but they may not reflect the actual market value, especially after a few years. The proposed AVMs in sections 3.1 and 3.2 can set the basis for deriving proper objective real estate values that reflect the current market values and thus be fairer while at the same time, the government collects fair taxes. Also, such a system can assist governments in implementing properties indices, and performance measurements and consequently, the operation of the markets can be more transparent and efficient for both investors and stakeholders. This can also promote cooperation towards public-private partnerships and projects of common interest. The simulation scenarios of section 3.3, on the other hand, can be exploited by investors and financial institutions to understand the uncertainty in the real estate market and take decisions accordingly.

Additionally, these methodologies can have a significant impact on the operational efficiency of commercial banks. Financial institutions can use the findings of this research, as presented in sections 3.1.4, 3.2.4 and 3.3.3, to improve their real estate valuation systems, particularly in markets characterised by heterogeneity. Having better real estate valuations is a powerful tool for loan pricing and risk monitoring. In particular, the proposed AVMs can be adapted in applications such as mortgage quality control or appraisal review, loss mitigation analysis, portfolio valuation and appraisal process redesign. For example, the mortgage quality control entails validation or verification of appraisals conducted to determine the market value of collateral properties securing purchase money or refinancing loans. Conventional quality control methods typically entail a manual review of a random sample of completed appraisals. The application of an AVM to this process offers the advantages of increased speed, reduced subjectivity, limiting the need for manual review to cases identified by the AVM as exceptional. In loss mitigation analysis, AVMs can be applied to estimate the current loan to value (LTV) ratio on non-performing loans to assist the lender or guarantor in determining optimal foreclosure strategies. Portfolio valuation is a natural application of AVM, providing an efficient means of marking-to-market many property values and is most closely aligned with the underlying statistical methods. Unlike real valuations based on expert opinions, automatic mass valuation can reduce operational costs since it is inexpensive and can be performed regularly. Besides, performing re-evaluation of properties on a regular basis can potentially shed additional light to inefficiencies of real estate markets.

Furthermore, the adoption of reliable AVMs enables supervisors of financial institutions to have more accurate control for the risk exposure of banks to real estate loans. AVMs can be used as an administrative tool in monitoring the trends of the property market and especially the level of mortgage risk that the commercial banks are likely to be exposed in terms of their LTV ratio. This administrative tool can also be used by policymakers to take proactive measures, where the economic environment is turbulent, and the economies are experiencing abnormal conditions. Finally, on what concerns this research, international organisations for valuation standards can use its outcomes to enhance the existing guidelines towards more effective analytical AVMs.

Based on the findings of this study, certain limitations and particular areas for future research can be identified. On the limitations, firstly, a large database was used with properties spanning over a specific time period. So, implicitly it is assumed that there is some homogeneity across time and that neither large structural changes have been made nor the data contains systematic inconsistencies (e.g., potential change in the definition of variables or in the way of their measurement). Dealing with a relatively unstable financial period for Greece allowed the assumption that the level of such market inefficiencies is controllable and that it can be handled within the model approach. Secondly, as the data refer to estimations made by a large number of different professional valuators and not to transactional values, it is assumed that the criteria provided by the bank were followed correctly and no systematic errors and biases have entered the database.

Furthermore, the database used was not homogeneous. There are geographical sectors with very few properties. To overcome this, the neighbouring sectors were aggregated. This implies an exchangeability assumption, meaning that information from neighbouring areas is useful and can be used. However, as already pointed out, in areas with very few properties and great inhomogeneity, large errors may incur.

Despite these limitations, the methodologies presented in sections 3.1 and 3.2 are dealing with a massive database of properties, which is not frequently encountered in the literature, providing valuable insights. In this context, various issues could be considered for future research. On what concerns the calibration and statistical methods used, the most definite, enjoying the agreement of most recent studies, involves the consideration of improved ways to incorporate spatial effects into the analysis, as done in 3.2. In 3.1, the spatial information was used implicitly either by using a local regression approach or by considering some distance measures between properties. In 3.2, more refined spatial models were used. This comparison can be also extended to cover relevant techniques from spatial econometrics.

Market segmentation could also be considered to improve the results further. Segmenting large markets into small and more homogeneous ones has been shown in previous studies to be advantageous (Bourassa et al., 2003; Füss & Koller, 2016). Except for geographical and price data, additional information could be considered for a comprehensive definition of market segments, such as information about points of interest and marketability assessments. Moreover, in a context of high volatility in the real estate market, incorporating information about the macroeconomic conditions could further improve the performance of AVMs. Furthermore, in 3.1, an ensemble of methods was considered to end up with a combination of them. Proper weighting for such forecasting is ongoing research. It is also worth exploring the combination of improved regression models with case-based approaches, such as the comparative sales method. Finally, relatively to managerial implications, a next step is to measure risk based on these models, as well as the impact and the feasibility of deriving objective values for properties for taxation properties based on such approaches.

In general, the critical challenge of AVM development is to find a statistical approach that applies well to the particularities of the real estate market in question and provides rational and trustworthy appraisals. The most common approach for ensuring the reliability of an AVM is to compare its predictive accuracy against other prevailing models that are found in the literature. Therefore, new models continuously emerge that come to overthrow the supremacy of other existing models promising improved accuracy, or to restore the superiority of existing models comparing them with others using different real estate data. It is evident that there is no one single approach and model that horizontally apply to all cases, outperforming all other approaches and models, without taking into account factors, such as the complexity and distinctiveness of the market in question, the intended use and the type of properties appraised. In the end, it is a multiple criteria decision analysis problem, as many recent studies suggest (Ferreira, Spahr, & Sunderman, 2016; Morano et al., 2018).

Given the complexity of the problem and the absence of one single superior model, hybrid models, combining different methods, are expected to continue to prevail. Through this approach, the different models combined can complement each other's advantages, conforming to the peculiarities and characteristics of the different data.

In any case, the increasing use of AVMs to provide estimates of market value in property markets internationally is undeniable. This trend is only expected to evolve in the coming years as the developed systems will become more robust and thus credible, ensuring an efficient replacement or complement of the relevant institutions' existing processes.

References

Abidoye, R. B., & Chan, A. P. C. (2017). Artificial neural network in property valuation: application framework and research trend. *Property Management*, *35*(5). https://doi.org/10.1108/PM-06-2016-0027

Abidoye, R. B., & Chan, A. P. C. (2018). Improving property valuation accuracy: A comparison of hedonic pricing model and artificial neural network. *Pacific Rim Property Research Journal*, *24*(1), 71–83. https://doi.org/10.1080/14445921.2018.1436306

Adair, A., Berry, J., Haran, M., Lloyd, G., & McGrreal, S. (2009). *The Global Financial Crisis : Impact on Property Markets in the UK and Ireland*. Retrieved from http://news.ulster.ac.uk/podcasts/ReiGlobalCrisis.pdf

Alcantud, J. C. R., Rambaud, S. C., & Torrecillas, M. J. M. (2017). Valuation fuzzy soft sets: A flexible fuzzy soft set based decision making procedure for the valuation of assets. *Symmetry*, *9*(11), 253. https://doi.org/10.3390/sym9110253

Alexandridis, A. K., Karlis, D., Papastamos, D., & Andritsos, D. (2019). Real Estate valuation and forecasting in non-homogeneous markets: A case study in Greece during the financial crisis. *Journal of the Operational Research Society*, *70*(10), 1769–1783. https://doi.org/10.1080/01605682.2018.1468864

Alexandridis, Antonios K., & Zapranis, A. D. (2013). Wavelet neural networks: A practical guide. *Neural Networks*, *42*, 1–27. https://doi.org/10.1016/j.neunet.2013.01.008

Anders, U., & Korn, O. (1999). Model selection in neural networks. *Neural Networks*, *12*(2), 309–323. https://doi.org/10.1016/S0893-6080(98)00117-8

Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural Economics*, *27*(3), 247–267. https://doi.org/10.1016/S0169-5150(02)00077-4

Antipov, E. A., & Pokryshevskaya, E. B. (2012). Mass appraisal of residential apartments: An application of Random forest for valuation and a CART-based approach for model diagnostics. *Expert Systems with Applications*, *39*(2), 1772–1778. https://doi.org/10.1016/j.eswa.2011.08.077

Arribas, I., García, F., Guijarro, F., Oliver, J., & Tamošiūnienė, R. (2016). Mass appraisal of residential real estate using multilevel modelling. *International Journal of Strategic Property*

Management, *20*(1), 77–87. https://doi.org/10.3846/1648715X.2015.1134702

Bagnoli, C., & Smith, H. (1998). The Theory of Fuzzy Logic and its Application to Real Estate Valuation. *Journal of Real Estate Research*, *16*(2), 169–200.

Bärnthaler, P., Elsinger, H., Fessler, P., Woschnagg, E., & Jakubik, P. (2018). Nonperforming exposures of Austrian banks – decomposing aggregate measures. *Financial Stability Report*, (36), 40–55.

Bellotti, A. (2017). Reliable region predictions for automated valuation models. *Annals of Mathematics and Artificial Intelligence*, *81*(1–2), 71–84. https://doi.org/10.1007/s10472-016-9534-6

Bidanset, P. E., & Lombard, J. R. (2014). Evaluating Spatial Model Accuracy in Mass Real Estate Appraisal A Comparison of Geographically Weighted Regression and the Spatial Lag Model. *Cityscape: A Journal of Policy Development and Research*, *16*(3), 169–182.

Bidanset, P., McCord, M., & Davis, P. (2016). Spatially Accounting for Spillover effects of Foreclosures in Automated Valuation Models to Promote Accuracy and Uniformity of Property Tax Assessments. *Journal of Property Tax Assessment and Administration*, *13*(1), 5–21.

Bin, O., Kruse, J. B., & Landry, C. E. (2008). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *Journal of Risk and Insurance*, *75*(1), 63–82. https://doi.org/10.1111/j.1539-6975.2007.00248.x

Bitter, C., Mulligan, G. F., & Dall'erba, S. (2007). Incorporating spatial variation in housing attribute prices: A comparison of geographically weighted regression and the spatial expansion method. *Journal of Geographical Systems*, *9*(1), 7–27. https://doi.org/10.1007/s10109-006-0028-7

Bogin, A. N., & Shui, J. (2020). Appraisal Accuracy and Automated Valuation Models in Rural Areas. *The Journal of Real Estate Finance and Economics*, *60*(1–2), 40–52. https://doi.org/10.1007/s11146-019-09712-0

Bourassa, S. C., Cantoni, E., & Hoesli, M. (2007). Spatial dependence, housing submarkets, and house price prediction. *The Journal of Real Estate Finance and Economics*, *35*(2), 143–160. https://doi.org/10.1007/s11146-007-9036-8

Bourassa, S. C., Hoesli, M., & Peng, V. S. (2003). Do housing submarkets really matter? *Journal of Housing Economics*, *12*(1), 12–28. https://doi.org/10.1016/S1051-1377(03)00003-2

Boyle, C. (1984). An expert system for valuation of residential properties. *Journal of Valuation*, *2*(3), 271–286. https://doi.org/10.1108/eb007957

Brasington, D. M., & Hite, D. (2008). A mixed index approach to identifying hedonic price models. *Regional Science and Urban Economics*, *38*(3), 271–284. https://doi.org/10.1016/j.regsciurbeco.2008.03.002

Breidert, C., Hahsler, M., & Reutterer, T. (2006). A review of methods for measuring willingness-to-pay. *Innovative Marketing*, *2*(4), 8–32. https://doi.org/10.3111/13696998.2011.644408

Breiman, L. (1996). Bagging predictors. *Machine Learning*, *24*(2), 123–140. https://doi.org/10.1007/bf00058655

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Byrne, P. (1995). Fuzzy analysis: A vague way of dealing with uncertainty in real estate analysis? *Journal of Property Valuation and Investment*, *13*(3). https://doi.org/10.1108/14635789510088591

Calem, P. S., Lambie-Hanson, L., & Nakamura, L. I. (2017). *Appraising Home Purchase Appraisals* (FRB of Philadelphia Working Paper No. 17–23).

Calka, B. (2019). Estimating residential property values on the basis of clustering and geostatistics. *Geosciences*, *9*(3), 143. https://doi.org/10.3390/geosciences9030143

Carbone, R., & Longini, R. L. (1977). A Feedback Model for Automated Real Estate Assessment. *Management Science*, *24*(3), 241–248. https://doi.org/10.1287/mnsc.24.3.241

Cerutti, E., Dagher, J., & Dell'Ariccia, G. (2017). Housing finance and real-estate booms: A cross-country perspective. *Journal of Housing Economics*, *38*, 1–13. https://doi.org/10.1016/j.jhe.2017.02.001

Cerved Property Services. (2020). *Property Market Annual Report 2019 - Greece*.

Chen, J. H., Ong, C. F., Zheng, L., & Hsu, S. C. (2017). Forecasting spatial dynamics of the housing market using Support Vector Machine. *International Journal of Strategic Property Management*, *21*(3), 273–283. https://doi.org/10.3846/1648715X.2016.1259190

Chen, Z., Hu, Y., Zhang, C. J., & Liu, Y. (2017). An optimal rubrics-based approach to real estate appraisal. *Sustainability*, *9*(6), 909. https://doi.org/10.3390/su9060909

Court, A. T. (1939). *Hedonic Price Indexes with Automotive Examples*. Retrieved from https://books.google.gr/books/about/Hedonic_Price_Indexes_with_Automotive_Ex.html?id=NCoVtwAACAAJ&redir_esc=y

D'Amato, M. (2007). Comparing Rough Set Theory with Multiple Regression Analysis as Automated Valuation Methodologies. *International Real Estate Review*, *10*(2), 42–65.

D'Amato, M. (2010). A location value response surface model for mass appraising: An "iterative" location adjustment factor in Bari, Italy. *International Journal of Strategic Property Management*, *14*(3), 231–244. https://doi.org/10.3846/ijspm.2010.17

D'Amato, M. (2017). A Brief Outline of AVM Models and Standards Evolutions. In M. D'Amato & T. Kauko (Eds.), *Advances in Automated Valuation Modeling: AVM After the Non-Agency Mortgage Crisis* (Vol. 86, pp. 3–21). Springer International Publishing. https://doi.org/10.1007/978-3-319-49746-4_1

Danninger, S., Balakrishnan, R., Elekdag, S., & Tytell, I. (2009). How financial stress spreads | VOX, CEPR Policy Portal. Retrieved April 3, 2020, from https://voxeu.org/article/how-financial-stress-spreads

Del Giudice, V., De Paola, P., & Cantisani, G. B. (2017). Rough set theory for real estate appraisals: An application to directional district of Naples. *Buildings*, *7*(1), 12. https://doi.org/10.3390/buildings7010012

Demetriou, D. (2017). A spatially based artificial neural network mass valuation model for land consolidation. *Environment and Planning B: Urban Analytics and City Science*, *44*(5), 864–883. https://doi.org/10.1177/0265813516652115

Demiroglu, C., & James, C. (2018). Indicators of collateral misreporting. *Management Science*, *64*(4), 1747–1760. https://doi.org/10.1287/mnsc.2016.2597

Demyanyk, Y., & Van Hemert, O. (2011). Understanding the subprime mortgage crisis. *The Review of Financial Studies*, *24*(6), 1848–1880. https://doi.org/10.1093/rfs/hhp033

Des Rosiers, F. (2012). Market efficiency, uncertainty and risk management in real estate valuation–how hedonics may help. *Aestimum*, 511–533. https://doi.org/10.13128/Aestimum-13159

Diewert, E., Saeed, H., & Silver, M. (2009). Hedonic Imputation versus Time Dummy Hedonic Indexes. In *Price index concepts and measurement* (pp. 161–196). University of Chicago Press. https://doi.org/10.3386/w14018

Dimopoulos, T., & Moulas, A. (2016). A Proposal of a Mass Appraisal System in Greece with CAMA System: Evaluating GWR and MRA techniques in Thessaloniki Municipality. *Open Geosciences*, *8*(1), 675–693. https://doi.org/10.1515/geo-2016-0064

Dimopoulos, Y., Bourret, P., & Lek, S. (1995). Use of some sensitivity criteria for choosing networks with good generalization ability. *Neural Processing Letters*, *2*(6), 1–4. https://doi.org/10.1007/BF02309007

Doumpos, M., Papastamos, D., Andritsos, D., & Zopounidis, C. (2020). Developing automated valuation models for estimating property values: a comparison of global and locally weighted approaches. *Annals of Operations Research*, 1–19. https://doi.org/10.1007/s10479-020-03556-1

Downie, M.-L., & Robson, G. (2008). Automated Valuation Models: an international perspective. In *RICS Automated Valuation Models Conference: AVMs Today and Tomorrow*. London: Royal Institution of Chartered Surveyors. https://doi.org/10.1108/17410391111097438

Duguay, P. (2009). *Financial stability through sound risk management*. Toronto, Ontario. Retrieved from https://www.bis.org/review/r090114e.pdf

Eppli, M. J. (1993). The theory, assumptions, and limitations of direct capitalization. *The Appraisal Journal*, *61*(3), 419. Retrieved from https://search.proquest.com/openview/3b92ddc2b42816eb46508939ddb4ccae/1?pq-origsite=gscholar&cbl=35147

European Commission. (2019a). *Enhanced Surveillance Report*. Retrieved from https://ec.europa.eu/info/sites/info/files/economy-finance/enhanced_surveillance_report_-_greece_april_2019_en.pdf

European Commission. (2019b). State aid : Commission approves market conform asset protection scheme for banks in Greece. Retrieved from https://ec.europa.eu/commission/presscorner/detail/en/IP_19_6058

European Mortgage Federation-European Covered Bond Council (EMF-ECBC). (2019). *HYPOSTAT 2019 A review of europe's mortgage and housing markets*. Retrieved from https://hypo.org/app/uploads/sites/3/2019/09/HYPOSTAT-2019_web.pdf

European Mortgage Federation and European AVM Alliance. (2016). *EMF/EAA Joint Paper on the Use of Automated Valuation Models in Europe*.

Ferreira, F. A. F., Spahr, R. W., & Sunderman, M. A. (2016). Using multiple criteria decision analysis (MCDA) to assist in estimating residential housing values. *International Journal of Strategic Property Management*, *20*(4), 354–370. https://doi.org/10.3846/1648715X.2015.1122668

Festić, M., Repina, S., & Kavkler, A. (2009). The up-coming crisis and the banking sector in the Baltic States. *Swiss Journal of Economics and Statistics*, *145*(3), 269–291. https://doi.org/10.1007/bf03399282

Fik, T. J., Ling, D. C., & Mulligan, G. F. (2003). Modeling Spatial Variation in Housing Prices: A Variable Interaction Approach. *Real Estate Economics*, *31*(4), 623–646. https://doi.org/10.1046/j.1080-8620.2003.00079.x

Fisher, J. D. (2002). Real time valuation. *Journal of Property Investment & Finance*, *20*(3), 213–221. https://doi.org/10.1108/14635780210433463

Follain, J. R., & Giertz, S. H. (2011). Using Monte Carlo simulations to establish a new house price stress test. *Journal of Housing Economics*, *20*(2), 101–119. https://doi.org/10.1016/j.jhe.2011.04.003

Füss, R., & Koller, J. A. (2016). The role of spatial and temporal structure for residential rent predictions. *International Journal of Forecasting*, *32*(4), 1352–1368. https://doi.org/10.1016/j.ijforecast.2016.06.001

Gabrielli, L., Giuffrida, S., & Trovato, M. R. (2017). Gaps and overlaps of urban housing sub-market: Hard clustering and fuzzy clustering approaches. In *Appraisal: From Theory to Practice*. Springer International Publishing. https://doi.org/10.1007/978-3-319-49676-4_15

García, N., Gámez, M., & Alfaro, E. (2008). ANN+GIS: An automated system for property valuation. *Neurocomputing*, *71*(4–6), 733–742. https://doi.org/10.1016/j.neucom.2007.07.031

Gloudemans, R. J., Almy, R. R., & International Association of Assessing Officers. (2011). *Fundamentals of mass appraisal*. International Association of Assessing Officers.

Glumac, B., & Des Rosiers, F. (2018). *Real Estate and Land Property Automated Valuation Systems: A Taxonomy and Conceptual Model. Luxembourg Institute of Socio-Economic Research (LISER)*. https://doi.org/10.2139/ssrn.3183132

Glumac, B., & Wissink, T. P. (2018). Homebuyers' preferences concerning installed photovoltaic systems. *Journal of European Real Estate Research*, *11*(1), 102–124. https://doi.org/10.1108/JERER-12-2016-0044

Gonzalez, M. A. S., & Formoso, C. T. (2006). Mass appraisal with genetic fuzzy rule-based systems. *Property Management*, *24*(1). https://doi.org/10.1108/02637470610643092

Grigsby, W. O. (1986, June). The Dynamics of Neighborhood Change and Decline. Retrieved from https://eric.ed.gov/?id=ED294934

Gröbel, S., & Thomschke, L. (2018). Hedonic pricing and the spatial structure of housing data–an application to Berlin. *Journal of Property Research*, *35*(3), 185–208. https://doi.org/10.1080/09599916.2018.1510428

Guan, J., Zurada, J., & Levitan, A. S. (2009). An adaptive neuro-fuzzy inference system based approach to real estate property assessment. *Journal of Real Estate Research*, *30*(4), 395–420.

Guo, J., Xu, S., & Bi, Z. (2014). An integrated cost-based approach for real estate appraisals. *Information Technology and Management*, *15*, 131–139. https://doi.org/10.1007/s10799-012-0152-7

Helbich, M., & Griffith, D. A. (2016). Spatially varying coefficient models in real estate: Eigenvector spatial filtering and alternative approaches. *Computers, Environment and Urban Systems*, *57*, 1–11. https://doi.org/10.1016/j.compenvurbsys.2015.12.002

Hill, R. J. (2013). Hedonic price indexes for residential housing: A survey, evaluation and taxonomy. *Journal of Economic Surveys*, *27*(5). https://doi.org/10.1111/j.1467-6419.2012.00731.x

Hoesli, M., & MacGregor, B. D. (2000). *Property Investment: Principles and Practice of Portfolio Management*. (P. Education, Ed.). Retrieved from https://www.amazon.com/Property-Investment-Principles-Portfolio-Management/dp/058231612X

International Association of Assessing Officers. (2017). *Standard on Mass Appraisal of Real Property*. Retrieved from www.iaao.org

International Association Of Assessing Officers. (2003). *Standard on Automated Valuation Models*. Retrieved from https://www.iaao.org/media/standards/AVM_STANDARD.pdf

International Association Of Assessing Officers. (2018). *Standard on Automated Valuation Models (AVMs)*. Retrieved from https://www.iaao.org/media/standards/AVM_STANDARD_2018.pdf

International Monetary Fund. (2020). *World Economic Outlook, April 2020: The Great Lockdown*.

Retrieved from https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/World-Economic-Outlook-April-2020-The-Great-Lockdown-49306

Jin, J. Y., Kanagaretnam, K., & Lobo, G. J. (2011). Ability of accounting and audit quality variables to predict bank failure during the financial crisis. *Journal of Banking and Finance*, *35*(11), 2811–2819. https://doi.org/10.1016/j.jbankfin.2011.03.005

Kannan, P., & Koehler-Geib, F. (2009). Why did the crisis go global? | VOX, CEPR Policy Portal. Retrieved April 3, 2020, from https://voxeu.org/article/why-did-crisis-go-global

Kannan, P., & Köhler-Geib, F. (2009). *The Uncertainty Channel of Contagion* (International Monetary Fund, Working Paper No. 09/219). https://doi.org/10.1596/1813-9450-4995

Kauko, T., & D'Amato, M. (2009). *Mass Appraisal Methods: An International Perspective for Property Valuers*. (John Wiley & Sons, Ed.), *Mass Appraisal Methods: An International Perspective for Property Valuers*. https://doi.org/10.1002/9781444301021

Kilpatrick, J. (2011). Expert systems and mass appraisal. *Journal of Property Investment and Finance*, *29*(4/5), 529–550. https://doi.org/10.1108/14635781111150385

Kontrimas, V., & Verikas, A. (2011). The mass appraisal of the real estate by computational intelligence. *Applied Soft Computing Journal*, *11*(1), 443–448. https://doi.org/10.1016/j.asoc.2009.12.003

Kuşan, H., Aytekin, O., & Özdemir, I. (2010). The use of fuzzy logic in predicting house selling price. *Expert Systems with Applications*, *37*(3), 1808–1813. https://doi.org/10.1016/j.eswa.2009.07.031

Lake, I. R., Lovett, A. A., Bateman, I. J., & Day, B. (2000). Using gis and large-scale digital data to implement hedonic pricing studies. *International Journal of Geographical Information Science*, *14*(6), 521–541. https://doi.org/10.1080/136588100415729

Lam, K. C., Yu, C. Y., & Lam, C. K. (2009). Support vector machine and entropy based decision support system for property valuation. *Journal of Property Research*, *26*(3), 213–233. https://doi.org/10.1080/09599911003669674

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132–157. https://doi.org/10.1086/259131

Landajo, M., Bilbao, C., & Bilbao, A. (2012). Nonparametric neural network modeling of hedonic prices in the housing market. *Empirical Economics*, *42*(3), 987–1009.

https://doi.org/10.1007/s00181-011-0485-9

Lasota, T., Telec, Z., Trawinski, B., & Trawinski, K. (2011). Investigation of the eTS evolving fuzzy systems applied to real estate appraisal. *Journal of Multiple-Valued Logic and Soft Computing*, *17*(2), 229–253.

Lin, C. C., & Mohan, S. B. (2011). Effectiveness comparison of the residential property mass appraisal methodologies in the USA. *International Journal of Housing Markets and Analysis*, *4*(3), 224–243. https://doi.org/10.1108/17538271111153013

Lins, M. P. E., De Lyra Novaes, L. F., & Legey, L. F. L. (2005). Real estate appraisal: A double perspective data envelopment analysis approach. *Annals of Operations Research*, *138*, 79–96. https://doi.org/10.1007/s10479-005-2446-1

Lockwood, T., & Rossini, P. (2011). Efficacy in modelling location within the mass appraisal process. *Pacific Rim Property Research Journal*, *17*(3), 418–442. https://doi.org/10.1080/14445921.2011.11104335

MacKay, D. J. C. (1992). Bayesian Interpolation. *Neural Computation*, *4*(3), 415–447. https://doi.org/10.1162/neco.1992.4.3.415

Maier, G., & Herath, S. (2015). *Immobilienbewertung mit hedonischen Preismodellen: Theoretische Grundlagen und praktische Anwendung*. Springer-Verlag. Retrieved from https://scholars.uow.edu.au/display/publication108358

Martin, W. B. (1993). Direct capitalization or discounted cash flow analysis? *The Appraisal Journal*, *61*(3), 390. Retrieved from https://search.proquest.com/openview/1a5119e3d7bfa7ff08c3bbc1b3408a91/1?pq-origsite=gscholar&cbl=35147

Mccluskey, W., Davis, P., Haran, M., Mccord, M., & Mcilhatton, D. (2012). The potential of artificial neural networks in mass appraisal: The case revisited. *Journal of Financial Management of Property and Construction*, *17*(3), 274–292. https://doi.org/10.1108/13664381211274371

McCluskey, W., McCord, M., Davis, P. T., Haran, M., & McIlhatton, D. (2013). Prediction accuracy in mass appraisal: A comparison of modern approaches. *Journal of Property Research*, *30*(4), 239–265. https://doi.org/10.1080/09599916.2013.781204

McCluskey, William, & Borst, R. (2011). Detecting and validating residential housing submarkets: A geostatistical approach for use in mass appraisal. *International Journal of Housing Markets* *and Analysis*, *4*(3), 290–318. https://doi.org/10.1108/17538271111153040

McCluskey, William, Dyson, K., McFall, D., & Anand, S. S. (1996). Mass Appraisal for Property Taxation: An Artificial Intelligence Approach. *Australian Land Economics Review*, *2*(1), 25–32.

McCluskey, William, Zulkarnain Daud, D., & Kamarudin, N. (2014). Boosted regression trees: An application for the mass appraisal of residential property in Malaysia. *Journal of Financial Management of Property and Construction*, *19*(2). https://doi.org/10.1108/JFMPC-06-2013-0022

Metzner, S., & Kindt, A. (2018). Determination of the parameters of automated valuation models for the hedonic property valuation of residential properties: A literature-based approach. *International Journal of Housing Markets and Analysis*, *11*(1), 73–100. https://doi.org/10.1108/IJHMA-02-2017-0018

Mimis, A., Rovolis, A., & Stamou, M. (2013). Property valuation with artificial neural network: The case of Athens. *Journal of Property Research*, *30*(2), 128–143. https://doi.org/10.1080/09599916.2012.755558

Morano, P., Tajani, F., & Locurcio, M. (2018). Multicriteria analysis and genetic algorithms for mass appraisals in the Italian property market. *International Journal of Housing Markets and Analysis*, *11*(2). https://doi.org/10.1108/IJHMA-04-2017-0034

Narula, S. C., Wellington, J. F., & Lewis, S. A. (2012). Valuating residential real estate using parametric programming. *European Journal of Operational Research*, *217*(1), 120–128. https://doi.org/10.1016/j.ejor.2011.08.014

Negnevitsky, M. (2005). *Artificial intelligence: A guide to intelligent systems* (2nd ed.). Pearson education.

Nguyen, N., & Cripps, A. (2001). Predicting Housing Value: A Comparison of Multiple Regression Analysis and Artificial Neural Networks. *Journal of Real Estate Research*, *22*(3), 313–336.

Papastamos, D., Matysiak, G., & Stevenson, S. (2015). Assessing the accuracy and dispersion of real estate investment forecasts. *International Review of Financial Analysis*, *42*, 141–152. https://doi.org/10.1016/j.irfa.2015.01.014

Peterson, S., & Flanagan, A. B. (2009). Neural network hedonic pricing models in mass real estate appraisal. *Journal of Real Estate Research*, *31*(2), 147–164.

Ramsey, R. (2004). The urban land economics tradition: how heterodox economic theory survives in the real estate appraisal profession. In *Research in the History of Economic Thought and Methodology* (Vol. 22, pp. 347–378). Emerald Group Publishing Limited. https://doi.org/10.1016/S0743-4154(03)22058-7

Ramskogler, P. (2015). Tracing the origins of the financial crisis. *OECD Journal: Financial Market Trends*, *2014*(2), 47–61. https://doi.org/10.1787/fmt-2014-5js3dqmsl4br

Rasmussen, C., & Williams, C. (2006). *Gaussian Processes for Machine Learning | The MIT Press*. (M. Press, Ed.). Cambridge. Retrieved from https://mitpress.mit.edu/books/gaussian-processes-machine-learning

Reyes-Bueno, F., García-Samaniego, J. M., & Sánchez-Rodríguez, A. (2018). Large-scale simultaneous market segment definition and mass appraisal using decision tree learning for fiscal purposes. *Land Use Policy*, *79*, 116–122. https://doi.org/10.1016/j.landusepol.2018.08.012

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, *82*(1), 34–55. https://doi.org/10.2307/1830899

Rossini, P. (2000). Using Expert Systems and Artificial Intelligence For Real Estate Forecasting. In *Sixth Annual Pacific-Rim Real Estate Society Conference*. Sydney, Australia.

Rossini, P., & Kershaw, P. (2008). Automated Valuation Model Accuracy: Some Empirical Testing. In *14th Pacific Rim Real Estate Society Conference*. Kuala Lumpur.

Royal Institution of Chartered Surveyors. (2017). *RICS Valuation – Global Standards 2017: A guide to key changes & basis of conclusions Purpose*. Retrieved from https://www.rics.org/globalassets/rics-website/media/upholding-professional-standards/sector-standards/valuation/red-book-2017-a-summary-of-key-changes-global-edition-rics.pdf

Rumelhart, D. E., Hinton, G. E., & Mcclelland, J. L. (1986). A General framework for Parallel Distributed Processing. In *Parallel distributed processing: explorations in the microstructure of cognition* (pp. 45–76). Cambridge: MIT Press.

Samarasinghe, S. (2016). *Neural networks for applied sciences and engineering: from fundamentals to complex pattern recognition*. *Neural Networks for Applied Sciences and Engineering*. New York, USA: Crc Press. https://doi.org/10.1201/9781420013061

Schulz, E., Speekenbrink, M., & Krause, A. (2018). A tutorial on Gaussian process regression:

Modelling, exploring, and exploiting functions. *Journal of Mathematical Psychology*, *85*, 1–16. https://doi.org/10.1016/j.jmp.2018.03.001

Schulz, R., Wersing, M., & Werwatz, A. (2014). Automated valuation modelling: a specification exercise. *Journal of Property Research*, *31*(2), 131–153. https://doi.org/10.1080/09599916.2013.846930

Selim, H. (2009). Determinants of house prices in Turkey: Hedonic regression versus artificial neural network. *Expert Systems with Applications*, *36*(2), 2843–2852. https://doi.org/10.1016/j.eswa.2008.01.044

Serwa, D. (2013). Measuring Non-Performing Loans During (and After) Credit Booms. *Central European Journal of Economic Modelling and Econometrics*, *5*(3), 163–183.

Shenkel, W. M. (1970). Computer Assisted Assessments: Potentialities and Implications for the Organizational Structure of Property Tax Administration. *Proceedings of the Annual Conference on Taxation under the Auspices of the National Tax Association*. National Tax Association. https://doi.org/10.2307/23407813

Thériault, M., Des Rosiers, F., & Joerin, F. (2005). Modelling accessibility to urban services using fuzzy logic: A comparative analysis of two methods. *Journal of Property Investment and Finance*, *23*(1), 22–54. https://doi.org/10.1108/14635780510575085

Tibshirani, R. (1996). Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society, Series B*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Trippi, R. R. (1990). Decision Support and Expert Systems for Real Estate Investment Decisions: A Review. *Interfaces*, *20*(5), 50–60. https://doi.org/10.2307/25061400

Uberti, M. S., Antunes, M. A. H., Debiasi, P., & Tassinari, W. (2018). Mass appraisal of farmland using classical econometrics and spatial modeling. *Land Use Policy*, *72*, 161–170. https://doi.org/10.1016/j.landusepol.2017.12.044

Wang, D., & Li, V. J. (2019). Mass appraisal models of real estate in the 21st century: A systematic literature review. *Sustainability (Switzerland)*, *11*(24), 1–14. https://doi.org/10.3390/su11247006

Wheeler, D. (2009). Simultaneous coefficient penalization and model selection in geographically weighted regression: The geographically weighted lasso. *Environment and Planning A: Economy and Space*, *41*(3), 722–742. https://doi.org/10.1068/a40256

Wheeler, D., & Tiefelsdorf, M. (2005). Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems*, *7*(2), 161–187. https://doi.org/10.1007/s10109-005-0155-6

Wilmath, T., & Engel, K. (2005). The mass appraisal of hotels. *Journal of Property Tax Assessment & Administration*, *2*(1), 15–31. Retrieved from https://researchexchange.iaao.org/jptaa/vol2/iss1/2/

Worzala, E., Lenk, M., & Silva, A. (1995). An Exploration of Neural Networks and Its Application to Real Estate Valuation. *Journal of Real Estate Research*, *10*(2), 185–201.

Wu, C., Ye, X., Ren, F., & Du, Q. (2018). Modified data-driven framework for housing market segmentation. *Journal of Urban Planning and Development*, *144*(4), 04018036. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000473

Zapranis, A., & Refenes, A.-P. (1999). *Principles of Neural Model Identification, Selection and Adequacy: With Application to Financial Econometrics*. Springer-Verlag. Retrieved from https://www.amazon.com/Principles-Neural-Identification-Selection-Adequacy/dp/1852331399

Zhang, R., Du, Q., Geng, J., Liu, B., & Huang, Y. (2015). An improved spatial error model for the mass appraisal of commercial real estate based on spatial analysis: Shenzhen as a case study. *Habitat International*, *46*, 196–205. https://doi.org/10.1016/j.habitatint.2014.12.001

Zhou, G., Ji, Y., Chen, X., & Zhang, F. (2018). Artificial neural networks and the mass appraisal of real estate. *International Journal of Online and Biomedical Engineering (IJOE)*, *14*(3), 180–187. https://doi.org/10.3991/ijoe.v14i03.8420

Zurada, J., Levitan, A. S., & Guan, J. (2011). A comparison of regression and artificial intelligence methods in a mass appraisal context. *Journal of Real Estate Research*, *33*(3), 349–387.