“Crime and Property Trends in Ireland: An Analytical Study of Regional and Temporal Patterns

Abstract- **This project explores the relationship between crime rates and housing prices across various Irish counties. The analysis focuses on whether crime in one year drives property prices the next year using lagged correlation models. These results reveal regional differences - strong negative correlations in some counties and weak or positive ones in others which point to a localized dynamic between crime and housing markets. Additionally, an interactive map combining choropleth layers for property prices and log-scaled crime markers was created to visualize these trends. This visualization explains key spatial patterns and outliers. The strongest correlations - Dublin and Wicklow - were analyzed at area level to identify finer spatial trends. Visualizations of area-specific trends provide a deeper understanding of how localities contribute to broader regional patterns, offering valuable insights into the spatial interplay between crime and property values. This work demonstrates a comprehensive, programmatic approach to data analytics, incorporating multiple data formats and technologies, and provides evidence-based policy recommendations for regional planning.**

Keywords – crime rates, property prices, counties, correlation, lagged correlation

I. INTRODUCTION

A house is one of the most important assets for individuals, serving not only as shelter but also as a significant form of property ownership. Understanding the factors that influence housing prices is crucial for both individuals and communities. Housing prices are shaped by various economic, social, and environmental factors, with crime rates being one of the key influences [5]. Research has consistently shown that higher crime rates negatively impact property values across various global contexts. This project explores the reciprocal relationship between crime levels and property values, examining how this dynamic varies regionally. Ireland’s real estate market, like others, is influenced by localized factors, including perceptions of safety. To understand these dynamics, this study analyzes whether crime rate fluctuations in one year affect property prices the next year. As crime rates increase, the perceived risk of living in each area also rises, which typically leads to decreased demand for property and, consequently, lower property prices. However, this relationship is not uniform across all regions, some buyers still willing to pay premium prices for homes in neighborhoods perceived as safe, even if nearby areas experience higher crime rates. [3]. By analyzing both county-level and area-specific trends, this project uncovers regional variations in how crime affects property prices. Using lagged correlation models, it examines whether rising crime in one year is linked to declining property values in the next, revealing localized patterns. These insights support evidence-based recommendations for urban planning, law enforcement, and real estate strategies. The study enhances existing literature by applying advanced methods to explore the link between crime and housing. It provides a foundation for targeted interventions to address crime and housing affordability in Ireland.

II. REALTED WORK

Crime–housing price relations have been studied in international contexts, particularly in the United States and Europe. Many studies agree that higher crime leads to lower property values due to reduced neighborhood desirability and increased perceived risk. Seminal work by Thaler [1] and Hellman and Naroff [2] used hedonic pricing models to demonstrate how both property and violent crimes impact housing prices. Subsequent research expanded these findings to urban settings where crime type, location, and urban form influence the strength of this relationship. More recent studies have incorporated spatial models. For instance, Ceccato and Wilhelmsson [3] investigated how crime shaped local housing prices in Stockholm using spatial lag models, capturing spillover effects from neighboring areas. Walter et al. [4] analyzed the link between property investment and crime in U.S. cities and concluded that improvements to the built environment on high-crime streets significantly reduced crime especially when applied to small geographic units such as street segments. These studies suggest that granular, localized analysis is essential when evaluating the crime–property relationship. In the Irish context, however, there is limited research using fine-grained, area-level data. Most analyses remain at broader county levels. Our study contributes to this literature by implementing a lagged correlation model within a reproducible ETL pipeline, linking crime in one year with housing prices in the next. By identifying counties with strong correlations such as Dublin and Wicklow we propose the foundation for more localized spatial analysis, potentially supporting micro-targeted policy interventions.

III. METHODOLOGY

A. Data Sources

To explore the relationship between crime rates and property trends in Ireland, this project utilizes two primary datasets:

- **Crime Data**: Sourced from the Central Statistics Office (CSO) of Ireland, which provides detailed, regularly updated crime statistics by Garda division and category (e.g., burglary, theft, drug offences), count of offences, year. This dataset was selected due to its official status, comprehensiveness, and availability of geographic and temporal granularity.
- **Property Data**: Obtained from The Residential Property Price Register (RPPR). These data offer transaction-level property data (prices, dates, types, and locations) and rental listings across Ireland.
- **Geojson data** : Obtained Ireland counties Geojson data from www.Simplemaps.com website.

Both datasets cover a similar time frame (2010–2024), allowing for various comparative analyses, including Correlation, Regression, time-series and geospatial studies.

B. Data processing and data storage.

Crime statistics data is fetched from the Central Statistics Office (CSO) API using the requests library. The pyjstat library parses JSON-stat data into pandas DataFrames, which are then converted into dictionary records. Records with ID '148896' are inserted into the 'CJA07' collection in MongoDB. The Dagster data orchestrator pipeline handles the ETL process by extracting crime data from MongoDB, cleaning and standardizing it, and loading it into a PostgreSQL database for further analysis. This automated process ensures the efficient management of crime data, enabling streamlined access and accurate analysis. The pipeline supports timely updates to the database and maintains the integrity of the crime data for ongoing reporting and insights.

Components of the ETL Pipeline:

- Extract (Fetch Crime Data from MongoDB): A pymongo library is used to make a connection to MongoDB Atlas using credentials stored in environment variables. Documents are then extracted from the CJA07 collection in the cso_data database. The raw data is converted into a pandas DataFrame, and any ObjectId fields (MongoDB's default primary key) are converted into strings for easier processing. Logs are used to monitor the execution of each step, providing detailed feedback on the number of documents fetched..
- Transform(lean and Standardize the Data): During the transformation process, checks are performed to ensure that the required columns are present in the dataframe, which is crucial after extracting data from MongoDB. Columns are renamed for consistency, and unnecessary ones like _id and STATISTIC are dropped. Additionally, a new column, 'county', is created by extracting county names from the 'garda division' field using regular expressions "re" library. Some edge cases, such as 'Cork City', 'Co Cork', 'Co Cork, Cork', 'Dublin Eastern', and 'D.M.R. Northern', are not standard county names but represent counties. Therefore, the ambiguous county names are standardized by replacing them with valid county names. Logging functions and exceptions are used to debug any issues and handle errors when any transformation fails.
- Load(Insert Data into PostgreSQL): The psycopg2 library was used to interact with the PostgreSQL database. A connection was established, and a table called "crime_data" was created in the "realestate" database. The transformed data from the DataFrame was then prepared and multiple rows were inserted into the crime_data table in PostgreSQL.

The ETL job is orchestrated using the **Dagster** library, chained these steps together for automation. This pipeline is designed for periodic execution, updating the PostgreSQL database with the latest crime data from MongoDB.

For the property dataset, a connection to the realestate PostgreSQL database is established, and the CSV file "PPR-ALL.csv" is read row-by-row using a CSV reader. Several transformations are performed on the data, such as removing the "€" symbol from the price column and converting the date format to one that is compatible with PostgreSQL. The dataset contains 714,406 records, so batch insertion is used for efficient data upload. Debugging and error handling mechanisms are implemented to track any issues with the data or database operations. Additionally, a progress bar is used to monitor the upload status in the database.

C. Data processing algorithms

After storing both datasets as tables in the PostgreSQL database, subsequent analysis was conducted. For the property data, descriptive statistical analysis was performed to determine the average, maximum, and minimum prices for each county. This analysis provided insights into the significant variation in property prices, particularly high prices in certain counties. Further visualization and investigation revealed that the high property prices were mainly associated with commercial units, gardens, complexes, and quarters records that were deemed unsuitable for our analysis. Since the focus of our analysis is on residential properties, these non-relevant records were removed, leaving a final dataset of 651,541 residential property records for further analysis. For the crime data, descriptive analysis was conducted to examine the crime count for each county. This also validated the accuracy of the previously generated feature. Further analysis identified the most common offenses across all counties, providing valuable insights into crime patterns in Ireland over the years.

The correlation between total crime and average property prices was initially analyzed at the county level, with visualizations created to highlight county-level patterns. To perform this analysis, we created two views in the database. The first view, for crime data, calculated the total crime count and selected features such as county and year. The second view, for property data, calculated the average property prices while setting the maximum price at €2,000,000 to ensure a reasonable price range. We also extracted the year from the Sale date to match the year in the crime data.

We then performed a JOIN operation between the crime and property datasets, using the temporal common key, year, and the geographical common key, county. This resulted in a new table being created in the database to store the JOIN results. In the crime dataset, some larger administrative Garda divisions (such as Laois/Offaly and Cavan/Monaghan) combine two districts, grouping multiple Garda stations for reporting purposes. To accurately map counties for these divisions, we separated each division based on the counties it covers. Given the complexity of the distribution across Ireland's 26 counties, we limited the analysis to the 16 counties that directly correspond with data from both the property and crime datasets.

We calculated the Pearson correlation coefficient and found a moderate positive linear relationship between total crime and average property prices, with a correlation of 0.573. Further visualization revealed regional differences, prompting us to expand our analysis by focusing on counties with strong correlations, specifically Dublin and Wicklow. For these counties, we conducted an area-level analysis by extracting area data from the property dataset and comparing it with areas defined by Garda divisions. Using fuzzy matching, we identified 78,320 records from Dublin County and 16,039 records from Wicklow County that corresponded to crime areas. We replicated the county-level analysis for these areas by creating two views for crime data: one selecting year, area, and total crime, and another selecting year, area, and average property prices. We then joined these two datasets on the year and area fields and stored the results in a new table.

After joining the datasets for each county separately, we calculated the Pearson correlation coefficient for both Dublin and Wicklow. The correlation between total crime and average property prices was -0.2759 for Dublin and 0.1259 for Wicklow. Additionally, we conducted lagged correlation and trend-over-time analyses at the area level.

D. Use of Programming languages, libraries and databases

We used MongoDB Atlas to store the raw semi-structured crime data, which was then transformed and loaded into a PostgreSQL database alongside the property dataset. Python was used throughout the project for ETL processes, data retrieval, and database operations. Key libraries included pandas, numpy, and re for data processing, geopandas for geojson handling, and folium for mapping crime rates and property prices across Irish counties. Visualizations were created using matplotlib and seaborn.

IV. RESULTS AND EVALUATION

A. Lagged Impact of Crime on Housing Prices by County (2010–2022)

To evaluate whether annual crime levels influence future housing market trends, we analyzed the lagged correlation between total reported crime in year Y and average property price in year Y + 1 across all available counties in Ireland, this done by shifting housing price data forward 1 year, then merged with previous year crime data for each county, then Computed Pearson correlation coefficients among year Y total_ crime and avg _ price (year Y + 1), and visualized correlation by diverging bar chart for each county, as shown in figure(1).

Findings for all counties:

The correlation values are -0.9 to -0.4, which suggests that in all counties, higher crime correlates with lower property prices the following year. The largest effects appear in counties with urban centers/commuter belt zones, such as Dublin and Wicklow, suggesting that crime perception might be most relevant to those markets.

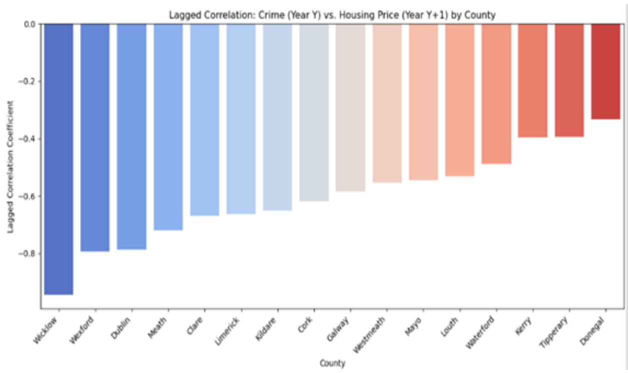

Fig. 1. Lagged Correlation for 16 counties within Ireland

B. Localized Correlation Analysis: Dublin and Wicklow Areas.

To test whether the strong negative correlation of crime with future housing prices at the county level is mediated by specific urban or suburban zones, we performed a lagged correlation analysis by area within Dublin and Wicklow. For each area within Dublin and Wicklow, we computed the Pearson correlation between total_crime (Year Y) and avg_price (Year Y+1). Crime and housing data were grouped by Areas (e.g., Bray, Arklow, Tallaght, Lucan.). Below are our findings

Findings for Areas within Dublin**:**

Strongest Negative Correlations in Crumlin, Inchicore, Kilmainham and Ballyfermot all show lagged correlations below -0.7, which are urban zones whose crime rates have historically been higher. Some central areas like Kevin Street, Store Street and Terenure have positive correlations and indicate complex market dynamics (gentrification, investor activity), as shown in figure(2)
In Dublin the most socioeconomically vulnerable areas show the greatest negative impact of crime on housing prices while some central districts show resilience or rebound despite crime.

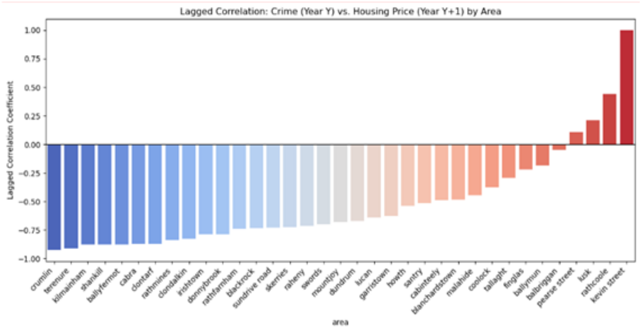

Fig. 2. Lagged Correlation for areas within Dublin

Findings for Areas within Wicklow:

Bray, Blessington, Greystones and Arklow showed Strongest Negative Correlations were “0.8 - 0.6”. Roundwood had slightly positive correlations, possibly due to low population density or rural housing demand trends, as shown in figure (3)
In Wicklow, larger population centers show clear negative impacts of crime on housing, while smaller, rural areas appear less sensitive.

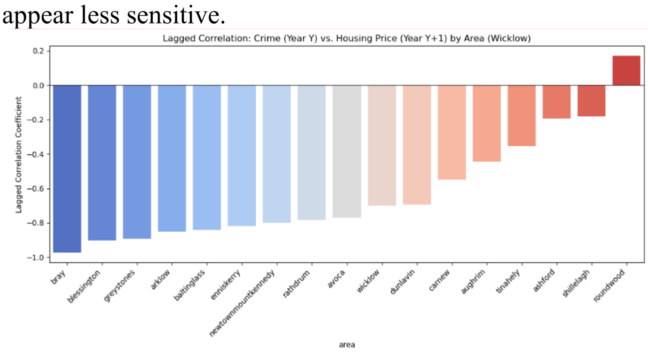

Fig. 3. Lagged Correlation for areas within Wicklow

C. Geospatial Visualization of Crime and Property Prices

The interactive Folium map combining crime rates and property prices in Ireland's counties gives a geospatial overview of how they change across the country. A choropleth layer for average property prices and the scaled circle markers showing total crime levels (color-coded by log-transformed crime count**)**

Method**:**

- Aggregated data from 2010–2022 by county.
- Property prices were visualized using a yellow-to-red color scale witch Light yellow = lower average prices, and Dark orange/red = higher average prices
- Crime data was log-transformed to smooth high variance and mapped using circle markers with

color green color for (low crime) and red color for high crime counts.

Findings:
Dublin and Wicklow have the largest and reddest markers for high crime. Western and rural counties such as Clare, Mayo, and Roscommon have smaller, greener markers and lower price bands. A clear visual pattern in the map figure (4) shown that Eastern counties have higher prices and higher crime rates, especially in commuter belt regions. Prices and crime are lower in Western and border counties.

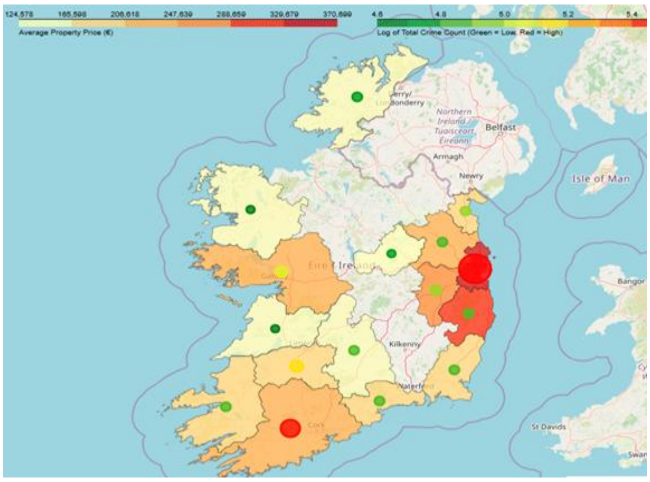

Fig. 4. Geographical distribution of crime rates and property Prices across Irish counties

V. Conclusions and Future Work

This work investigated the association of crime rates with housing prices across Ireland using geospatial visualization, lagged correlation analysis, and granular local data from urban and rural settings.

Clear Geographic Patterns:
Our national map shows an obvious east-west divide, with eastern counties (particularly Dublin, Wicklow, Meath) showing higher housing prices and crime volumes, while western counties have lower values for both.

Negative Lagged Correlation is Consistent:
Virtually all counties negative lagged correlations were found between crime (year Y) and property prices (year Y + 1), suggesting that crime may temporarily affect buyer sentiment, investment confidence, or policy responses.

Local Analysis Deepens Insight:
Areas such as Crumlin, Kilmainham, and Ballyfermot showed the most negative relationships in Dublin, driven by urban density and historical socioeconomic conditions.
Commuter towns like Bray, Blessington, and Greystones in Wicklow confirm this view that perceived safety is a key driver of housing demand in transitional or suburban zones.

Resilience in Some Areas:
Strangely though, some zones in both counties - Kevin Street (Dublin) and Roundwood (Wicklow) - have positive correlations - perhaps due to gentrification, low crime volatility, or strong underlying demand overcoming safety concerns.
In conclusion, crime influences housing prices, but the relationship is complex and varies across regions due to social, economic, and contextual factors. This project lays the groundwork for targeted analyses that can inform evidence-based policy, planning, and investment. While the focus was on crime's impact on property values, the findings reveal nuanced and sometimes conflicting patterns across counties and localities, highlighting the need for deeper investigation into the contextual elements that shape the crime–price relationship.

A. *Future Work*

Future work could distinguish between urban, suburban, and rural zones, as each may respond differently to crime due to varying density and community dynamics. Additional features like public transport access, proximity to amenities (e.g., schools, healthcare, retail), environmental factors, and planning zones can enhance analysis. Separating crime by offence type since not all crimes impact perception equally can reveal which are most predictive of housing market sensitivity. For instance, violent crimes or burglaries may be more deterrent than minor offences or administrative infractions. Such a multifactorial, typology sensitive approach would enable more holistic and actionable understanding of what drives property valuation in Ireland and how crime interacts with place-based and perceptual characteristics to shape real estate dynamics.

VI. References

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