IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101214

Data-driven insights for community investment through mortgage-backed securities

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Abstract: Unconventional mortgage-backed securities (MBS) present an opportunity for the capital markets to support community investment on behalf of issuers interested in less-distant stakeholders with their investors. Such instruments seek to link offers-of-capital to on-the-ground housing finance provision that helps build community identity, which can be expressed through local economic linkages, participatory governance mechanisms and the creation of tangible assets that build personal equity. These securities can be differentiated from conventional MBS by the sectors of the economy they support, the connections they maintain with community actors, and their potential for piquing the interest of market investors through risk-return enhancements. An innovative aspect of the securities is that, through a designated capital flows mechanism, they can recirculate capital within a defined region, creating direct and indirect effects through a filtering process. By bringing together a range of institutions from diverse sectors, the paper aims to provide a stepping stone to the innovative finance communities. The paper discusses the theory behind the securities and their capital flows, gives examples of community reinvestment assistance programs, describes possible roles that different stakeholders can take on, and details the type of support socially responsible investors seek. The results clearly show that financing the housing recovery efforts in high-vacancy areas poses unique risks, and there is a widespread concern that the downside risks could be compounded through demand for low-cost, high-volume investments.

In this context, the motivation for community groups is to bring visibility to the housing market in which they operate, and to identify specific instruments that suit their investment philosophy. At present, there are very few, if any, housing rehabilitation mortgage-backed securities the investment community could focus on. These securities would not be about the issuance of collateralized mortgage obligations that operatively bundle the best assets in the market and re-label them to fit an investor-defined credit quality; the securities would rather be about the capital that operates at a local level, where default risk can be better realized, and the product sold delivers what the investor would expect: a return of their values, along with their expected return.

Keywords: Unconventional MBS, Community Investment, Capital Markets, Housing Finance, Community Identity, Economic Linkages, Participatory Governance, Tangible Assets, Personal Equity, Capital Flow Mechanism, Regional Recirculation, Innovative Finance, Reinvestment Programs, Socially Responsible Investors, Housing Recovery, High-Vacancy Areas, Investment Philosophy, Local Capital, Default Risk, Values-Based Returns.

1. INTRODUCTION

Community development is vitally important to the nation's economy. In recent decades, our nation has evolved into a service economy, with both population and employment growth shifting to urban areas. These metropolitan regions see much of the nation's vitality. However, within these regions, there are pockets of disinvestment and decline. Welfare dependency, crime, joblessness, and poverty are concentrated in those neighborhoods; and to a large degree, Americans who live in them are cut off from the opportunities that the local economy creates. Many of America's communities are failing. People and businesses are leaving behind closed stores, abandoned factories, and deteriorating properties.

The nation's banks and thrifts are attempting to break the residential cycle of disinvestment. They are increasingly investing in neighborhoods that have long been neglected. The mortgage-backed securities market can be an important tool for accelerating this work. Using many of the same incentives that revitalize the residential sector, the mortgage-backed securities market can be mobilized to facilitate local investment, increasing the capital available for low-income housing rehabilitation and revitalization. Moreover, by facilitating investment in "environmentally distressed" neighborhoods, localized investment can generate a financial return as well as jobs. Finally, the mortgage-backed securities market can assist developments that create the infrastructure for economic expansion. Local partnerships that produce the greatest investment returns will also maximize the social benefit.

In summary, the mortgage-backed securities market can speed local investment in three ways. It can mobilize more capital for low-income real estate. It can facilitate investments that create the economic infrastructure for successful business operations, and it can assist developments in the nation's decaying neighborhoods that have high risk but also high potential returns.

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DOI: 10.17148/IJIREEICE.2022.101214

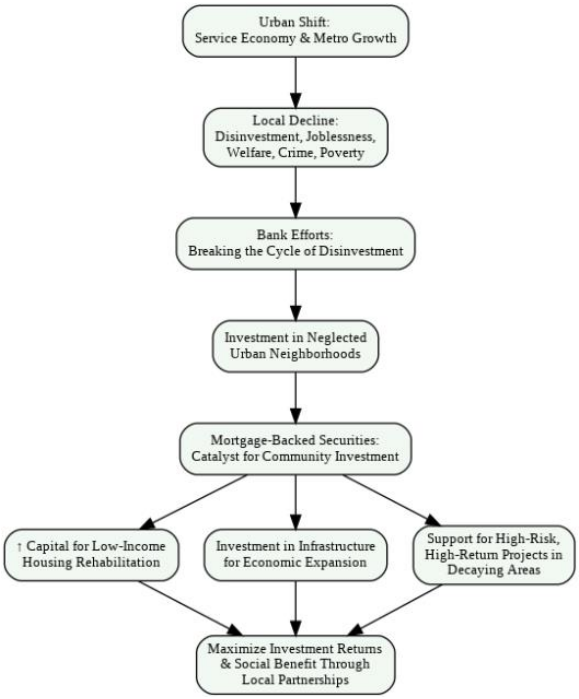

Fig 1 : Mortgage-Backed Securities & Community Development

1.1. Overview of the Importance of Mortgage-Backed Securities in Community Development

The great shortage of affordable rental housing in the United States, affecting every community to some degree, is a major cause of homelessness and increasingly blighted neighborhoods. A recent report highlights a gap of more than 650,000 rental units available to very low-income households in the U.S. Consequently, the availability of household capital at a lower cost level is critical to the encouragement of the development and preservation of affordable rental units. The current relative scarcity of tax-exempt loan capital for investing in low-income housing has sharpened interest in the potential for raising and allocating private-sector capital through mortgage-backed securities. The relevant authorities have indicated a willingness to employ the design of mortgage-backed securities for this purpose. The funds available for investment in mortgage-backed securities mediating between the capital and real estate markets, however, appear insufficient to considerably affect the overall cost of apartment operating capital. Resource commitments by the government in the form of guarantees or tax expenditures will probably be necessary to stimulate considerable increases in private investment in securities of this form.

This paper investigates the design of mortgage-backed securities for the purpose of promoting investment in rental housing for very low-income households. The goal is to identify mechanisms which would (1) stimulate a higher volume of financing through the securities; (2) reduce the cost of capital associated with the securities to a level where the subsidies they provide are perceived as being necessary to compensate investors for incurring the risk associated with low-income mortgage portfolios; and (3) help create a sufficiently secure claim structure such that an adequate volume of funds would be available for investing in them.

2. UNDERSTANDING MORTGAGE-BACKED SECURITIES

Mortgage-Backed Securities (MBS) provides a tool for converting assets of illiquid mortgages into a liquid investment vehicle that facilitates investments in residential real estate and real estate development. MBS come in many types, with the primary source of diversification being the reference pool of mortgages. In the early years of creation of MBS, private label securities dominated the market, but the share of GSE and other government-backed MBS increased during financial and economic crises. Collateralized Mortgage Obligations (CMOs) was introduced in the 1980s and expanded the pool of MBS investors by meeting their demand for additional customizability of cash flows. The structure of the economy influences the development and innovations in the MBS market. For three decades during the late 20th century, the U.S. economy experienced a prolonged period of stability. Thus, there are limited needs for increasing the flexibility of MBS cash flows. However, the MBS market innovated rapidly in the early 2000s driven by the emergence of the Great Moderation. After the subprime mortgage bust and the global financial crisis, the MBS market moves towards greater simplicity and transparency and the share of GSE-backed MBS rises sharply.

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MBS is an asset class that is used for both portfolio diversification and interest rate risk management. As collateralized products, MBS have an additional prepayment risk embedded within that investors have to manage. The prepayment risk of MBS depends on the geographic region of collateral mortgages, the coupon rate of the MBS, the current state of interest rate, underlying housing market conditions and the current condition of investors' balance sheets. Like most other public fixed income securities, MBS is traded in the secondary market and issued through an auction process. Whereas U.S. Treasury securities are backed by the federal government, MBS from U.S. GSEs are partially or fully backed by the federal government and MBS from private-label issuers are not backed by the government.

Equation 1 : Community Investment Index (Data-Weighted):

$$C_i = \sum_{j=1}^{n} (L_j \cdot W_j)$$

C_i = Community investment index

L_j = Loan volume in community j

W_j = Weight based on social impact score (e.g., affordability, revitalization)

n = Number of communities

2.1. Key Characteristics and Functionality of Mortgage-Backed Securities

Mortgage-Backed Securities (MBS) are capital market debt instruments that allow multiple lenders, known as mortgage originators, to pool a large quantity of mortgages and sell the cash flows from these loans, typically on a much more favorable basis than could be achieved if the mortgage originator were to borrow against or sell a single loan. An MBS is backed or collateralized by a pool of mortgage loans. Each mortgage loan in the pool will possess certain values and characteristics, including the amount of the loan, the interest rate, and the amortization methodology. The mortgage pool includes all of the mortgage loans being offered as collateral.

MBS have three characteristics that increase their usefulness to their owners in managing interest rate risk. A mortgage has an embedded option as a callable bond; the option allows the borrower to prepay the mortgage at any time, which is equivalent to the lender giving the borrower the right to buy the mortgage from the lender. A MBS is short relative to the prepaid mortgage, which enhances its interest rate risk characteristics. When the borrower prepays the mortgage, the MBS investor receives back the principal of the investment. As the borrower prepays, the MBS is shorted more, which means less principal is owed to the MBS investor. Presumably, as interest rates fall, prepayments of the loans underlying the MBS accelerate, but the bond is shorted even more and its value declines even less than a similar maturity bond without the prepayment penalty.

3. The Role of Data in Community Investment

Data-driven analytics are becoming increasingly important in helping public officials and private funders analyze the need for community investments, pinpoint priorities, and ascertain costs and social benefit from investments in education and youth services, transportation, affordable housing and neighborhood revitalization, foreclosure prevention, access to capital for businesses, and key environmental and health concerns. Despite the increasing professionalization of philanthropy over the past decades, collective-impact activities tend to focus on establishing broad consensus among key stakeholders about the importance of specific problems in particular communities rather than drawing on specific relevant data.

Philanthropy has the financial resources and provides the financial backing to assist local stakeholders that are unable and/or unwilling to provide the necessary data or analyze it. In areas such as education policy, several foundations have made substantial investments in creating both standardized databases and related nonprofits that focus on collecting data, and designing and implementing analytic models. For areas of community investment that are not as well developed, the need and potential for similar analytical work is equally compelling. For large, high-profile housing-focused foundations, which focus on vulnerable neighborhoods, the failure to maintain a detailed ongoing research program is puzzling.

Foundations and nonprofits can make important contributions to fulfilling this need. For instance, a report expressed concern that the lack of stable and consistent data necessary to assess community needs over time and develop and evaluate programs to meet those needs threatens effective place-based policy. It proposed the creation of a Neighborhood Reinvestment Data System, a collaborative initiative that would consolidate and maintain core protocol data shared and used by public agencies, private businesses, and nonprofit organizations.

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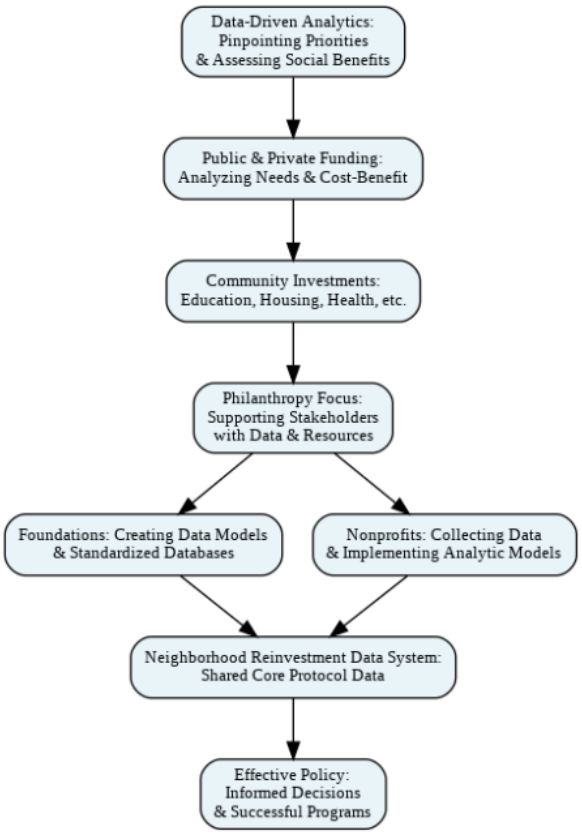

Fig 2 : Data-Driven Community Investment & Philanthropy

3.1. Harnessing Data-Driven Insights for Community Financing

Data is an incredibly useful tool which, when harnessed correctly, can inform community financing efforts much in the way it drives investment among private sector stakeholders. The following sections lay out various ideas on how stakeholders can leverage existing data and infrastructure to enhance associated efforts. These ideas range from helpful contextual data that can augment a stakeholder's existing body of knowledge and influence strategies relating to community financing, to the creation of a dedicated data platform that can be commonly utilized by all stakeholders. In reflection of commercial industry practice, these ideas also explore ways in which housing finance-related data can be complemented by non-housing finance data. Performing this type of analysis across multiple industry verticals can provide a fuller picture of economic development at the community level, enabling stakeholders to identify which of their efforts may be most impactful, which may be under-resourced, or which may be funding "black holes." Such insights can help health networks grow, for example, in areas where there is a lack of health funding, but with a sickly population, or where housing development is badly needed but for which financing is lacking. The ability to perform this type of analysis requires data from multiple industry verticals to be linked to one another at the community level; that data is already publicly available, and can be accessed and harmonized by the creation of a market-wide data platform. Once created, that platform would not only enable existing government stakeholders to leverage existing data as described above, but could also serve as a way to operationalize the recommendations made by policy proposals. By creating a platform of what would essentially be a "Community Development Treasury," stakeholders could have the resources needed to focus on underwriting, and enable investments to occur nationally, in partnership.

4. ANALYZING COMMUNITY NEEDS THROUGH DATA

Investors make decisions based on data analyses. Communities can express their needs through data, ideally showing their investment priorities and any desired social dividend. Community investment needs can be identified from a multitude of possible data sources – demographic, economic, social, cultural, and other qualitative and quantitative measures. This chapter illustrates some of the key community indicators which can be accessed for more specific community needs analyses. Further community analyses can be made by integrating the various community data sectors together to create multidimensional matrices which allow for a comparison of communities with similar characteristics and circumstances. Matching particular need indicators with investment and social impact goals allows for strategies that can deliver mutual benefits for the communities and the investors. This chapter first summarizes some of the key

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characteristics of communities that are used by funders and investors to guide their decision-making. It then describes various data resources available from publicly accessible data banks. These data allow investors to make their own community analyses or allow others to make their analyses for them with their social investment priorities. The chapter focuses on specific indicators that can be used under different social mandate priorities of the investor. Each investor will have unique goals for each community characteristic sector for which they seek investment. This allows them to prioritize each sector based on the desired impact, whether it be through job creation, affordability, sustainable investment, or a combination of targeted sector investment priorities.

4.1. Demographic Analysis

To form an analytic description of the community we begin by examining the demographic data. The census provides a variety of demographic and social population characteristics variables, which quantify the composition of the population by geographic unit. Generally, for the population at risk for residing in a unit we characterize the need for investment resources. For example, many housing and social assistance resources are traditionally allocated on a per capacity ratio, so data on individuals at or below some poverty level threshold is important.

The census also provides data on the total number of families in poverty – a crude indicator of the need for larger resources. There are also population characteristics that are related to the risk of default of loans made, such as the percentage of the population that is nonwhite or the percent of families that receive food stamps. Given that many mortgage loans with small down payments are insured by federally backed programs, it may also be informative to examine how close families might be to the poverty threshold for those that are under 130 percent of the poverty level. Data on the percent of families that speak a language other than English at home may be another risk factor for mortgage-backed securities with respect to default risk.

Data on age, household type, family composition, and ward level fertility may also influence household size. Furthermore, many relevant social indicators come not just from the census but also from various surveys. According to the Foundation, severe poverty (family income less than one-half the federal poverty threshold) affects approximately 2.9 million children.

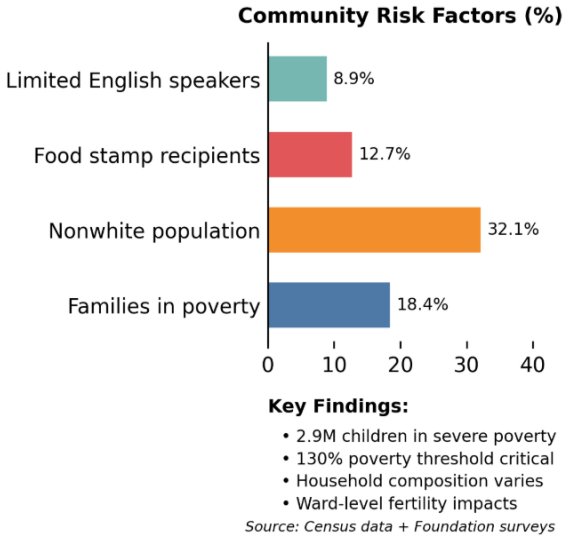

Fig 3 : Community Risk Factors (%)

4.2. Economic Indicators

The first major goal of every family is to meet its basic needs, and to do so, especially in urban areas, it needs to have a job that pays enough to meet these needs. When we look at job data, we see that many people do not earn enough to make the basic purchases needed to enjoy a reasonable standard of living. However, about 33% of the families in New London County, Connecticut, and 31% of the families in Shawnee County, Kansas, have an income below the national average with a significant amount below. We see these same trends, if not deeper, for people living alone, as about 50% of those living alone in four of the relevant counties in Southeastern Connecticut make less than $50,000 per year.

While about 25% of Americans are self-employed, we see a similar number of people in the service and lower-paying jobs with 22% working for companies like restaurants, hotels, health care, etc. Because these are usually jobs that pay less than $50,000, we should also consider the job categories where income is more concentrated. Fortunately, there are lists of these job categories and what they pay on a regular basis. Data is provided about whom these jobs serve. If area needs are being met by temporary labor, we should discount the role of those lower-paying jobs in determining the

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vibrancy of a local economic area, as there are many communities in this country that are not benefiting from the growth of the service economy.

4.3. Housing Market Trends

Investing in mortgages is a probabilistic investment. Given a "pool" of mortgages, probability models are used to estimate the loss to the investor from defaults. For a pool with sufficient similarity to other pools in the market in terms of tenant quality, leverage, housing market risk, and geographical concentration, the risks to the investor can be quantified based on historical observed defaults. Generally, one data item is crucial to observing both the general default risk of the pool and the relative default risk compared to other similar pools: the home price appreciation associated with the pool. Thus we can investigate whether a particular pool can be invested in without excessive risk. Lowering the risk to acceptable levels with respect to pooling norms is a major determinant of the interest rate charged to tenants residing in such properties. Housing market data and estimates of home values throughout the rental period of a frequently exchanged tenant pool are necessary to conduct sensitivity checks on pool probabilities.

Housing demand is intimately connected to local population and employment growth, the underlying demographics of household formation and immigration, interest rates and income growth, investor activity, relative rental rates, and alternative homeownership costs as expressed through mass sentiment. Inertia limits volatility around these local equilibriums, but they are subject to anomalies created by external economic shocks. Over time, excess rental demand creates excess rental supply as homeowners shift from investment to usage mode and more expensive utilization in the mortgage versus rental markets reduces resident disposable income. Over a cycle, the cap rate in the investor market falls as speculative capital competes for distressed real estate assets during decline windows of the investor ROI cycle.

5. DATA SOURCES FOR MORTGAGE-BACKED SECURITIES

The primary data source for mortgage-backed securities (MBS) is the MBS themselves. Secondary MBS market transactions are recorded at the Federal Reserve Bank, which collects all transactions and reports them in publicly available MBS Transaction Tables. To gather data on MBS characteristics—for example, the underlying loans along with their current values and characteristics, coupon, and where, when, and by whom they were issued—we rely primarily on TBA MBS transaction data from the Federal Reserve Bank. The MBS Backed Security Detail dataset contains a consolidated file from two other sources. The first derives MBS characteristics from the MBS Topology data set and price and valuation service. The second is the Volatility Table Quantity and Derivative Data set, which is summarized every 15 minutes. The MBS Backed Security Detail dataset's source is identified as either CS OIS or another service.

1. Public Data Sets

We begin by scanning the MBS Transaction Tables and compiling an extensive list of publicly available data on MBS security characteristics. The data is summarized on integrated Data Stream tables, which we use to create a cohesive data timeline. Company-by-CDO classifications of MBS transactions are valuable for understanding the portfolios: Company-CDO are classified using Loan-level Data. TBA MBS transaction volume is reported.

2. Private Data Providers

We also use proprietary datasets available from various providers. These are customer solutions with varying configurations; Functionally, they are based on counting previous MBS transactions across ID CUSIPs and reporting volume at various time intervals; and data for economically active days are aggregated. To get reliable estimates of the number of bonds in issuance and liquid for MBS strategy, we extract data screens and reformat the information into a database.

3. Geospatial Data

MBS loans are for houses in unique geographic locations. Geospatial information enhances our understanding of the underlying houses by allowing us to augment MBS transactions with property-specific information. We accomplish this by identifying the geography information location: We search for geo identifiers in several datasets and merge the datasets on geo identifiers.

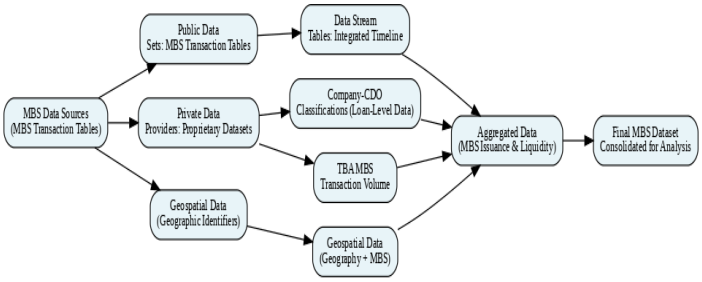

Fig 4 : MBS Data Collection Process

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5.1. Public Data Sets

The programs and processes that govern the flow of fixed-rate mortgage lending from banks and other lenders to MBS conduits and ultimately to investors is transparent, mature and well documented, due at least in part to the legislative mandate of ongoing supervision and reporting carried out by the Office of the Comptroller of the Currency and the Federal Deposit Insurance Corporation of the national banking system. The public reporting of entities engaged in the business of mortgage origination, securitization or servicing, along with general description of these same entities, can also be found in reports that monitor systemic risks within the sector and whose reports to Congress contain the same. These sources report branch banking information and specific MBS conduit information that can be linked to those born from specific lenders through their respective MBS Pool Numbers.

The Federal Housing Finance Agency publishes estimates of outstanding single-family mortgage debt guaranteed by government-sponsored enterprises, including both the Fannie Mae and Freddie Mac portfolios, but which does not differentiate between these two entities. As a result, properties located in census tracts of the San Francisco Bay Area with high concentrations of mortgage debt may be due primarily, or entirely, to only one entity. This balance sheet information is reported as part of the empirical validation of performing loan securitizations by the entities, and described in detail by the monitoring council. These balances, together with other property transaction data, describe the national MBS sector, since the entities account for about one-half of MBS debt currently outstanding. These same lenders also are the primary purchasers of private label MBS issued into the market by non-GSE conduits.

$$S_r = \frac{B_s + H_u}{C_m}$$

S_r = Social return per MBS dollar invested

B_s = Budget savings from stabilized communities

H_u = Number of housing units financed in underserved areas

C_m = Total capital from MBS allocation

Equation 2 : MBS Social Return on Investment (SROI)

5.2. Private Data Providers

While public data available through the Census Bureau, the Bureau of Labor Statistics, and other government sources provide valuable statistics on housing, lending, and employment, the data often lacks the granularity needed to estimate the effect of different data on mortgage-backed security (MBS) values, particularly in a pricing or re-pricing context. Several private companies compile large historical datasets of mortgage applications, and to a lesser extent, closings that enable MBS researchers and traders to explore relationships between loan-level characteristics and loan performance.

The largest and most well-known firm focusing on the MBS market is a financial services company that operates a database that tracks mortgages and mortgage-related liens. After its founders launched a system designed for electronic storage of mortgage-related documents, they began printing and storing physical documents to provide their services to more lenders. The company changed its name in 2014 after having been acquired a few years earlier by another financial entity. In addition to historical mortgage application data, this company also provides access to current mortgage application, pipeline, and schedule data.

Another data provider with MBS pipelines that are heavily used in commercial applications has products that have integrated into many of the portfolio analytics systems used by lenders and investment firms. Their database includes aggregate data and maps that have been used to analyze fraud risk. Loan-level historical data can be useful for examining relationships between mortgage performance, macroeconomic factors, and local markets. Due to this provider's historical focus on providing products and service to lenders, their product includes indexes based on pricing models.

5.3. Geospatial Data

A variety of geospatial data can be applied to evaluate risk in mortgage-backed securities. Natural hazard risk data is the main form of geospatial data used in real estate research and investment. Hazard data on natural hazards is produced by various organizations, some available for purchase. Reports specify modelled risks from a variety of natural hazards for the entire U.S. and display the impacts of climate-related extreme weather events on municipal bond defaults. There are a variety of models available for natural hazard risk; some models have been certified by relevant commissions. Certain firms use these models to set up internal limits. Furthermore, reports specify that some products are endorsed by a significant number of the largest insurers. Investment managers also employ these models for their portfolios that measure the risk from insurance underpricing.

The market has contracted because of at least one data provider closing down its catastrophe modeling division, which made moves seamless. Another large provider of hazard data and risk models has evolved into a "necessary evil" for many investment managers. Natural hazard data is typically sensed through satellite optical and radar imagery, but is also sensed through ground sensors for events such as hurricanes and flooding. Firms detecting and quantifying different

DOI: 10.17148/IJIREEICE.2022.101214

bubbles and craters utilize satellite-based optical sensors, synthetic aperture radars, and optical satellites carrying imaging spectrometers; flood depths may also be obtained through laser targets on airborne systems or bent-pulsing satellites. Algorithms for estimating the utility loss from specific hazards are being developed. Using these platforms, data providers may also charge for estimating information such as transportation loss due to flooding. Geospatial data may also be used to evaluate other financial risks, particularly ESG. Recommendations for investment managers on how to avoid anthropogenic ESG disasters by using geospatial data are available. Suggestions for using alternative data to mitigate risks across several sectors are also provided. Other than the natural catastrophe sector, data on other ESG events detecting damaged power supply assets utilizes satellite optical imagery as well.

6. RISK ASSESSMENT IN MORTGAGE-BACKED SECURITIES

Risk assessment is essential to understanding a proposed investment product such as mortgage-backed securities (MBS) and the risks inherent in their development. Those risks can be classified into various categories. Those most relevant to MBS include credit risk, market risk, operational risk, and reputational risk. Other forms, like financial risk, are very significant. MBS should have a differential profile of these risks as they are made from the underlying mortgage loans which are economically sensitive to the same factors. Generalizations about the risk profiles of MBS may be apt but not completely precise. Also, entanglements and interconnections may create unique risks with MBS portfolios, particularly in crisis situations. The valuing of the risk of any particular MBS portfolio or loan pool is computationally complex and requires sophisticated systems.

Credit risk is the risk of default by the borrower on the loan. In the context of MBS, it concerns the possibility that the MBS might not make timely payment of interest and principal because the underlying loans could default. The amount of loss from this is directly related to the amount of the loan and the corresponding value of the underlying collateral. Market risk is the risk that the market value of the position will move adversely, which causes an unrealized loss. This may especially arise from a liquidity shortage, but is also influenced by inadequate collateralization of credit risk. Computationally, this is reflected in the Value-at-Risk or average shortfall measure.

Operational risk is the risk of loss due to system failures, people errors, or fraud. This might stem from computer hacking, gross errors in algorithms, or not getting proper loan documentation. As MBS are developed further as community investment vehicles, it will be important to assess more systematically the operational risk questions. MBS can and have created significant operational risks for market participants.

6.1. Credit Risk

Mortgage-Backed Securities (MBS) are a unique security, housing two distinct but not equal sources of risk – the underwriting credit risk inherent in the residential mortgage loans that back the securities, and the collateral market risk associated with holding a frozen portfolio of illiquid assets. Before embarking on a discussion on the risk assessment of MBS, it is important to first define the main types of risks involved in a standard MBS transaction. The credit risk on MBS is essentially, therefore, a question of the probability of default of the underlying loans and the expected loss severity, should a default occur. A Probabilistic Model should be employed to assess default probabilities, loss severities, and issue expected losses. When assessing loss severities, care should be taken to evaluate the expected losses from all the various risk components, including delinquency cure rates, projected default timing, home-price dip severity, seasonality effects, shape of the home-price dip, insured vs. uninsured mortgages, homeowner demographics and socio-economics, and expected cash-flow timing. This said, it is important to note that the assessment of default probabilities and loss severities is at best difficult and subjective, although the goal of employing a well-researched, validated model is to at least allow practitioners to quantify their subjective assessment, and to establish a disciplined basis for consistency in the application of inputs and models across the evaluation of individual loans, as well as MBS transactions. It is also important to note that many investors do not have the expertise or risk tolerance to assess the credit risk of individual loans and transactions that may be done on the MBS.

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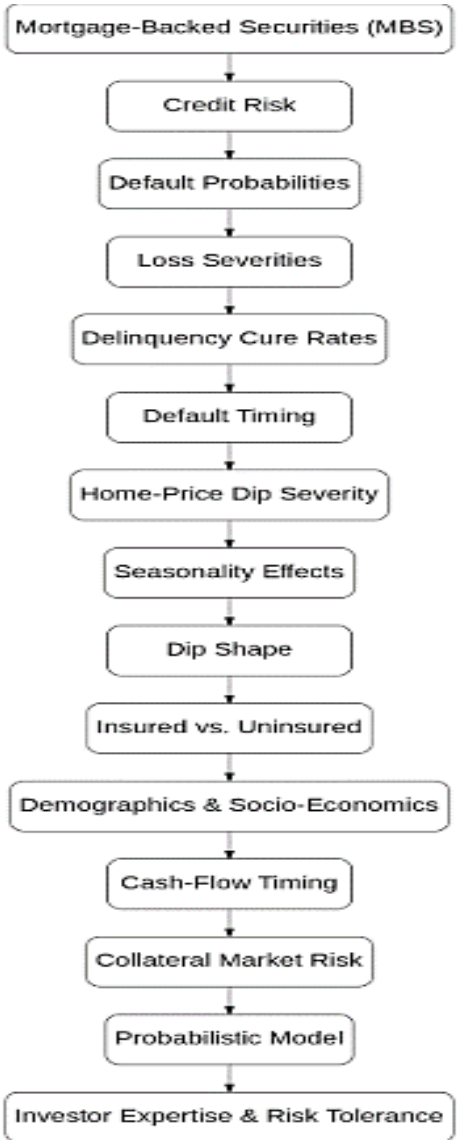

Fig 5 : Mortgage - Backed Securities(MBS)

6.2. Market Risk

Market risk arises from fluctuations in market prices leading to a loss either from the exposure decreasing in value, or an exposure cost increasing due to price changes or associated market curves or surfaces. In the case of an MBS investment vehicle, the market risk is present through its interest rate risk, prepayment risk, liquidity risk, or foreign exchange risk. Interest rate movements affect the present value of the cash flows paid by MBS. In the case of bonds, the cash flows are known at issue and interest rate risk is commonly defined as the potential decline in the present value of the bond due to upward shifts in equilibrium yield curves. MBS are more complicated, since portions of their cash flows can be prepayable, hence MBS market risk is more complicated. MBS typically trade on a spread basis, related to the treasury yield curve plus an MBS excess spread over T securities.

MBS cash flow prepayment options need to be valued from a borrower default and MBS servicer incentive perspective. It has been noted that MBS are subject to negative convexity and suffer the worst market price changes from expected interest rate increases and decreases. An increase in rates diminishes their value, as the probable cash flow remains on the assumption of no further prepayments; a decrease in rates increases their value, since they are likely to become prepayable sooner and sooner as rates fall and burn off. MBS are meant to have positive duration, duration management being key to higher excess spreads. These negative convexity characteristics are more important for some loan types, like poverty loans, lending to low borrowers at higher interest rates.

6.3. Operational Risk

Mortgages and asset-backed securities (ABS) trade in the capital markets, and as such, are exposed to the same kind of

DOI: 10.17148/IJIREEICE.2022.101214

operational risk as any other traded security. Operational risk here refers to the risk of loss due to human error, adverse external events, or inadequate or failed internal processes, people or systems and is also associated with the management of the operational functions supporting the investment and servicing of these instrument classes. For example, an important aspect of trading is the execution of trades and delivery of timely, accurate and exploitable pre- and post-trade data to uphold pricing efficiencies. Given the complexities of these instruments, trade capture complexities are increased by many considerations such as modeling, trade entry, confirmation, collateral posting, cost basis and accrual setup as well as actual performance accounting. Because of the complex nature of mortgages, the post-trade performance is expected to contain many moving parts. Although there is a complete set of components that comprise the return, their accuracy becomes an issue due to the underlying risk management processes. Because of the complexities of trading, portfolio management, performance analysis and accounting, they may induce negative effects on the entire investment process that may in turn affect the return.

Including the additional layers of risk and trade parameters offers a finer assessment of investment policy rulings. For example, monitoring excess returns with multi-index and enhanced risk budgets allows management to better identify appropriate attribution timing windows for such investment issues as liquidity trading, market timing, borrower prepayment options, and convexity management, which can become even more important in crisis or dislocation environments where returns can be subject to wide dispersion.

7. Investment Strategies for Community Development

Previous sections introduced various types of data for asset managers who want to engage in targeted investment strategies to increase community development in low- and moderate-income areas. Information for refining investment strategies is summarized here to inform decisions. Patterns of historical fixed-income investment approaches are described. And lastly, recommendations for connecting with community organizations and residents are outlined.

Previous sections identified a variety of community investment indicators. Targeted investment approaches can be guided by the data, including the historical performance of bond investments in particular areas or regions that may have experienced a lack of investment in historical periods. Analysis of community demographic data can help identify which parts of an investment area are falling behind relative to other neighborhoods or geographies and should be prioritized for investment.

Investor-community organization partnerships can be used to actively manage these strategies to ensure that they yield the desired results. Local organizations may be able to provide insight about potentially useful directories of local neighborhood businesses and services, including nonprofit organizations, to contact for community gathering recommendations. Organizations may also be able to refer community residents willing to share their knowledge about the area with investment managers. Connecting with local organizations and residents can also make community presence more likely and enhance the investor's understanding of housing affordability and other community issues during the investment period.

7.1. Targeted Investment Approaches

Targeted investment approaches to community development minimize the risk inherent to local interventions, creating reliable partnerships with local institutions. Direct investments in local projects. These include non-convertible loans to project developers, lenders, and intermediaries. Subordinate and other investment products that aim at enhancing the local equity base of businesses development are also part of this category. This type of investment comes with low liquidity, high operational complexity, specific expertise, and client-based portfolio management at origin. Performance Monitoring will require the establishment of a quality control team to verify compliance with specifications.

Participation-based investments. Community investment partnerships based on investment products that are designed to provide superior returns, while ensuring that proceeds are reinvested locally. This investment approach is based on the confidence that expertise comes from local stakeholders, whose desire for an impact persists throughout the investment duration. Designated local partners ensure that projects to be financed with investors' funds yield optimal impact, such as job creation for disadvantaged populations. Measuring financial success calls for methodologies that capture an internal rate of return that combines both financial and impact dimensions. Tailor-designed funds. Which pool funds from many investors, such as pension funds and tax-exempt organizations. Offered investment products providing guaranteed returns available in taxable formats, such as fixed maturities, will cover only a small share of the market for financially-based community investment, as investors remain sensitive to the relatively small amount of dollars involved.

7.2. Partnerships with Local Organizations

Local organizations, businesses, and institutions can provide valuable insights to asset managers who wish to invest more directly in underserved areas. The more directly they engage in the investment process, the more their investments can align with local priorities. Given potential informational asymmetries regarding local growth opportunities and risks, as well as local idiosyncrasies, it may be more effective to outsource investment decisions to local organizations that are

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101214

already closely engaged in their communities than to organize the information collection effort themselves. Local businesses and nonprofits may also be better positioned to track outcomes in their communities, improving the chances of mutual accountability.

A potential source of collaboration is nonprofit Community Development Financial Institutions, which primarily invest in local residents and organizations through loans, equity investments, and other financial products. These institutions are already equipping businesses and developers with the capital necessary to build local demand. As such, they are well placed to prioritize and manage projects while engaging in impact monitoring. Partnerships with local organizations may help to ensure that the risk characteristics of the securities developed are aligned with the idiosyncratic risk exposures of the investors in them.

Strategic partnerships with large local businesses that directly serve their communities could facilitate the kind of community-centered impact information gathering that might otherwise be too costly for organizations or their partners to do alone. Corporations with a conscience are well positioned both to identify project candidates to be prioritized and to help monitor impact after the fact, potentially reducing the chances of mutual accountability failure. Programs such as local first initiatives and community shared investment could be helpful in identifying volunteer local business partners.

Equation 3 : Data-Powered Risk Adjustment for Targeted Lending:

$$R_a = R_m - \Delta_d$$

R_a = Adjusted risk score using local data insights

R_m = Market-based risk estimate

Δ_d = Risk delta from community-level analytics

8. CONCLUSION

In this report, we have reviewed relevant literature and proposed applied processes that utilize publicly available datasets and mortgage-backed securities to generate evidence-based, data-driven insights for community investment stakeholders and advocate organizations. The prospective investments for tax-exempt investors in bonds backed by mortgage pools of low- and moderate-income borrowers can be compared to the macro-level projected performance of each bond to generate MBS demand. Life cycle income and MBS sensitivity are a few dimensions of any consideration set for bonds backed by the MBS. Design of the pool is critical to building MBS demand in communities. The active acquisition of the targeted pool design can proceed in two main phases. The first phase starts when potentially investable pools are identified and includes selectively purchasing MBS on the secondary market during the targeted MBS due months. The second phase is a post-acquisition phase where pooled MBS are passively managed to identify small MBS positions leaving the target for reinvestment.

Our conclusions can inform policy priorities and data needs to create efficient markets for community investment. Our methodology offers a way to estimate and model community investment MBS demand, including neighborhood-decomposed forecasts of community investment tax-exempt MBS demand, which policymakers can use for community mapping and target selection. Stakeholders can use the specific categories of loans included in the pools to discuss bank credit direction with financial institutions. The pool data can make it easier to discuss affordable housing issues in the community by reducing the polemic nature of arguments concerning local affordable housing needs. Our proposed processes model community investment demand to validate if bond issuances were optimally marketed. Finally, we introduce community performance metrics, including mapping diagrams, designed to appeal to stakeholders not experienced in bond market analysis.

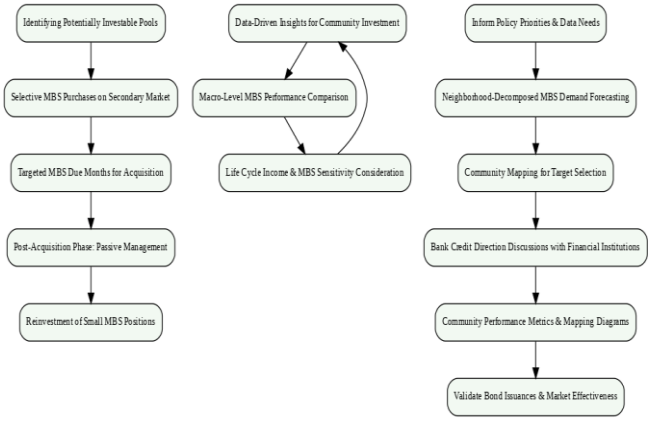

Fig 6 : Community Investment MBS Demand & Policy Insights

DOI: 10.17148/IJIREEICE.2022.101214

8.1. Final Thoughts and Future Directions

The dissertation has explored existing data-driven methodologies used for evaluating residential mortgage and mortgage-backed security performance and pricing, and has developed a set of new data-driven methodologies that focus on using behavioral and individual loan-level drivers of performance to enrich statistical models of mortgage performance in the areas of prepayment, default, and delinquency. The results of this research are two-fold. First, we propose enhancements to existing data-driven approaches that focus on individual loan behavioral factors. These give additional layers of intelligence to macroeconomic and credit-risk modeling experts focused on mortgage prepayment, delinquency, and default modeling for the purposes of cash flow generation and risk appetite setting that also consider investor interests and goals. The second, more substantive contribution arises from the creation of community-lending tools and resource/portfolio allocation frameworks such as loan pricing decisions and capital allocation for community-lending initiatives should appropriate investor yield expectations be met. While any capital needs framework faces its greatest challenge in downturns, our contribution is towards developing a fuller understanding of the ways in which investor preferences can be aligned with community support and development while encouraging the private marketplace to serve as a catalyst. This can also potentially ease some pressure on subsidized housing finance. Finally, while the research questions we address are all data-driven, the understanding of the role of targeted-investor behavior and return objectives is an equally important and, in fact often, more pertinent component of strategic discussions as further exploration of datasets can additionally support strategy effectiveness.

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