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LAND BANKING, INVESTMENT BEHAVIOURS AND URBAN SPRAWL: Evidence from Citizens and Businesses in Lahore

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Abstract

Urban expansion in Lahore, Pakistan, is increasingly driven by speculative investments in non-productive assets such as land plots and real estate, leading to inefficient urban sprawl, infrastructure strain, and limited economic productivity. This study examines the behavioural, financial, institutional, and urban factors influencing investment choices among youth, employees, and business owners in Lahore, drawing on survey data from 641 respondents. Employing multinomial logit models for stated preferences and fractional logit models for revealed portfolio shares, the analysis reveals that higher financial literacy promotes productive investments (e.g., business ventures and skill development), while family influence, herd behaviour, and urban effects like quality of life, perceived car-oriented planning, and sprawl cost perception favour non-productive assets. These patterns exacerbate sprawl and hinder agglomeration benefits, with notable heterogeneity across groups (herding effects are concentrated among youth, while institutional and quality-of-life effects are more pronounced among business owners). Policy implications emphasise regulatory reforms, such as easing zoning restrictions and incentivising dense, mixed-use development, to redirect capital toward sustainable urban growth. Findings contribute to understanding investment inertia in developing cities and support strategies for resilient, inclusive urbanisation.

Keywords: Urban Sprawl, Investment Behavior, Land Banking, Financial Literacy, Behavioral Economics, Lahore, Sustainable Cities.
JEL Classification: O18, R11, R14, R52, G11.

I. Introduction

Urban development in Lahore, Pakistan's key economic centre, features rapid outward expansion fueled by speculative real estate investment (Abbas & Wakil, 2023; Afzal et al., 2024; Haque & Khurshid, 2023; Nasar-u-Minallah et al., 2021; Rahman, 2022). However, this growth has not boosted productivity, innovation, or industrial development proportionally (Nadeem et al., 2021). Instead, private capital often flows into non-productive assets like land plots and residential holdings, which serve as stores of value but fail to enhance the city's economic capacity (Hunter, 1967; Kurysheva &

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Vernikov, 2024; Marshall, 2000; Matos & Hall, 2021; Papadogiannis, 2025; Rao & Behera, 2017; Yang & Stanley, 2012). This misallocation worsens congestion, strains infrastructure, and limits job opportunities for residents (Haque, 2014; Haque et al., 2022; Haque & Nayab, 2020).

Calling investments like speculative real estate and land plots 'unproductive' isn't just an opinion; it's grounded in economic theory and evidence showing they don't create new value or boost long-term growth the way productive investments do, such as factories or skills training. Productive investments ramp up output, jobs, and efficiency, lifting total factor productivity, while unproductive ones mostly shuffle existing assets around, betting on price hikes from speculation or the 'greater fool' idea where you hope to sell higher later (Arcand et al., 2015; Baqaee & Farhi, 2020; Bezemer & Hudson, 2016; Hsieh & Klenow, 2009; Huang et al., 2021). In developing spots like Pakistan, this misallocation hits hard because scarce resources get stuck in bubbles that spike inequality and stall innovation.

For clarity, the study defines productive investment as capital allocated to activities that generate new output, productivity, or employability, whereas non-productive investment refers to assets held primarily for wealth preservation, speculative gains, or status rather than for direct productive expansion.

Instability in policy, inconsistent incentives, and a difficult business environment have eroded investor confidence in productive sectors such as manufacturing and technology, making speculative real estate comparatively more attractive (Ahmad et al., 2022). Historical and institutional dynamics such as elite capture of public land, preferential land allocations, and cumbersome regulatory procedures further skew incentives toward land-based speculation and away from business (Mehmood, 2021; Rana & Bhatti, 2018).

These dynamics are visible on the ground in Lahore. Public land allocation practices, sometimes described as 'Plotistan' (Ali, 2024; Mehmood, 2021), and high commercialisation or conversion fees limit access to land for entrepreneurs and firms (Dowall & Ellis, 2009), while encouraging the holding and trading of plots as speculative assets. Rent-seeking, regulatory uncertainty and weak support for enterprise growth make real estate a safer perceived bet than riskier but potentially more productive investments (Amin et al., 2020; Suzuki et al., 2017). The result is urban sprawl that produces little in the way of innovation or broad-based employment, and which strains public services and the city's environmental quality (Afrakhteh & Shahbakhsh, 2022; Stratford, 2023; Vercellone, 2010).

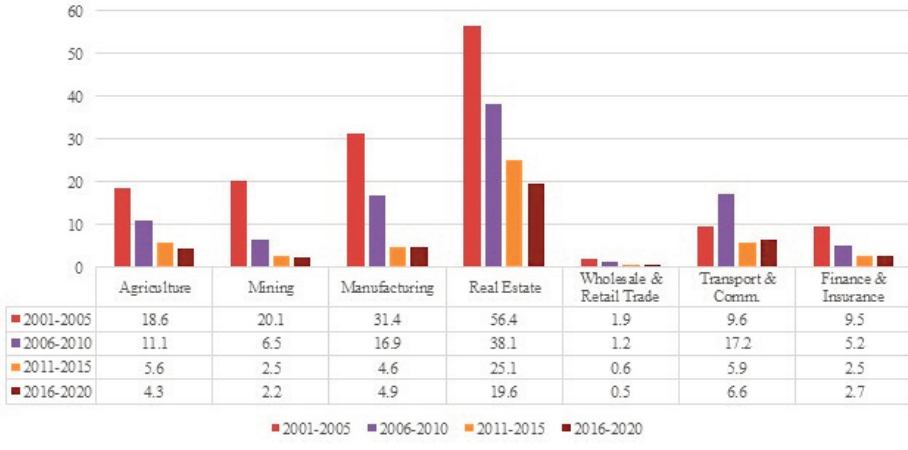
The problem is not only local but reflects broader national patterns. Pakistan's low investment-to-GDP ratio contrasts sharply with neighbouring countries and economies in the region, where rates are far higher (Ahmad et al., 2022). Pakistan's economy needs much more investment to grow faster, as the current investment levels are below 15 per cent of GDP, that is, too low, and it is imperative for Pakistan to simplify rules and attract more capital so growth could potentially reach around 8 per cent (Haider, 2025).

In Figure 1, sectoral data further reveal this distortion: average investment-to-sectoral-GDP ratios show real estate commanding 56.4 per cent in 2001–2005 and remaining the dominant recipient, specifically, 19.6 per cent by 2016–2020, while manufacturing fell from 31.4 per cent to 4.9 per cent and agriculture from 18.6 per cent to 4.3 per cent over the same period (Qasim & Aslam, 2025). This disproportionate allocation to real estate underscores a speculative bias that diverts resources from productive sectors.

The concentration of investment in non-productive assets also has welfare consequences. Studies of other countries show that over-reliance on housing or non-productive stores of value can produce short-term GDP gains but long-run instability, while investments in infrastructure and human capital yield sustained productivity and higher employment (Amendola et al., 2017; Heintz et al., 2009; Hongyu et al., 2002; Kanyenze, 2011). In Lahore, the consequences appear in shrinking public green space, worsening traffic and air quality, and dissatisfaction with housing affordability and public services (Amin et al., 2020; Hanit et al., 2020a; Muhammad, 2013). These deficits reduce the city's 'convenience of living' and limit the agglomeration benefits that should make cities engines of inclusive growth.

For Lahore, this means sprawl eats up land without firing up the economy, echoing how urban expansion in the Global South tanks peri-urban farming and sustainability without real gains (Hatab et al., 2019).

Responding to these problems requires policy and institutional reform; the literature calls for revising restrictive master plans, easing rigid zoning rules, encouraging high-rise and mixed-use development in city centres, and simplifying permission processes



	Agriculture	Mining	Manufacturing	Real Estate	Wholesale & Retail Trade	Transport & Comm.	Finance & Insurance
2001-2005	18.6	20.1	31.4	56.4	1.9	9.6	9.5
2006-2010	11.1	6.5	16.9	38.1	1.2	17.2	5.2
2011-2015	5.6	2.5	4.6	25.1	0.6	5.9	2.5
2016-2020	4.3	2.2	4.9	19.6	0.5	6.6	2.7

Source: Various Reports, Pakistan Economic Survey, Finance Division, Government of Pakistan.

FIGURE 1

Sector-wise Investment to Sectoral GDP Ratio (Period Averages, per cent)

to enable market-responsive, denser, and more productive urban forms (Asian Development Bank, 2024; Haque, 2015; Nabi & Shaikh, 2013). Such changes aim to redirect private capital toward productive uses, improve public service delivery, and create more compact, transit-oriented neighbourhoods that can sustain business growth and broaden employment opportunities.

Against this backdrop, the present study asks why private capital in Lahore continues to flow toward speculative land rather than productive investment, and what that implies for urban sprawl. It answers this by combining stated and revealed investment preferences across youth, employees, and business owners within a spatially structured sample; an approach that, to our knowledge, has not previously been applied to investment behaviour in a Pakistani city.

This paper is organized as follows. Section II presents the literature review and highlights the key theoretical and empirical studies related to investment preferences and behavioral factors. Section III outlines the research objectives and hypothetical statements that guide the empirical analysis. Section IV develops the theoretical framework, while Section V describes the data collection procedures and sampling strategy. Section VI explains the reliability tests and factor construction, Sections VII and VIII present the preference measures and econometric methodology, and Sections IX and X discuss the empirical results and their interpretation. Finally, Sections XI provide policy implications, study limitations, and the conclusion.

II. Literature Review

Modern cities need capital to flow into assets that raise productivity, such as factories, equipment, skills, and infrastructure, rather than into stores of value such as plots, gold, or durable consumption goods. The tendency to concentrate savings in non-productive assets reduces aggregate demand for goods and services, hurts employment, and limits long-run growth (Amendola et al., 2017). Behavioural forces loss aversion, present bias, and herd behaviour often amplify this tendency: when people fear losses or face uncertainty, they prefer tangible, low-risk stores of value (Baddeley, 2010; Kahneman & Tversky, 1979; Laibson, 1997).

Historical and cross-country evidence highlights the cost of over-reliance on non-productive investment. China's rapid housing expansion after market reforms delivered short-term growth but also created vulnerabilities: housing drove a large share of investment and GDP growth, and later housing volatility threatened broader stability (Hongyu et al., 2002; Zhang, 2024). Similarly, in the United States, long-run public infrastructure investment has clear productivity and employment multipliers; declines in such investment were correlated with slower GDP growth, while renewed infrastructure spending returned sizeable economic and job gains (Heintz et al., 2009). In Nigeria, investments in human capital (education and health) improved productivity and sustainability when combined with physical capital, underscoring that productive invest-

ments in people raise firm-level innovation and national competitiveness (Olayemi, 2012). These studies collectively argue for diversifying capital toward productive uses: infrastructure, firms, and human capital to support resilient growth.

Urbanisation and the 'Convenience of Living – COL' (Okulicz-Kozaryn, 2015) are related pieces of this puzzle. Rapid, unplanned urban growth often channels private capital into land and housing at the expense of public goods and services, creating sprawling cities with weak accessibility to amenities (Habibi & Asadi, 2011; Hussain, 2016; Rana & Bhatti, 2018; Shah et al., 2024). Research on Lahore and comparable cities shows the consequences: residents value proximity to transit, parks, shops and health facilities (Hanit et al., 2020b; Zhang et al., 2019), but investment patterns have favoured commercial real estate and luxury projects over affordable housing, green space, and transport infrastructure (Amin et al., 2020; Muhammad, 2013). This misallocation aggravates traffic congestion, environmental decline, and social stress, factors linked to worse mental health and lower well-being in Lahore (Khan et al., 2012). International cases from Curitiba and Indian metropolitan areas reinforce that when planning prioritises profit over public welfare, livability declines (Macke et al., 2018; Pandey et al., 2014).

A particularly close empirical analogue is Gul et al. (2018) on Bahria Town, Lahore. Their case study shows that when residential land is supplied as serviced plots rather than built houses, speculative holding is encouraged, land is kept out of the current market, and development is pushed farther into peri-urban areas. The study is directly relevant to the present paper because it links plot-based speculation in Lahore itself to outward expansion and weaker compact-city outcomes.

Comparable evidence from other rapidly growing urban regions reinforces the same mechanism. (Kinuthia et al., 2021) show that in peri-urban Nairobi, public notification of infrastructure planning altered land subdivision and transfer behaviour, encouraged speculative activity, and allowed development to proceed outside normal procedures. Gemeda et al. (2019, 2020) for Shashemene, Ethiopia, finds that speculative activity is shaped not only by profit motives but also by motivational reasoning, self-worth, and weak regulatory control, based on questionnaire evidence from land developers and public officials.

A growing body of micro-level evidence from other developing economies provides a useful comparative benchmark for these mechanisms. In Nigeria, Olayemi (2012) links human capital investment to industrial productivity, underscoring the productivity gains that arise when resources are directed toward capability formation rather than passive asset holding. Field-experimental evidence from South Asia points in the same direction: De Mel et al. (2008) document very high marginal returns to capital in microenterprises. Against this backdrop, Pakistan's land-banking pattern is not an isolated case but a particularly sharp expression of a wider Global-South tendency, which the present study helps document through both stated and revealed investment behaviour.

Although a substantial literature examines urban sprawl, investment behaviour, and household financial decision-making, these strands have largely developed in isolation. Urban economics research treats sprawl mainly as an outcome of land and transport policy; behavioural finance research explains asset choice through individual biases; and development studies document widespread land banking without linking it to micro-level investment decisions. Much of the behavioural evidence, moreover, originates in high-income settings, and work on Pakistani cities rarely connects individual investment psychology to city-scale sprawl. Two gaps follow. First, few studies jointly model how behavioural, financial, social, and urban factors interact to shape investment choice in a fast-growing Global South city. Second, studies seldom test whether stated investment intentions actually match observed allocation behaviour. This study addresses both. It triangulates stated preferences (estimated with a multinomial logit model) against revealed portfolio shares (estimated with a fractional logit model) across three economically distinct groups within a spatially explicit, concentric-ring sampling design that captures Lahore's urban density gradient. In doing so, it contributes novel micro-level evidence linking the behavioural and institutional drivers of asset choice to land-banking and urban sprawl in a major Pakistani city, and offers a transferable empirical template for other developing-country metropolises.

III. Research Objectives

This study examines the behavioural, financial, social, and urban factors driving investment preferences in Lahore, focusing on why individuals favour non-productive assets (e.g., land plots, gold, vehicles) over productive ones (e.g., business ventures, skill development, financial markets). By analysing revealed (actual monthly allocations) and stated (hypothetical choices) preferences across youth, employees, and business owners, the research integrates behavioural economics (e.g., prospect theory for risk and loss aversion), urban economics (e.g., transport burden and livability effects on capital allocation), and investment theory to explain misallocation contributing to urban sprawl and low productivity.

The study addresses the following research questions:

- What behavioural, financial, and social factors determine the choice between productive and non-productive investments in Lahore, and how do these differ across respondent groups (youth, employees, business owners)?
- How do urban conditions such as transport satisfaction, sprawl costs, and quality of life influence the allocation of resources to productive versus speculative assets?
- To what extent do institutional support, policy restrictions, and planning biases affect investment preferences, and can targeted interventions shift allocations toward productivity?

These questions are tested using fractional logit models for revealed shares (productive, semi-productive, non-productive, consumption) to quantify how predictors shift actual income allocation, and multinomial logit models for stated preferences (productive, semi-productive, non-productive/speculative, mixed) to assess hypothetical choices, with group interactions capturing heterogeneity.

1. Hypothetical Statements

Building on prospect theory (Kahneman & Tversky, 1979) for behavioural biases, urban agglomeration models (Glaeser, 2011) for livability effects, and investment misallocation literature (Amendola et al., 2017), the following hypotheses (H) are tested:

i. Higher financial literacy is positively associated with increased allocation to productive assets (e.g., business, skills, financial markets) and reduced non-productive choices.
ii. Greater family influence and social land pressure increase the preference for non-productive assets (e.g., land/property), particularly among business owners.
iii. Herding behaviour and loss aversion drive preferences toward land and other perceived safe stores of value, reducing the probability of productive investment.
iv. Herding effects are stronger among youth than among income-earning adults (employees, business owners), reflecting their thinner financial experience and greater reliance on peer signals before they control substantial discretionary capital.
v. Higher urban transport burden, longer commute times, and lower quality-of-life satisfaction increase non-productive asset allocation, while better services and pro-density policies promote productive shifts.
vi. Stronger perceived institutional support and fewer policy restrictions are associated with a shift in preferences toward productive assets, whereas greater perceived policy restrictions increase non-productive or speculative allocation.

IV. Theoretical Framework

Cities concentrate people and firms, generating agglomeration economies such as knowledge spillovers, input sharing, thicker labour markets, and improved matching, which raise productivity and create incentives for productive investments (Duranton & Puga, 2004). These forces make dense urban environments natural incubators for entrepreneurship, innovation, and scale. However, whether such benefits materialise depends critically on urban form, infrastructure provision, and institutional incentives. When land-use regulations, taxation, and market signals favour real estate speculation over enterprise formation, capital is diverted into non-productive assets such as land banking, encouraging horizontal expansion and eroding the density advantages that underpin agglomeration economies (Brueckner, 2000; Glaeser & Kahn, 2004; Gul et al., 2018).

At the micro level, investment choice theory predicts that individuals allocate capital across assets based on expected returns, risk, liquidity, and constraints such as income and access to credit. Behavioural economics, however, shows that actual decisions often depart systematically from this rational benchmark. Prospect theory highlights loss aversion and probability weighting (Kahneman & Tversky, 1979), while models of present bias explain preferences for liquid or immediately tangible assets over longer-horizon investments (Laibson, 1997; Thaler & Sunstein, 2009). These mechanisms help explain persistent preferences for assets such as land or gold, which may offer perceived safety or status despite lower social and productivity returns relative to business investment or human capital accumulation.

Social and institutional contexts further shape these individual-level choices, since the quality of institutions conditions whether capital flows toward productive uses or rent-seeking and speculation (Acemoglu & Robinson, 2012). In many developing-country urban settings, family norms, inheritance expectations, and peer pressure generate strong intergenerational preferences for land ownership and housing as stores of value and status, often overriding private return calculations (Baig et al., 2019; Pandey et al., 2014). From a public-choice perspective, political and bureaucratic incentives tend to favour visible, short-term projects, such as road expansion or land release, that reinforce car-oriented mobility and speculative real estate development, rather than long-term, productivity-enhancing public goods (Mueller, 1976). Where public services are unreliable, households and firms internalise service provision by investing in private substitutes (e.g., vehicles, generators), further distorting urban investment patterns.

Applied to Lahore, this framework conceptualises observed investment outcomes as the interaction of four forces: (a) agglomeration opportunities that favour productive investment, (b) market and policy incentives that may privilege land and speculation, (c) individual constraints and behavioural traits (financial literacy, risk tolerance, time preference), and (d) social pressures related to family expectations and status. Empirically, this motivates a triangulated measurement strategy that combines stated preferences (hypothetical lump-sum allocations), revealed behaviour (actual portfolio compositions and past investments), and policy counterfactuals (responses to simulated interventions, such as higher land taxation). This approach mitigates hypothetical-bias concerns and allows identification of underlying mechanisms, including mediation effects (e.g., whether family pressure weakens the influence of financial literacy on productive investment).

To explain individual and aggregate investment choices in urban settings, the study combines urban agglomeration theory, behavioural economics, and public-choice/institutional perspectives (Acemoglu & Robinson, 2012). Agglomeration benefits include knowledge spillovers, input sharing, and thicker labour markets that create incentives for productive investment in cities (Duranton & Puga, 2004; Glaeser, 2011). However, weak or distorted institutions, regulatory bottlenecks, and speculative incentives can

divert capital toward land banking and low-productivity uses (Gul et al., 2018). Behavioural economics complements this view by showing how cognitive biases (loss aversion, probability weighting) and time preferences skew choices toward safe or status-bearing assets such as plots or gold (Kahneman & Tversky, 1979; Laibson, 1997; Thaler & Sunstein, 2009).

The empirical literature identifies several determinants of investment behaviour that are operationalised in the study's survey and econometric models. Financial literacy and investment knowledge are consistently associated with participation in productive and diversified assets (Atkinson & Messy, 2012; Lusardi et al., 2010; Shah et al., 2024; Van Rooij et al., 2011). Income and life-cycle factors shape saving capacity (Modigliani & Brumberg, 1954) while risk preferences and behavioural traits influence the relative appeal of productive versus speculative assets (Kahneman & Tversky, 1979). Finally, the quality of urban infrastructure, access to formal finance, and regulatory burdens affect the costs and expected returns of enterprise activity, thereby influencing reinvestment decisions (Brueckner, 2000; Glaeser, 2011).

This framework leads to clear hypotheses: higher financial literacy and stronger agglomeration benefits should increase investment in productive assets such as businesses, skills, and financial instruments, whereas greater risk-seeking and herding tilt allocations toward speculative or safe stores of value. In contrast, stronger family influence, inheritance expectations, and poor public services are expected to incline portfolios toward land and other non-productive assets, reinforcing urban sprawl, while weaker institutional support and greater perceived policy restriction are expected to push allocations further toward speculative land-banking rather than enterprise. Thus, the theoretical framework is conceptualised in Table 1.

V. Data Collection and Sampling

This study employs a structured primary data collection approach and focuses on three key respondent groups in Lahore; i.e. youth, business owners, and professional employees. The design aims to capture a comprehensive picture of investment preferences and behaviours across demographic and occupational categories that represent Lahore's active economic population. The total number of samples for each audience is consolidated in Table 2 as follows.

1. Sampling - Youth

The youth sample targets students enrolled in public and private universities in Lahore, particularly from the social sciences disciplines such as economics, management, and sociology. University students are an important segment as they represent future investors and decision-makers, whose financial literacy, aspirations, and perceptions of investment risks shape long-term economic trends.

TABLE 1

Theoretical Framework – Constructs, Measures and Foundations

Construct/ Block	Key Measured Variables/Items (Used in Models)	Theoretical/Behavioral Foundation	Empirical Testing in This Study
Financial & Behavioral Factors	- Financial literacy and confidence (knowledge of finance, confidence in decisions, training received, willingness to pay for advice) - Risk tolerance vs. loss aversion (comfort with business vs. land risks) - Time preference (prefer money now or more later) - Herd behavior and risk-herding tendencies	Prospect theory (loss aversion, risk perception) Hyperbolic discounting Behavioral biases & nudges (Atkinson & Messy, 2012 Kahneman & Tversky, 1979 Laibson, 1997)	Standardized scales for financial literacy/confidence and risk/herding behavior Main effects + interactions with respondent group (youth, employees, business owners) in fractional logit (revealed shares) and multinomial logit (stated preferences)
Social & Cultural Influences	- Family pressure and inheritance expectations (family pushing for land, expected land transfer) - Social prestige of owning land/property - Peer and community norms around property investment	Social norms & cultural transmission of wealth strategies Family influence on risk-averse asset choices (Baig et al., 2019 Mehmood, 2021 Pandey et al., 2014)	Standardized scale for social & cultural land pressure Main effects + group interactions (especially strong among business owners) in both models
Urban Productivity & Livability Conditions	- Daily commute time and transport burden - Quality of life and public services (parks, internet access, safety, waste management) - Housing preference (central city vs. suburban) - Perceived increase in travel cost/time due to urban sprawl - Satisfaction with public transport - Urban planning bias toward cars over public transport	Urban agglomeration & livability effects on capital allocation Transport costs & spatial inefficiency Urban amenity valuation (Brueckner, 2000 Glaeser, 2011Gul et al., 2018 Hanit et al., 2020a Haque & Nayab, 2020)	Standardized scales for quality of life & urban services, sprawl cost increase, public transport satisfaction, and car-priority planning Direct effects in fractional logit (revealed) and multinomial logit (stated) models
Institutional & Market Environment	- Perceived institutional support & pro-density policies - Perceived policy restrictions & road/car bias - Access to finance/startup funding - Regulatory/licensing costs - Trust in government & planning institutions	Discrete choice under constraints Institutional barriers to entrepreneurship Land-use policy distortions (Acemoglu & Robinson, 2012 Haque, 2015 McFadden, 1972 Papke & Wooldridge, 1996)	Standardized scales for institutional support/pro-density and policy restrictions/road bias Direct effects in both fractional logit and multinomial logit models

Continue

TABLE 1 *(Continued)*

Theoretical Framework – Constructs, Measures and Foundations

Construct/ Block	Key Measured Variables/Items (Used in Models)	Theoretical/Behavioral Foundation	Empirical Testing in This Study
Demographic & Group Controls	- Age - Gender - Type of residence (e.g., owned, rented, hostel) - Born in Lahore or migrant - Time preference - Housing preference - Daily commute time - Main mode of travel - Respondent group (Youth, Employees, Business Owners)	Life-cycle & demographic heterogeneity Group-specific exposure to urban & institutional factors (Duranton & Puga, 2004 Glaeser & Kahn, 2004 Train, 2009 Van Rooij et al., 2011)	Direct controls (age, gender, residence type, born in Lahore, time preference, housing preference, commute time, travel mode, group indicator) + interactions between group and key behavioral scales (financial literacy, risk/herding, social land pressure)
Outcome Variables	Revealed preferences: Monthly income shares allocated to productive (business investment, skills, financial markets), semi-productive (savings/deposits), non-productive (land/property, gold, vehicles), and consumption (food, transport, rent, etc.) Stated preferences: Top priorities for hypothetical investment choice (productive, semi-productive, non-productive/speculative, mixed)	Behavioral misallocation to non-productive assets Urban sprawl & land banking as dominant wealth strategy	Fractional logit regression for revealed shares (bounded [0,1]) Multinomial logit for stated categorical preferences (base: non-productive/speculative)

Source: Author's estimation.

To ensure geographic representation and to analyze spatial investment behavior, we employed a spatial proximity–based sampling strategy using concentric distance rings drawn from a central reference point in Lahore. The geographic centre used for all calculations was the coordinate (31.50475, 74.33150), corresponding to the urban core of Lahore, specifically the Kalma Flyover. The straight-line distance (in kilometers) from this centre to each university was computed using the Haversine formula, which measures the great-circle distance between two points on the Earth's surface (Dauni et al., 2019; Sinnott, 1984). Based on these distances, universities were grouped

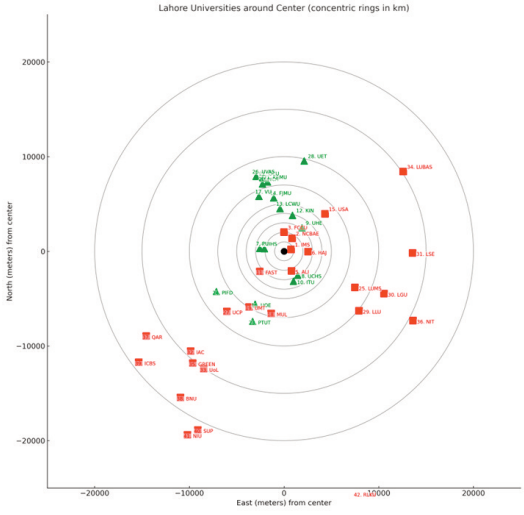
TABLE 2

Survey Audience Composition*

Survey Audience	Frequency	Percent	Cumulative Percent
Youth	243	37.91	37.91
Employees	217	33.85	71.76
Business Owners	181	28.24	100
Total	641	100	

Source: Author's estimation from World Bank's WDI and Central Bank of Nigeria (CBN) Statistical Bulletin.
Note: The sample is broadly balanced across future investors (youth), salaried employees, and business owners, capturing heterogeneity in economic participation within Lahore.

into nine concentric circles (0–1 km, 1–2 km, 2–3 km, 3–4 km, 4–5 km, 5–7 km, 7–10 km, 10–15 km, and 15–20 km). As illustrated in Figure 2, from each ring, a proportional sample of universities and students was selected, ensuring spatial variation in socio-economic background, access to educational infrastructure, and exposure to urban density gradients. Rings closer to the core are associated with older, denser institutional environments, while outer rings represent newer, more dispersed educational



Source: Author's estimation.
Notes: ●Reference Point *(Kalma Flyover)* ▲Public Sector University ■Private Sector University

FIGURE 2

Lahore Universities around Center *(concentric rings in kilometers)*

* Complete details of variable construction, measurement, and the questionnaire are available upon request from the corresponding author (yasirzkhan09@gmail.com).

zones, thus capturing urban spatial-economic heterogeneity. This method aligns with spatial sampling approaches used in urban economic geography and educational access studies (Fotheringham et al., 2000; Inostroza et al., 2013; LeSage & Pace, 2009).

Selection of universities followed a mixed spatial–thematic rule to ensure geographic coverage across the nine concentric rings while prioritising institutions that teach social sciences, business, management, economics, or related programs (to maximise relevance for the study). Criteria used: (1) academic profile; presence of departments/programmes in economics, management, business, social sciences, or public policy; (2) sector balance; include both public and private institutions; (3) spatial representation; select at least one institution per inner/mid/outer ring where feasible; (4) enrolment and representativeness; favor larger institutions (greater student populations) for proportionate sampling; (5) accessibility and cooperation likelihood; preference to universities with clear contact/procurement channels (to ease data collection). From each selected university, we drew a proportional quota of social-science students (stratified by year and gender); the final student sample reflects both institutional size and ring distribution.

A proportionate stratified random sampling strategy was employed to balance public (≈60 per cent) and private (≈40 per cent) institutions, reflecting Lahore's higher education composition, while prioritising universities offering relevant social-science programs. Within each selected institution, students were sampled proportionally to enrollment size, stratified by academic year and gender to enhance representativeness. Data were collected via structured questionnaires administered both in person and online, achieving a final usable sample of 243 respondents after cleaning for completeness and consistency. This spatial–thematic sampling design captures variation in several factors which may lead to heterogeneity.

Table 3 presents the universities included in the youth sample and the number of students selected from each institution.

2. Sampling - Professional Employees (Labour)

The employee sample comprises 217 respondents working across major economic sectors in Lahore. Employees were targeted because they represent a large segment of the urban workforce with regular salaries, enabling meaningful allocation decisions between consumption, savings, and limited investment options. Unlike business owners, who actively reinvest or speculate, employees typically have less control over capital deployment but still exhibit revealed preferences shaped by financial literacy, job security, and urban living costs (Amendola et al., 2017; Cheema et al., 2018).

The target sample size was guided by respondent-to-item ratio recommendations applied at the construct level, rather than the full instrument. While the survey comprised 27 items in total, factor analysis was conducted separately for the theoretically defined scales, with the largest construct containing 10 items and most scales contain-

ing between 2 and 7 items. Following established guidelines recommending a minimum ratio of 5:1 and a preferred ratio of 10:1 respondents per item for exploratory analyses (Gorsuch, 1983; Hatcher, 1994; Memon et al., 2020; Suhr, 2006), a conservative minimum of 100–180 respondents was deemed sufficient to ensure robustness. The final usable sample of 217 employees comfortably exceeds these thresholds. Respondents were drawn from approximately 40 well-established firms across multiple sectors in Lahore, with an average of 5–10 participants per organisation. Selection focused on mid-level to senior professionals with at least five years of experience to ensure informed and reliable responses regarding financial decision-making and investment behaviour.

TABLE 3

Distribution of Student Respondents by University

University	Number of Students
Lahore School of Economics	24
University of Central Punjab (UCP)	23
National College of Business Administration & Economics (NCBA&E)	23
LEADS University	23
Superior University	22
Beaconhouse National University (BNU)	18
Lahore University of Management Sciences (LUMS)	18
Government College University Lahore (GCU)	17
FAST National University (FAST-NUCES)	15
University of Lahore (UOL)	15
University of the Punjab (PU)	13
Kinnaird College for Women University	9
University of Education	8
Forman Christian College (FCCU)	5
University of Management and Technology (UMT)	4
University of Engineering and Technology (UET)	2
Minhaj University	2
Hajvery University	1
Quaid-i-Azam University	1
Total	243

Source: Author's estimation.

Note: Social Sciences formed the largest share of respondents at about 49 per cent. Business & Management followed at roughly 38 per cent, while Computer Studies, Law/Public Policy, Humanities & Arts, and Medical & Health Sciences together accounted for the remaining 13 per cent.

Data were collected through structured questionnaires administered in-person and online by trained enumerators. Companies were purposively selected from official lists registered with the Securities and Exchange Commission of Pakistan (SECP) and supplemented by sector directories to ensure operational relevance and diversity. In Table 4 the samples of employees collected from each sector.

3. Sampling - Business Owners

Due to the absence of a complete official sampling frame for informal and semi-formal enterprises in Lahore, a market-cluster-based stratified convenience sampling strategy was adopted. Eleven major commercial hubs were selected to represent traditional wholesale/retail bazaars, modern corridors, and high-income service zones. Within each market, enumerators applied consecutive-walk convenience sampling during business hours, approaching available proprietors. Quota controls were used to ensure diversity across business types (retail, wholesale, manufacturing, services, food & beverage, electronics, apparel, real-estate dealing, hospitality), guided by on-site observations and market profiles. This method aligns with standard practice for

TABLE 4

Summary of Employee Sample by Sector

Sector	Count	% of Total
Banking and Finance	29	13.40%
Information Technology	20	09.20%
Manufacturing and Production	58	26.70%
Real Estate and Construction	21	09.70%
Marketing and Advertising	2	0.90%
Telecommunications	3	01.40%
Retail and Wholesale Trade	24	11.10%
Consulting Services	6	02.80%
Education and Research	28	12.90%
Healthcare and Pharmaceuticals	26	12.00%
Total	217	100.00%

Source: Author's estimation.

Note: Employees were mid-level to senior professionals (with a minimum of 5 years' experience) from SECP-registered companies. Stratification by gender and job level applied where possible. Data collected via structured questionnaires (in-person and online).

urban SME surveys in Pakistan where formal registries are incomplete, and market clustering offers practical representativeness (Abbas et al., 2020; Mustaghis-ur-Rahman & Jalees, 2015).

The final sample of 181 business owners was determined based on respondent-to-item ratio guidelines applied to the largest analytical construct rather than the full questionnaire. Although the survey instrument included 27 items, factor analyses were conducted separately for each behavioural and institutional scale, with no construct exceeding 10 items. Methodological guidance suggests that a minimum ratio of 5:1 respondents per item is acceptable, while a 10:1 ratio is preferred for stability and generalizability (Gorsuch, 1983; Hatcher, 1994; Memon et al., 2020; Suhr, 2006). The achieved sample therefore meets and slightly exceeds the preferred threshold. Data were collected through structured face-to-face interviews administered by trained enumerators using a conversational approach to enhance trust and response accuracy. The resulting sample provides adequate statistical power for fractional logit estimation and captures meaningful sectoral and spatial variation across Lahore's commercial landscape. A summary of sample characteristics is presented in Table 5.

4. Informed Consent

All participants were clearly informed about the purpose of the study prior to data collection, and informed consent was obtained from each respondent. Participation was entirely voluntary. To protect privacy and confidentiality, no personally identifiable or sensitive information was collected or disclosed, including (but not limited to) names of individuals, businesses, companies, universities, geographic representation areas, or any other identifying details. The data were used exclusively for academic research purposes and were analysed and reported only in aggregate form.

VI. Reliability Tests and Factor Construction

To ensure the robustness of the survey measures, reliability and validity assessments were conducted on key constructs derived from the questionnaire items common across the three respondent groups. The data from these groups were appended into a single dataset, with group identifiers assigned to distinguish between audiences. Common variables were consolidated for scale construction, while group-specific or standalone items were treated separately. Cronbach's alpha was calculated for each proposed scale to assess internal consistency (Peterson, 1994). Principal Component Analysis (PCA) was conducted separately for each theoretically defined construct (Costello & Osborne, 2005). Components were retained based on eigenvalues greater than one from the unrotated solution. Varimax rotation was then applied to aid interpretability of retained components. Factor scores were predicted and standardised (z-scores) for use in subsequent regressions, facilitating comparability across scales

TABLE 5

Summary of Business Owners Sample by Market and Business Type

Market/Location	Count	% of Total	Retail Shop	Food & Beverage	Construction/ Building	Service-Based	Other Categories	Key Notes/Coverage
MM Alam Road Gulberg III	42	23.20%	9	29	3	0	1	Modern commercial corridor high-end services & retail
Ichhra Bazaar	24	13.30%	14	5	0	5	0	Local retail & small service businesses
Shah Alam Market	23	12.70%	14	2	3	0	4	Major wholesale textiles, electronics & food
Urdu Bazaar	21	11.60%	14	0	0	5	2	Book/stationery, printing & wholesale focus
DHA Lahore	15	8.30%	2	7	0	2	4	Premium planned area real-estate & services
Misri Shah Lahore	13	7.20%	4	0	6	3	0	Industrial supplies & construction materials
Anarkali Old Food Street	9	5.00%	0	9	0	0	0	Street food & commerce focus
Iqbal Town	9	5.00%	0	9	0	0	0	Emerging mixed commercial area
Bahria Town Lahore	8	4.40%	3	5	0	0	0	Planned high-income residential/commercial
Mall Road	8	4.40%	0	8	0	0	0	Central high-street retail/services
Other (Cantt, Johar Town, Model Town, Gulberg)	9	5.00%	0	0	0	0	9	Scattered high-value or emerging zones
Total	181	100.00%	60 -0.331	74 -0.409	12 -0.066	15 -0.083	20 -0.11	Diverse coverage across traditional bazaars, modern corridors & planned zones

Source: Author's estimation.
Note: Sampling used market-cluster convenience with quotas for diversity across retail, wholesale, services, and food sectors. Markets were selected to represent Lahore's commercial heterogeneity: traditional (Anarkali, Shah Alam, Urdu Bazaar), central high-street (Mall Road), emerging (Iqbal Town), industrial (Misri Shah), and planned/high-income (Bahria Town, DHA). Data were collected via face-to-face structured questionnaires.

(DiStefano et al., 2009). Single-item measures, such as those related to perceptions of transport and urban sprawl, were standardised directly without aggregation.

All key behavioural, social, and institutional constructs were measured using multi-item survey questions and transformed into standardised indices for analysis. Financial literacy and confidence were measured using two items and reduced to a single underlying factor via principal component analysis (PCA), with acceptable internal consistency confirmed by Cronbach's alpha; standardised scores and predicted factor values were generated. Risk and herding behaviour, measured using five items reflecting risk-taking and peer influence, also formed a single coherent factor, with reliability verified and standardised scales constructed. Social and cultural pressures related to land ownership were assessed using six items capturing family influence, social status, and intergenerational expectations; PCA confirmed a unidimensional structure with strong internal consistency, leading to standardised indices. Quality of life and urban services were measured using ten indicators of living conditions and amenities in Lahore; PCA and reliability tests supported aggregation into a reliable standardised scale. Institutional support and pro-density attitudes were derived from seven items reflecting business opportunities, trust in institutions, and perceptions of high-rise development, again yielding reliable standardised measures. Policy restrictions and road bias were measured using two items and combined into a validated standardised index. In contrast, transport and urban sprawl perceptions were treated as separate, standardised variables rather than aggregated scales, to preserve their distinct and policy-relevant effects in the empirical models.

To summarise the Principal Component Analysis (PCA) and reliability assessments, Table 6 presents key statistics for each constructed scale. The table includes the scale name, number of items, Cronbach's alpha (measuring internal consistency), number of retained components (based on eigenvalues >1 from an unrotated PCA), and the cumulative variance explained by the retained components. Notes highlight notable patterns in loadings or structure. All analyses were conducted on a sample of 641 observations. Cronbach's alpha values indicate reliable scales, while PCA reveals underlying dimensionality, with most scales dominated by a primary component suggesting one-dimensionality. Although two components met the eigenvalue >1 criterion for Quality of Life and Institutional Support, the first component accounted for the majority of explained variance and exhibited coherent loadings consistent with the theoretical construct; therefore, a single standardised factor score was retained for parsimony.

The Policy Restrictions/Road Bias index combines two items and returns a Cronbach's alpha of 0.657, below the conventional 0.70 threshold. We retain it as a short composite for two reasons. First, alpha is mechanically downward-biased for two-item scales, for which the inter-item correlation (0.489) and the single retained component (eigenvalue 1.49, explaining 74.45 per cent of variance) are more informative and indicate a coherent single dimension. Second, the two items per-

TABLE 6

Summary - Reliability Tests and Factor Scoring

Scale	Number of Items	Cronbach's Alpha	Average Interitem Correlation	Retained Components (Eigenvalue >1)	First Component Eigenvalue	Cumulative Variance Explained by Retained Components	Items Included (Conceptual Description)
Financial Literacy/Confidence	2	0.7500	0.6000	1	1.6000	80.00%	Self-assessed financial knowledge confidence in making investment decisions
Risk & Herding Behavior	5	0.7888	0.4276	1	2.7275	54.55%	Willingness to take risks in business and land peer discussions fear of missing out concern over losses
Social & Cultural Land Pressure	6	0.8573	0.5004	1	3.5247	58.74%	Family/friends' influence willingness to pay more near family family pressure to invest in land social respect from ownership relatives' advice intergenerational expectations
Quality of Life & Urban Services	10	0.8847	0.4342	2	5.1026	71.94%	Overall life satisfaction air quality neighborhood safety healthcare access education facilities parks waste management internet quality city center attractiveness preference for new societies
Institutional Support/Pro-density	7	0.8575	0.4623	2	3.8638	72.21%	Business opportunities institutional/bank support ease of startup financing trust in government beliefs about cost/job benefits of high-rises tolerance for informal vendors
Policy Restrictions/Road Bias	2	0.6568	0.4890	1	1.4890	74.45%	Perceived restrictions on high-rise development preference for public transport investment over roads

Source: Author's estimation.
Note: The table reports internal consistency and factor extraction results for all constructed scales. Principal Component Analysis (PCA) with varimax rotation was applied separately to each theoretically defined construct, retaining components with eigenvalues greater than one. All scales exhibit acceptable to strong reliability and coherent factor structures, justifying the use of standardised factor scores in subsequent regressions[2].
[2] Detailed statistics are available upon request from the corresponding author (yasirzkhan09@gmail.com).

ceived regulatory restriction of high-rise development, and a perceived policy bias toward roads over public transit are theoretically central to the paper's argument about the institutional drivers of sprawl. We nonetheless flag the modest reliability of this index as a limitation.

The average factor values reported in Table 7 consolidate standardised attitudinal indices and selected Likert-scale perceptions across Youth, Employees, and Business Owners. The first six constructs (Financial Literacy/Confidence; Risk & Herding Behaviour; Social & Cultural Land Pressure; Quality of Life & Urban Services; Institutional Support/Pro-Density; Policy Restrictions/Road Bias) are expressed as standardised z-scores (mean ≈ 0, SD ≈ 1 overall), allowing direct comparison across groups relative to the full sample. Positive values indicate above-average agreement or intensity of the underlying construct, while negative values reflect below-average positioning. The final three indicators are reported on the original 1–5 Likert scale (Disagree to Agree), capturing perceived travel costs from sprawl, satisfaction with public transport, and perceptions of car-oriented planning.

TABLE 7

Key Attitudinal Scales by Group

Scale/Group	Youth	Employees	Business Owners	Overall
Financial Literacy/ Confidence (z)	-0.41 (0.88)	0.70 (0.83)	-0.30 (0.88)	0.00 (1.00)
Risk & Herding Behavior (z)	-0.48 (0.71)	0.05 (1.25)	0.58 (0.61)	0.00 (1.00)
Social & Cultural Land Pressure (z)	-0.19 (0.93)	0.09 (1.31)	0.14 (0.50)	0.00 (1.00)
Quality of Life & Urban Services (z)	-0.32 (0.70)	0.30 (0.65)	0.07 (1.46)	0.00 (1.00)
Institutional Support/ Pro-Density (z)	-0.30 (0.79)	-0.32 (0.74)	0.79 (1.09)	0.00 (1.00)
Policy Restrictions/ Road Bias (z)	0.08 (0.83)	0.54 (0.99)	-0.76 (0.71)	0.00 (1.00)
Urban Sprawl ↑ Travel Cost (	3.34 (1.05)	3.88 (1.02)	3.12 (0.75)	3.46 (1.01)
Satisfied with Public Transport (1–5)	2.45 (0.97)	2.26 (0.96)	2.72 (0.97)	2.46 (0.98)
Planning Prioritizes Cars (1–5)	3.83 (0.74)	3.79 (1.01)	3.28 (1.16)	3.66 (0.99)

Source: Author's estimation.
Note: values represent 'Mean (SD)'; z = standardized ~0 overall; Like rt 1–5: Disagree to Agree.

VII. Preferences (Outcome Variables)

Stated and revealed preferences are used together to capture both what respondents say they would choose under hypothetical scenarios and what they actually do with their investments (observed behaviour), allowing the study to compare real-world actions with underlying intentions and policy responses. Thus, we develop a primary dependent variable from stated preferences and an alternative dependent variable from revealed preferences of the citizens.

1. Stated Preferences

The primary dependent variable captures respondents' stated preferences for allocating a hypothetical lump-sum amount across investment options, with group-specific sums to reflect realistic scales (PKR 1 million for youth, emphasising entry-level choices; PKR 5 million for employees, aligning with mid-career aspirations; PKR 10 million for business owners, suited to expansion needs). Respondents ranked their top priorities (up to three), implying at least 40 per cent allocation to the primary choice. This aligns with discrete choice theory, in which individuals select among unordered alternatives based on utility maximisation (McFadden, 1972). For each respondent, the latent utility of an alternative is modelled as Equation (1):

$$U_{ij} = X_i \beta_j + \varepsilon_{ij} \tag{1}$$

where includes individual characteristics (e.g., financial literacy scale, risk tolerance, family influence, demographics, urban perceptions), are alternative-specific parameters, and follows an independent and identically distributed type I extreme value distribution. The probability of choosing option is as explained in Equation (2):

$$P_{ij} = \frac{\exp\,(X_i \beta_j)}{\sum_k \exp\,(X_i \beta_k)} \tag{2}$$

To prepare the dependent variable, investment priorities were harmonised into three base categories (plus a derived Mixed category) and, by group, assumed to reflect contextual relevance. Table 8 summarises the category mappings for each group, based on the questionnaire options.

The threefold classification (productive, semi-productive, and non-productive/speculative) detailed in Table 8 is grounded in well-established theory and empirical evidence. Productive investments increase human or physical capital and have measurable effects on earnings, firm productivity and aggregate growth (Becker, 1964; Bloom et al., 2013; De Mel et al., 2008; Hsieh & Klenow, 2009). Semi-productive as-

sets deliver recurring income or capital preservation (e.g., rents, interest) without directly increasing productive capacity (Brueckner, 2000). Non-productive/speculative holdings are primarily stores of value or bets on price appreciation; empirical work from urban and developing-country contexts documents widespread land-banking, gold as a cultural store of value, and volatile asset speculation (plots, gold, cars) that can divert capital from productive uses and promote outward urban expansion (Baur et al., 2018; Glaeser & Kahn, 2004; Gul et al., 2018; Nasar-u-Minallah et al., 2021; Rahman, 2022; Shahbaz et al., 2014). Financial literacy, liquidity needs, life-cycle stage, institutional incentives (tax, land registration, credit access), and behavioural biases explain why different groups choose different asset types, making the classification measurable and falsifiable in survey data (De Mel et al., 2008; Lusardi et al., 2010; Van Rooij et al., 2011).

TABLE 8

Group-Specific Classification of Investment Options into Preference Categories

Group	Productive (growth-enhancing)	Semi-productive (income-generating/ secure)	Non-productive/ Speculative (store of value/appreciation)
Youth	Business/startup education & skills financial assets (stocks, mutual funds, bonds). Investments that build skills, firm capacity, or productive financial claims.	Rental property bank deposits. Provide regular income or safe liquidity but do not directly expand productive capacity.	Plots/undeveloped land gold/jewelry crypto/ NFTs vehicles ROSCAs Held mainly for capital gains, status, or precaution rather than to increase production.
Employees	Side business professional certification financial market investments. Raise labor productivity and long-term earnings potential.	Commercial/rental property fixed savings. Generate steady income or preserve capital for security.	Vacant plots gold consumer durables. Retained as stores of value, inheritance, or resale items rather than productive capital.
Business Owners	Business expansion/upgrade new ventures staff training productive financial investments. Directly increase firm output, productivity and employment.	Commercial property (diversification) rental units. Add income and risk-hedging capacity but are secondary to core productive reinvestment.	Land-banking speculative plots idle cash/gold. Investments oriented to price appreciation and wealth storage rather than firm productivity.

Source: Author's estimation.

The overall preference was then derived via logical rules to aggregate rankings, weighting the primary choice heavily as it reflects the strongest utility:

- Case 1: All priorities in the same category → Assigned that category, assuming consistent preferences under rational choice.
- Case 2: Primary (p1) productive or non-productive, without opposites in others → Assigned p1, prioritising the top-ranked to capture decision confidence amid biases like present bias.
- Case 3: Primary semi-productive → Assigned semi, as it often balances risk and stability.
- Case 4: Mix of productive and non-productive across priorities →'Mixed', acknowledging ambiguity and herd behaviour in uncertain urban contexts.
- Fallback: Assigned to p1 if unresolved, ensuring no missing values while emphasising revealed top preference.

This rule-based aggregation theoretically justifies capturing preferences, avoiding oversimplification in heterogeneous groups, and aligns with prospect theory's emphasis on weighted utilities (Geng et al., 2020). Cross-tabulations by group confirmed balanced distributions, supporting model validity. Table 9 summarises the distribution of investment preferences across survey audiences, highlighting counts and column percentages.

TABLE 9

Summary - Stated Preferences by Audience Group

Investment Preference Category	Youth (n=243)	Employees (n=217)	Business Owners (n=181)	Business Owners (n=181)	Total (n=641)
Productive	93 (38.27)	8 (3.69)	8 (3.69)	24 (13.26)	125 (19.50)
Semi-Productive	44 (18.11)	51 (23.50)	51 (23.50)	33 (18.23)	128 (19.97)
Non-Productive/Speculative	80 (32.92)	75 (34.56)	75 (34.56)	35 (19.34)	190 (29.64)
Mixed	26 (10.70)	83 (38.25)	83 (38.25)	89 (49.17)	198 (0.89)

Source: Author's estimation.

2. Revealed Preferences (Portfolio Shares)

The alternative dependent variable captures revealed investment preferences, which focus exclusively on employees and business owners, excluding youth respondents. Youth typically depend on limited allowances or part-time earnings, which are predominantly allocated to immediate consumption needs such as food, transport, education, and personal expenses, rather than discretionary investment decisions (Amendola et al., 2017). In contrast, adults with stable employment or business income have greater financial capacity and regularity to allocate resources meaningfully toward productive or non-productive assets, making them the appropriate population for examining investment behaviour and its implications for urban sprawl and productivity. This approach follows the rationale that investment patterns are more discernible and impactful among working adults, where capital misallocation can directly influence economic outcomes (Hongyu et al., 2002).

The dependent variables are constructed as fractional shares of total reported monthly allocation. We classify each allocation category into productive, semi-productive, non-productive, or consumption based on its contribution to long-term economic productivity. The shares are defined as Equations (3), (4), (5), and (6) respectively as follows:

$$Productive = \frac{\sum_{k \in P} a_k}{\sum_{j=1}^{J} a_j} \tag{3}$$

$$Semi\ Productive = \frac{\sum_{k \in S} a_k}{\sum_{j=1}^{J} a_j} \tag{4}$$

$$Non\ Productive = \frac{\sum_{k \in N} a_k}{\sum_{j=1}^{J} a_j} \tag{5}$$

$$Consumption\ (base) = \frac{\sum_{k \in C} a_k}{\sum_{j=1}^{J} a_j} \tag{6}$$

where;

a_j is the reported allocation to category $j (j = 1, \ldots, J)$,

P, S, N and C denote the sets of productive, semi-productive, non-productive, and consumption categories, respectively,

$\sum_{j=1}^{J} a_j$ = total monthly allocation.

This formulation shows that each share is a normalised proportion, ensuring the total sum is one, and is suitable for fractional logit estimation (Papke & Wooldridge, 1996).

These classifications are theoretically grounded and supported by economic literature. The categorical explanation of the revealed asset class allocation is presented in Table 10.

As consolidated in Table 11, the allocation patterns show that the largest share of reported funds is directed toward consumption (60.63 per cent), followed by non-productive assets (19.46 per cent) and productive assets (14.23 per cent). Within productive uses, business investment accounts for the majority (10.26 per cent), while financial investments remain relatively modest (3.97 per cent). Semi-productive savings constitute 5.68 per cent overall, indicating that precautionary motives are present but secondary to immediate consumption and asset-based allocations.

TABLE 10

Classification of Asset Classes for Respondents

Category	Allocation Items Included	Classification
Business Investment (merged)	New Business Ventures/Partnerships (Employees) Reinvestment in Existing Operations (Business Owners)	Productive
Skill Development	Training, Certifications, Courses	Productive
Financial Investments	Stocks, Mutual Funds, Bonds	Productive
Savings/Deposits	Bank Savings, Fixed Deposits	Semi-Productive
Land/Property	Plots, Files, Commercial/Residential Property	Non-Productive
Gold/Jewelry	Gold, Jewelry, Physical Assets	Non-Productive
New Vehicles	Cars, Bikes, Luxury Durables	Non-Productive
Household Consumption	Food, Transport, Clothing, Rent, Mobile/ Internet, Other	Consumption

Source: Author's estimation.
Notes: The categorisation of the Asset Class Allocation follows similar criteria as detailed in Table 8, respectively.

TABLE 11

Summary - Revealed Preferences by Audience Group

Allocation Category	Employees	Business Owners	Total
Productive Assets	13.11%	15.58%	14.23%
Business Investment	8.89%	11.91%	10.26%
Financial Investments	4.22%	3.67%	3.97%
Semi-Productive (Savings)	6.89%	4.23%	5.68%
Non-Productive Assets	18.80%	20.25%	19.46%
Land/Property	7.97%	7.40%	7.71%
Gold/Jewelry	5.76%	6.10%	5.92%
New Vehicle	5.07%	6.74%	5.83%
Consumption	61.20%	59.94%	60.63%
Other Uses	1.01%	1.22%	1.11%

Source: Author's estimation.

VIII. Methodology (Econometric Modelling)

The study employs a multi-model econometric approach to analyse investment preferences across youth, employees, and business owners in Lahore, combining stated-choices and revealed/informed allocations. The framework draws from discrete choice theory (McFadden, 1972), fractional response modelling (Papke & Wooldridge, 1996), and behavioural economics.

1. Multinomial Logit Models (MNL)

Stated investment preferences were analysed using the multinomial logit (MNL) model with robust standard errors to account for potential heteroskedasticity and mild model misspecification. The MNL framework is appropriate for modelling discrete, unordered choice outcomes and is widely applied in urban and investment economics where individuals choose among mutually exclusive alternatives under constraints (Greene, 2018). The model relies on the independence of irrelevant alternatives (IIA) assumption implied by the extreme value type I error structure.

a) Baseline Model (I)

The baseline model (I) excludes interactions for parsimony and comparison, as explained in Equation (7):

$$U_{ij} = \beta_{j0} + X_i \beta_j + Z_i \gamma_j + \delta_j \cdot group_i + \epsilon_{ij} \quad (7)$$

where U_{ij} is utility for respondent i and alternative j, X_i are standardized scales explaining factors as consolidated in Table 6 and 7 respectively, Z_i denotes demographic and control covariates, $group_i$ is the audience indicator, and $\epsilon_{ij} \sim$ i.i.d. extreme value type I. Base outcome $j = 3$ (i.e. non-productive preference outcome) normalizes $\beta_3 = \gamma_3 = \delta_3 = 0$.

Respective to the latent-utility form, the Equation (8) explains predicted probabilities as:

$$P_{ij} = Pr(Y_i = j) = \frac{exp(V_{ij})}{(\sum_{\ell=1}^{J} exp(V_{i\ell})}, \text{with } V_{ij} = \beta_{j0} + X_i \beta_j + Z_i \gamma_j + \delta_j \cdot group_i. \quad (8)$$

where V_{ij} is the observable part of utility and that the denominator sums over all J alternatives.

b) Average Marginal Effects (AMEs)

Because MNL coefficients are not directly interpretable in probability terms, results are presented as AMEs. For the baseline model (I), AMEs are computed as the sample average of individual-specific marginal effects evaluated at observed covariate values, as explained in Equation (9):

$$AME_{jk} = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} \frac{\partial P_{ij}}{\partial X_{ik}} \quad (9)$$

For continuous predictors, the marginal effect is in Equation (10):

$$\frac{\partial P_{ij}}{\partial X_{ik}} = P_{ij} (\beta_{jk} - \sum_{l=1}^{J} P_{il} \beta_{lk}) \quad (10)$$

Thus, AMEs represent the average change in the probability of choosing alternative jassociated with a one-unit (here, one standard deviation) increase in predictor X_k, holding other variables at their observed values (Greene, 2018; Long & Freese, 2014).

c) Full Model (II): Interaction Specification

The full model equation (II) incorporates interactions on behavioral scales with group to test heterogeneity, as explained in Equation (11).

$$U_{ij} = \beta_{j0} + X_i \beta_j + Z_i \gamma_j + \delta_j \cdot group_i + (X_i^{beh} \times group_i) \theta_j + \epsilon_{ij} \quad (11)$$

where X_i^{beh} subsets to interacted scales, and θ_j captures differential effects.

Likewise, AMEs for the full model (II) i.e. incorporating interaction terms for conditional impacts and therefore depend on both the main behavioral coefficient and its interaction with group membership. The marginal effect of predictor X_k on outcome probability P_{ij} is computed as explained in Equation (12):

$$AME_{jk} = \frac{1}{N} \sum_{i} \left[\frac{\partial P_{ij}}{\partial X_{ik}} \right] \tag{12}$$

where the derivative reflects the combined contribution of β_{jk} and the interaction parameter θ_{jk}, evaluated at observed covariate values.

d) Group-Specific AMEs

Group-specific AMEs disaggregate effects by audience, computing equation (8) conditionally on group strata to reveal audience-varying marginal impacts, crucial for policy insights across youth, employees, and business owners. For group *g*, the conditional AME of predictor X_{ik} on outcome probability P_{ij} is explained in Equation (13):

$$AME_{jklg} = \frac{1}{N_g} \sum_{i \in g} \left[\frac{\partial P_{ij}}{\partial X_{ik}} \right] \tag{13}$$

where:

N_g = number of observations in group *g*

P_{ij} = predicted probability that individual *i* chooses alternative *j*

$\frac{\partial P_{ij}}{\partial X_{ik}}$ = incorporates both the main effect and interaction term from model (II)

These conditional AMEs reveal how behavioral and contextual drivers shift predicted probabilities within youth, employee, and business-owner subsamples, providing insights into audience-specific investment preferences.

e) Model Fit and Classification Accuracy

Model fit was additionally evaluated using classification accuracy. Predicted probabilities were generated for each alternative, and the chosen category was assigned as represented in Equation (14):

$$\hat{J}_i = \arg\max_j \hat{P}_{ij} \tag{14}$$

Count R^2 was computed from the confusion matrix as the trace (diagonal sum) divided by N, representing the proportion of correctly classified observations (Train, 2009) as represented in Equation (15):

$$\text{Count } R^2 = \frac{1}{\text{N}} \sum_{i=1}^{N} I(\hat{J}_i = j_i) \tag{15}$$

where $I(\cdot)$ is an indicator function equal to one when predicted and observed categories match.

2. Fractional Logit Model

To examine revealed allocation of income across investment categories, we employ a fractional logit model i.e. suitable for dependent variables bounded between 0 and 1, where each share is estimated via separate quasi-maximum likelihood fractional logit regressions (Papke & Wooldridge, 1996; Ramalho et al., 2011). Let s_{ij} denote the fraction of respondent *i's* monthly income allocated to investment category *j* (productive, semi-productive, non-productive, or consumption). The expected share conditional on covariates X_i is modeled as Equation (16):

$$E[s_{ij} \mid X_i] = \Lambda(X_i \gamma_j),\ \Lambda(z) = \frac{e^z}{1+e^z} \tag{16}$$

where:

s_{ij} = fractional share of income allocated by respondent i to category *j*, bounded in [0,1]

X_i = vector of predictors including standardized behavioral scales (financial literacy/confidence, risk/herding, social/cultural land pressure, quality of life, institutional support, policy restrictions), demographic and control variables (age, gender, type of residence, birthplace, time preference, housing preference, commute time, and travel mode), and group indicators (employees, business owners)

γ_j = vector of coefficients specific to category *j*

$\Lambda(z)$ = logistic cumulative distribution function (CDF), ensuring predicted shares are constrained between 0 and 1

This functional form is consistent with fractional outcomes and provides consistent and asymptotically normal quasi-MLE estimates under correct specification of the conditional mean, even if the Bernoulli likelihood is misspecified.

a) Interaction Specification

To capture heterogeneity across respondent groups, interactions between behavioral scales and group membership are included as modeled in Equation (17):

$$E[s_{ij} \mid X_i, group_i] = \Lambda(X_i \gamma_j + (group_i \times Z_i)\ \delta_j) \tag{17}$$

where:

$group_i$ = categorical variable indicating employee or business owner (youth excluded for revealed allocation)
Z_i = subset of behavioral predictors (financial literacy, risk/herding, social pressure)
δ_j = vector of interaction coefficients for category *j*

This allows the effect of behavioral predictors to vary across groups.

b) Average Marginal Effects (AMEs)

AMEs are computed as the sample average of the individual marginal effects evaluated at observed covariates as in Equation (18):

$$AME_{jk} = \frac{1}{N} \sum_{i=1}^{N} \Lambda(X_i \hat{\gamma}_j),\ (1 - \Lambda(X_i \hat{\gamma}_j))\ \hat{\gamma}_{jk} \tag{18}$$

where:
AME_{jk} = average marginal effect of predictor k on share s_{ij}
$\hat{\gamma}_{jk}$ = estimated coefficient from the fractional logit model for category *j*

AMEs translate the logit-scale coefficients into interpretable changes in the expected fraction of income allocated, allowing comparisons across categories and groups.

3. IIA Diagnostics

Because the multinomial logit (MNL) model relies on the Independence of Irrelevant Alternatives (IIA) assumption, we assessed this assumption explicitly before interpreting the stated-preference estimates. Since formal IIA diagnostics are known to exhibit weak finite-sample properties and may generate negative, unstable, or sample-split-dependent statistics, particularly in moderate samples, we adopted a triangulated robustness strategy rather than relying on a single test (Cheng & Long, 2007; Long & Freese, 2014). First, we implemented the Hausman-McFadden specification test by sequentially omitting each alternative from a parsimonious MNL specification estimated under maximum likelihood (Hausman & McFadden, 1984). Second, we employed the Small-Hsiao specification test, repeating the procedure across multiple random seeds because the test depends on random sample partitioning and may exhibit seed sensitivity (Cheng & Long, 2007; Small & Hsiao, 1985). Third, we estimated an IIA-free multinomial probit model, which permits correlated disturbances across alternatives and therefore does not impose the IIA restriction, and compared its average marginal effects with those obtained from the MNL specification (Chang, 1992). Fi-

nally, we re-estimated the parsimonious model after excluding the constructed mixed alternative and examined the stability of the remaining coefficients. Collectively, these formal, simulation-based, and substantive robustness checks allow the validity of the MNL specification to be assessed without relying on any single diagnostic test and provide a comprehensive evaluation of whether the principal findings are sensitive to the IIA assumption.

4. Youth-inclusive Fractional-logit Robustness Check

The main fractional-logit models focus on employees and business owners because revealed allocation shares are defined from monthly income portfolios that are directly comparable across those two adult groups. Youth respondents were therefore excluded from the main revealed-preference specification, as already noted in the limitations section. To check whether that decision materially affects the results, we constructed harmonised four-part shares for all groups and pooled youth into the fractional-logit framework as a robustness exercise. For youth, productive allocation combines side-business/freelance and education/skills spending, semi-productive allocation corresponds to big-item saving, non-productive allocation corresponds to real-estate/plot purchase, and consumption aggregates the remaining expenditure items. For employees and business owners, the same four broad categories were constructed from the relevant monthly allocation items, and the model was re-estimated with a leaner common control set and robust standard errors. Because the youth menu is narrower and harmonised rather than identical to the adult allocation module, this specification is reported as an indicative robustness check rather than as the paper's main revealed-preference model.

IX. Results

1. Stated Preference Estimations - Multinomial Logit Results

Although both the baseline and full multinomial logit specifications are reported for transparency, the discussion primarily focuses on the full model (Model II). The baseline specification establishes the relationship between the principal behavioural and urban-planning determinants and investment preferences, whereas Model II incorporates demographic controls and group-specific heterogeneity, thereby providing a more comprehensive representation of the decision-making environment. Model II demonstrates superior model fit, as indicated by its higher pseudo-(R^2),improved log-likelihood, and stronger predictive performance. Because it better captures observed variation in investment preferences while preserving the substantive patterns identified in the baseline model, Model II is used as the principal specification for interpretation and policy discussion.

Table 12 presents results from MNL regressions examining stated investment preferences, with choices categorised as explained in Tables 8 and 9. Two models are shown for each outcome contrast: a baseline model (I) without group interactions and a full model (II) including interactions.

Table 13 presents the AMEs from the baseline (I) and full model (II) estimating stated investment preferences, with the non-productive/speculative category as the base outcome. AMEs indicate the average change in probability of selecting each outcome (productive, semi-productive, mixed) per unit increase in predictors, facilitating interpretation of how factors shift preferences relative to the base.

Table 14 displays group-specific average marginal effects (AMEs) from the full multinomial logit model (II) with interactions, disaggregated by audience, with non-productive/speculative as the base outcome. The estimates explain interaction terms allowing predictor effects to vary across groups. Group-specific AMEs are computed by averaging the partial derivative of predicted probabilities with respect to each predictor over observations within each group, allowing both main and interaction effects to determine conditional probability shifts.

Table 15 is a confusion matrix from the multinomial logit model's predictions, comparing actual stated investment preference categories (rows) to predicted ones (columns), based on maximum predicted probabilities.

The 'Mixed' category is economically meaningful rather than a residual. It captures respondents whose top priorities straddle the productive and the non-productive/speculative poles, a hedging or diversification stance rather than commitment to either enterprise or speculation. Its high correct-classification rate (71.2 per cent) and its concentration among the income-earning groups (employees 38.3 per cent, business owners 49.2 per cent, versus only 10.7 per cent of youth) indicate that, for households and firms with deployable capital, the modal stated strategy is to hold a productive bet and a speculative anchor (typically land or gold) simultaneously. This is consistent with portfolio diversification under uncertainty and with the present-bias and loss-aversion mechanisms emphasised in the framework: a speculative store of value is kept for perceived safety even as productive options are pursued. The policy implication is direct: the 'mixed' margin, rather than the committed speculator, is likely the most movable target for interventions that aim to tilt allocations toward productive uses.

In Table 16, the formal IIA diagnostics are mixed rather than perfectly decisive. In the Hausman-McFadden test, several omitted-alternative statistics are negative, which is a known finite-sample problem and means that those outcomes should not be interpreted as a clean pass/fail test. The Small-Hsiao test also varies across seeds, with rejections appearing in some draws and not others. Taken together, these patterns do not justify an absolute claim that IIA is 'confirmed'; they do, however, justify moving to robustness checks that do not rely on IIA.

In Table 17, the IIA-free multinomial probit estimates support that strategy. The average marginal effects from multinomial probit are almost identical to the multino-

TABLE 12

Multinomial Logit Coefficients: Stated Investment Preferences
(Base outcome: Non-Productive/Speculative)

	Productive		Semi-Productive		Mixed	
	(I)	(II)	(I)	(II)	(I)	(II)
Financial literacy/ confidence (z)	0.290*	0.843***	0.107	0.512*	-0.069	0.820***
Risk & herding behavior (z)	-0.597***	-0.580**	0.645**	0.687*	0.054	0.593
Social & cultural land pressure (z)	0.149	0.094	0.462*	0.315	-0.564***	-0.46
Quality of life & urban services (z)	0.676***	0.566**	0.067	-0.033	-0.116	-0.127
Institutional support/ pro-density (z)	0.412*	0.430*	-0.06	0.397*	0.046	-0.145
Policy restrictions/ road bias (z)	0.094	-0.063	-0.219	-0.536***	-0.623***	-0.529***
Urban sprawl ↑ travel cost (α)	-0.413**	-0.346	-0.041	-0.012	-0.116	-0.119
Satisfied with public transport (α)	0.102	0.152	-0.254	-0.085	-0.078	-0.151
Planning prioritizes cars (α)	0.068	0.19	0.767***	0.797***	0.603***	0.705***
Age	-0.058	-0.041	0.014	0.035	-0.048**	-0.031
Gender	-0.814**	-0.731*	0.744**	0.824**	0.382	0.227
Type of residence	-0.166**	-0.131*	-0.036	-0.018	-0.061	-0.022
Born in Lahore	-0.121	-0.106	-0.186	-0.129	0.06	0.077
Time preference	0.413	0.313	0.149	0.117	0.36	0.198
Housing preference	0.437**	0.393**	0.348*	0.142	0.031	-0.008
Commute time (daily)	-0.245	-0.216	-0.103	-0.161	-0.07	0.016
Mode of Travel	-0.196	-0.217*	-0.131	-0.159	-0.1	-0.156
Youth	0	0	0	0	0	0
Employees	-4.040***	-5.227***	-1.454*	-2.517**	2.623***	1.719***
Business Owners	0.078	-1.474	0.129	-1.489	3.683***	2.157**
Financial Literacy/ Confidence (z)		0		0		0

Continue

TABLE 12 *(Continued)*

Multinomial Logit Coefficients: Stated Investment Preferences
(Base outcome: Non-Productive/Speculative)

	Productive		Semi-Productive		Mixed	
	(I)	(II)	(I)	(II)	(I)	(II)
Youth # Financial Literacy/Confidence (z)		0		0		0
Employees # Financial Literacy/Confidence (z)		-0.728		-1.500***		-1.538***
Business Owners # Financial Literacy/Confidence (z)		-1.442***		-1.203**		-0.761
Risk & Herding Behavior (z)		0		0		0
Youth # Risk & Herding Behavior (z)		0		0		0
Employees # Risk & Herding Behavior (z)		-0.447		-0.959		-1.542***
Business Owners # Risk & Herding Behavior (z)		1.657*		0.451		0.56
Social & Cultural Land Pressure (z)		0		0		0
Youth # Social & Cultural Land Pressure (z)		0		0		0
Employees # Social & Cultural Land Pressure (z)		-0.512		2.155**		-0.237
Business Owners # Social & Cultural Land Pressure (z)		-2.189		-2.316*		-0.136
Constant (z)	4.365**	3.363*	-3.757**	-4.022**	-2.647**	-2.247*
	(I)	(I)	(I)	(II)	(II)	(II)
	Baseline (No Interactions)			Full (With Interactions)		
Observations	641	641	641	641	641	641
Pseudo R^2	0.28	0.28	0.28	0.325	0.325	0.325
Log Pseudo likelihood	-628.592	-628.592	-628.592	-589.13	-589.13	-589.13
Wald χ^2	322.312	322.312	322.312	335.422	335.422	335.422
Prob > χ^2	0	0	0	0	0	0

Source: Author's estimation.

Notes: Coefficients indicate changes in log-odds relative to the base outcome (non-productive/speculative preference), with improved model fit in the full model reflected by higher pseudo R^2 and log-likelihood values. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$, based on robust standard errors.

TABLE 13

Average Marginal Effects from Multinomial Logit Models: Stated Investment Preferences
(Base outcome: Non-Productive/Speculative)

	Productive		Semi-Productive		Non-productive		Mixed	
	(I)	(II)	(I)	(II)	(I)	(II)	(I)	(II)
Financial literacy/confidence (z)	0.029*	0.023	0.009	-0.040*	-0.013	0.006	-0.025	0.035
Risk & herding behavior (z)	-0.074***	-0.050*	0.081***	0.042	-0.009	-0.001	0.003	0.032
Social & cultural land pressure (z)	0.024	-0.033	0.070**	0.017	0.018	0.034	-0.112***	-0.144**
Quality of life & urban services (z)	0.070***	0.060***	-0.002	-0.012	-0.024	-0.012	-0.043**	-0.041
Institutional support/pro-density (z)	0.041*	0.037*	-0.017	0.036*	-0.02	-0.024	-0.004	-0.067
Policy restrictions/road bias (z)	0.035*	0.023	-0.001	-0.034*	0.059**	0.067***	-0.093***	-0.094**
Urban sprawl ↑ travel cost (α)	-0.036*	-0.03	0.009	0.011	0.031	0.024	-0.003	-0.02
Satisfied with public transport (α)	0.018	0.022	-0.027	-0.007	0.015	0.009	-0.006	-0.034
Planning prioritizes cars (α)	-0.029	-0.023	0.059***	0.051***	-0.092***	-0.097***	0.062***	0.118***
Age	-0.004	-0.004	0.005*	0.006**	0.006*	0.003	-0.006**	-0.008
Gender	-0.109***	-0.097***	0.084**	0.093***	-0.032	-0.022	0.057	0.023
Type of residence	-0.014**	-0.012*	0.002	0.002	0.014	0.008	-0.003	-0.001
Born in Lahore	-0.01	-0.01	-0.02	-0.014	0.01	0.004	0.021	0.028
Time preference	0.026	0.021	-0.006	-0.003	-0.057	-0.034	0.037	0.033
Housing preference	0.035**	0.035**	0.028	0.006	-0.040*	-0.022	-0.024	-0.019
Commute time (daily)	-0.02	-0.018	-0.004	-0.012	0.022	0.015	0.001	0.018
Mode of Travel	-0.014	-0.012	-0.006	-0.006	0.024	0.028*	-0.004	-0.023
Employees (vs Youth) (z)	-0.319***	-0.324***	-0.169**	-0.171*	0.025	0.059	0.463***	0.516***
Business Owners (vs Youth) (z)	-0.163	-0.188	-0.109	-0.256***	-0.190**	-0.003	0.461***	0.538***

Source: Author's estimation.

Notes: AMEs represent the average percentage-point change in probability of selecting each outcome for a one-standard-deviation increase in standardised predictors (or discrete change for binary variables). All models use robust standard errors. Base outcome: Non-Productive/Speculative. N = 641 across models. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 14

Group-Specific Average Marginal Effects from Multinomial Logit – Stated Investment Preferences (Full Model)

	Productive Preference			Semi-Productive Preference			Mixed Preference		
	Youth	Employees	Business Owners	Youth	Employees	Business Owners	Youth	Employees	Business Owners
Financial literacy/confidence (z)	0.068**	0.006	−0.045	0.006	−0.047	−0.047	0.022	−0.078*	0.071
Risk & herding behavior (z)	−0.131***	−0.005	0.024	0.120***	0.01	0.02	0.032	−0.128**	0.128
Social & cultural land pressure (z)	0.003	−0.001	−0.128	0.05	0.193**	−0.096	−0.037*	−0.177***	0.07
Quality of life & urban services (z)	0.081**	0.006*	0.058**	−0.036	0.001	−0.007	−0.018*	−0.021	−0.050*
Institutional support/pro-density (z)	0.038	0.005	0.039*	0.035	0.032*	0.031*	−0.026*	−0.037	−0.067*
Policy restrictions/road bias (z)	0.033	0.003	0.029	−0.062**	−0.021	−0.018	−0.019*	−0.063**	−0.079**
Urban sprawl ↑ travel cost (α)	−0.044	−0.003	−0.026	0.021	0.003	0.01	−0.000	−0.015	−0.007
Satisfied with public transport (α)	0.029	0.002	0.022	−0.018	−0.001	−0.003	−0.010	−0.021	−0.033
Planning prioritizes cars (α)	−0.035	−0.002	−0.030	0.088***	0.034**	0.028*	0.021**	0.080***	0.096***
Age	−0.007*	−0.000	−0.003	0.008**	0.003	0.005***	−0.002*	−0.005*	−0.006
Gender	−0.153***	−0.009*	−0.092**	0.157***	0.051**	0.068*	0.009	0.013	0.043
Type of residence	−0.016*	−0.001	−0.011	0.006	−0.001	0.002	0.002	−0.002	0.003
Born in Lahore	−0.008	−0.002	−0.011	−0.014	−0.011	−0.012	0.01	0.016	0.026
Time preference	0.032	0.002	0.017	−0.006	0.002	−0.005	0.003	0.024	0.019
Housing preference	0.045*	0.004	0.034*	−0.003	0.01	0.005	−0.011	−0.008	−0.026
Commute time (daily)	−0.020	−0.002	−0.018	−0.011	−0.012	−0.010	0.009	0.009	0.021
Mode of travel	−0.017	−0.001	−0.010	−0.007	−0.006	−0.002	−0.002	−0.017	−0.014
Employees (vs Youth)(α)	−0.307***	−0.307***	−0.307***	−0.193**	−0.193**	−0.193**	0.521***	0.521***	0.521***
Business owners (vs Youth)(z)	−0.189	−0.189	−0.189	−0.145	−0.145	−0.145	0.585***	0.585***	0.585***

Source: Author's estimation.
Notes: Values are AMEs (percentage-point changes in probability) from the full mlogit model. Robust standard errors. Base outcome: Non-Productive/Speculative. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = 641. The table shows heterogeneity across groups, with Youth more influenced by literacy for productive choices, Employees by land pressure for semi-productive, and Business Owners by risk for non-productive preferences.

TABLE 15

Confusion Matrix of the Multinomial Logit Investment Preference Model

Actual Preference Category	Predicted 1 (Productive)	Predicted 2 (Semi-Productive)	Predicted 3 (Non-Productive)	Predicted 4 (Mixed)	Total
Productive	80	5	12	28	125
Semi-Productive	14	65	20	29	128
Non-Productive/Speculative	20	7	111	52	190
Mixed	15	7	35	141	198
Total	129	84	178	250	641
Count R^2	0.619				

Source: Author's estimation.

Notes: Reports the confusion matrix based on maximum predicted probabilities from the multinomial logit model, comparing actual and predicted investment preference categories. Diagonal elements indicate correct classifications, while off-diagonal cells represent misclassifications. The Count R^2 (0.619) measures overall predictive accuracy as the share of correctly classified observations.

mial logit AMEs in sign and significance for the key policy variables, including financial literacy, risk/herding, quality of life, institutional support, policy restrictions, and car-priority planning. The same qualitative pattern holds for the group indicators.

The robustness check that drops the mixed category also points in the same direction. Once the constructed mixed alternative is excluded, the main productive and semi-productive coefficients remain broadly similar in magnitude and sign, which suggests that the overlapping mixed category is not driving the key results.

2. Revealed Preferences Estimations: Fractional Logit Results

Table 18 presents the results of the fractional logit regression models for actual monthly income allocation across four categories: productive, semi-productive, non-productive, and consumption. Columns labelled 'Coef' report the log-odds coefficients from the fractional logit model, while the 'AME' quantify the expected percentage-point change in the share for a one standard deviation increase in the predictor. Standardised behavioural scales and control variables are included, with interactions for business owners and employees. Positive AMEs indicate a higher expected allocation to that category, while negative values indicate lower allocation. Robust standard errors are used, and all predictors are standardised.

In Table 19, the youth-inclusive fractional-logit check is also reassuring. After harmonising the youth menu into the same four broad categories, the productive-share model continues to show positive effects of financial literacy and quality of life, negative effects of risk/herding and time preference, and strong group differences relative

TABLE 16

IIA Diagnostics and Robustness Checks

Diagnostic	What was estimated	Main result	How to read it
Hausman-McFadden Test	Parsimonious MNL, base = non-productive, omit each alternative in turn	Productive: $\chi^2 = -4.437$; Semi-productive: $\chi^2 = -21.233$; Non-productive: $\chi^2 = -48.944$; Mixed: $\chi^2 = 15.811$, df = 39, p = 1.00	Negative statistics indicate the asymptotic assumptions are not met this is not a clean "pass/fail" verdict, so the result is treated cautiously.
Small-Hsiao Test	Same parsimonious MNL, repeated across 5 seeds	Rejections vary by draw; Productive rejects in 3/5 seeds; Semi-productive in 2/5; Non-productive in 4/5; Mixed in 3/5	Seed sensitivity means a single run is not decisive the formal tests are informative but mixed.
IIA-free Multinomial Probit	Same covariates, robust VCE	Signs and significance are closely aligned with MNL AMEs	This is strong evidence that the substantive conclusions are not driven by IIA.
Drop Mixed Alternative	Re-estimate MNL without mixed category	Main productive and semi-productive coefficients remain broadly similar N drops to 442	The overlapping mixed category is not driving the core results.

Source: Author's estimation.

Note: The Hausman-McFadden and Small-Hsiao outputs are from the parsimonious baseline MNL used for IIA testing; the multinomial probit comparison is the IIA-free robustness check, and the mixed-category exclusion is the substantive check.

to youth. The non-productive-share equation likewise retains the expected signs for the main urban and institutional variables. Because the youth measure is harmonised rather than identical to the adult allocation module, this is described as an indicative robustness check, not as a replacement for the main adult-only revealed-preference model.

X. Interpretations & Discussions

Based on the results obtained from the Stated and Revealed Preferences models and estimates, this section compiles key findings and relates them to the research objectives and hypotheses, respectively.

TABLE 17

Selected Average Marginal Effects: MNL versus Multinomial Probit

Predictor	MNL AME (Productive)	Probit AME (Productive)
Financial literacy / confidence (z)	0.029*	0.027*
Risk & herding behavior (z)	-0.074***	-0.076***
Social & cultural land pressure (z)	0.024	0.025
Quality of life & urban services (z)	0.070***	0.066***
Institutional support / pro-density (z)	0.041*	0.035*
Policy restrictions / road bias (z)	0.035*	0.037*
Urban sprawl ↑ travel cost/time	-0.036*	-0.041**
Planning prioritizes cars	-0.029	-0.03
Employees (vs youth)	-0.319***	-0.315***
Business owners (vs youth)	-0.163	-0.149

Source: Author's estimation.

Note: The full side-by-side AME comparison shows the same pattern across all four outcomes, not just productive preferences: key signs and significance are highly stable under the IIA-free multinomial probit. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1. Multinomial Logit Coefficients

Results report raw coefficients from the baseline and full multinomial logit models, showing changes in log-odds of selecting productive, semi-productive, or mixed preferences relative to the base (non-productive/speculative). Positive coefficients mean a one-unit increase in the predictor raises the log-odds of the outcome versus base (higher likelihood); negative means lower log-odds (lower likelihood). The full model adds group interactions on behavioural scales, improving fit (Pseudo R^2 from 0.28 to 0.325).

The findings support partial heterogeneity in drivers. For example, a one-SD increase in financial literacy raises log-odds of productive over non-productive by 0.843 in the full model, supporting H1, while risk/herding lowers it by 0.597 in baseline, backing H3. Social land pressure increases semi-productive log-odds by 0.462 but decreases mixed by 0.564, aligning with H2. Quality of life boosts productive log-odds by 0.676 in baseline, supporting H5, while institutional support raises productive log-odds by 0.412 and policy restriction lowers mixed log-odds by 0.623 in baseline, supporting H6. Employees have lower productive log-odds by 4.040 but higher mixed log-odds by 2.623 versus youth, with interactions such as negative literacy for business owners (-1.442) and stronger risk/herding effects for youth than for either adult group (Table 14), consistent with H4, showing youth-specific effects.

TABLE 18

Consolidated Table: Average Marginal Effects (AMEs) from Fractional Logit Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Productive Coef	Productive AME	Non-Prod Coef	Non-Prod AME	Semi-Prod Coef	Semi-Prod AME	Consumption Coef	Consumption AME
Financial literacy/ confidence (z)	0.129	0.019**	-0.049	-0.001	-0.055	-0.019***	0.009	-0.001
Risk & herding behavior (z)	-0.320***	-0.021**	0.071	0.004	0.104	-0.002	0.113**	0.014
Social & cultural land pressure (z)	0.007	-0.024**	0.028	0.030*	0.023	0.002	-0.062	-0.007
Quality of life & urban services (z)	0.147***	0.017***	-0.100***	-0.016***	0.05	0.003	-0.021	-0.005
Institutional support/ pro-density (z)	0.025	0.003	0.054	0.008	-0.362***	-0.019***	0.016	0.004
Policy restrictions/ road bias (z)	-0.031	-0.004	-0.047	-0.007	-0.087	-0.005	0.025	0.006
Urban sprawl ↑ travel cost (α)	-0.099	-0.012	0.057	0.009	-0.107	-0.006	0.046	0.011
Satisfied with public transport (α)	0.019	0.002	-0.090*	-0.014*	0.04	0.002	0.035	0.008
Planning prioritizes cars (α)	-0.025	-0.003	0.053	0.008	0.003	0	-0.007	-0.002
Age	0.013*	0.002*	0.006	0.001	-0.008	0	-0.007*	-0.002*
Gender	-0.046	-0.005	0.068	0.01	-0.043	-0.002	-0.022	-0.005
Type of residence	0.04	0.005	-0.033	-0.005	0.004	0	-0.002	0
Born in Lahore	0.029	0.003	0.04	0.006	0.026	0.001	-0.041	-0.01
Time preference	-0.086	-0.01	-0.024	-0.004	0.176*	0.009*	0.036	0.008
Housing preference	-0.129**	-0.015**	-0.009	-0.001	0.001	0	0.039	0.009
Commute time (daily)	0.012	0.001	-0.025	-0.004	0.005	0	-0.003	-0.001
Mode of Travel	-0.043	-0.005	0.008	0.001	-0.036	-0.002	0.024	0.006
Employees	0	0	0	0	0	0	0	0
Business Owners	0.12	0.026	0.016	0.015	-0.581***	-0.030***	0.032	-0.001
Employees # Financial Literacy/ Confidence (z)	0		0		0		0	

Continue

TABLE 18 *(Continued)*

Consolidated Table: Average Marginal Effects (AMEs) from Fractional Logit Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Productive Coef	Productive AME	Non-Prod Coef	Non-Prod AME	Semi-Prod Coef	Semi-Prod AME	Consumption Coef	Consumption AME
Employees # Financial Literacy/ Confidence (z)	0		0		0		0	
Business Owners # Financial Literacy/ Confidence (z)	0.059		0.096		-0.878***		-0.03	
Risk & Herding Behavior (α)	0		0		0		0	
Employees # Risk & Herding Behavior (z)	0		0		0		0	
Business Owners # Risk & Herding Behavior (z)	0.295*		-0.093		-0.435		-0.121	
Social & Cultural Land Pressure (z)	0		0		0		0	
Employees # Social & Cultural Land Pressure (z)	0		0		0		0	
Business Owners # Social & Cultural Land Pressure (z)	-0.429**		0.354		0.025		0.068	
Constant (z)	-1.803***		-1.795***		-2.258***		0.433*	
Observations	398	398	398	398	398	398	398	398
Pseudo R^2	0.032		0.012		0.032		0.002	
Wald χ^2	161.619		77.91		161.373		21.024	
Prob > χ^2	0		0		0		0.457	

Source: Author's estimation.

Notes: Robust standard errors. All predictors are standardised (z-scores).

Main effects of interacted variables are omitted due to collinearity; results focus on marginal effects and interactions. Coefficients are log-odds from fractional logit; AMEs are average percentage-point changes. All predictors are standardised z-scores. Group interactions included. N = 398 across models. *p < 0.10, **p < 0.05, ***p < 0.01.

TABLE 19

Youth-Inclusive Fractional-Logit Robustness Check (Harmonised Shares)

Predictor	Productive Share AME	Non-Productive Share AME
Financial literacy / confidence (z)	0.024***	-0.005
Risk & herding behavior (z)	-0.025***	0
Social & cultural land pressure (z)	-0.013	0.016*
Quality of life & urban services (z)	0.020***	-0.007*
Institutional support / pro-density (z)	-0.006	0.011**
Policy restrictions / road bias (z)	0.001	-0.005
Urban sprawl ↑ travel cost/time	-0.007	0.013*
Planning prioritizes cars	0.002	0.001
Time preference	-0.031***	-0.001
Employees (vs youth)	-0.094***	0.144***
Business owners (vs youth)	-0.02	0.138***

Source: Author's estimation.
Notes: The youth-inclusive model uses harmonised shares and robust standard errors, with youth as the base group and a leaner common control set. It is best reported as an indicative robustness check because the youth allocation menu is narrower than the adult revealed-preference menu. Even so, the main direction of effects is preserved: financial literacy and quality of life increase productive allocation, while risk/herding and time preference work in the opposite direction.

2. Multinomial Logit using AMEs

Results report AMEs from both the Base Model and the Full Model, expressed as average percentage-point changes in predicted probabilities for each investment category relative to the non-productive/speculative reference group. AMEs translate log-odds into probability terms; thus, a one standard deviation increase in a predictor changes the predicted probability of an outcome by the reported AME value (positive values indicate increases, negative values indicate decreases).

The findings largely confirm the behavioural and urban investment hypotheses. Financial literacy exhibits a positive and statistically meaningful effect on productive investment in the Base Model of approximately 0.029 percentage points, supporting H1, though its magnitude moderates to 0.023 in the Full Model after accounting for interactions. Herding behavior reduces the probability of productive investment by 0.074 points in the baseline model (0.050 in the full model) and significantly raises the likelihood of semi-productive allocation approximately 0.081 points in the baseline model (0.042 in the full model), supporting H3, while policy restriction raises non-pro-

ductive probability by 0.059 percentage points in the baseline model (0.067 in the full model), and lowers the probability of a mixed preference by 0.093 points (0.094 in the full model), supporting H6.

Social pressure positively influences semi-productive investment by 0.070 points in the baseline model and significantly reduces the probability of mixed allocations by −0.144 in the full model, providing strong support for H2. Urban livability factors also matter: higher perceived quality of life increases the probability of productive investment by 0.060 points, and institutional support is associated with a 0.037 percentage-point increase in the probability of productive choice, supporting H6. In contrast, car prioritisation, a proxy for lifestyle-driven consumption preference, raises the likelihood of semi-productive by 0.059 points and mixed investments by 0.062 points in the baseline model (0.051 and 0.118, respectively, in the full model), consistent with H5.

Occupational heterogeneity remains pronounced. Relative to youth (reference category), employees and business owners exhibit lower probabilities of productive investment of approximately −0.324 and −0.188 points, respectively, but significantly higher probabilities of mixed investment around 0.516 and 0.538 points. This suggests stronger portfolio diversification tendencies among income-earning groups compared to youth respondents.

Overall, the Full Model demonstrates that once interaction effects are incorporated, several baseline relationships attenuate or redistribute across categories, indicating that investment behaviour is jointly shaped by behavioural traits and urban-economic context rather than isolated determinants.

3. Multinomial Logit Group-Specific AMEs

Results show conditional AMEs from the full model, disaggregated by group, showing how predictor effects on probabilities vary across audiences. AMEs interpret as: a one-SD predictor increase changes the outcome probability by the value for that group (positive for rise, negative for fall).

Key findings highlight audience heterogeneity. For youth, a one-SD financial literacy increase raises productive probability by 0.068 points and quality of life by 0.081 points, supporting H1/H5, but risk/herding lowers it by 0.131 points, aligning with H3, and this effect is both larger and more significant than the corresponding (statistically insignificant) coefficients for employees and business owners, directly supporting H4's claim that herding effects are concentrated among youth rather than income-earning adults. Employees show social pressure raising semi-productive by 0.193 points and reducing mixed by 0.177 points, per H2. Business owners gain productive from quality of life by 0.058 points and institutional support by 0.039 points, backing H5, with car prioritisation raising semi-productive by 0.028 points and mixed by 0.096 points. Overall, urban factors consistently deter non-productive across groups, while behavioural effects are strongest in youth, supporting H4.

4. Confusion Matrix and Predictive Accuracy

The confusion matrix compares actual to predicted investment preference categories (based on maximum predicted probabilities with diagonal cells indicating correct classifications and Count R^2 (0.619) as overall accuracy (trace/N = 641). It shows model fit: of actual productive cases, 80 are correctly predicted as productive (64 per cent), with misclassifications spread across others.

Key findings indicate reasonable predictive performance. The model correctly classifies 61.9 per cent of cases, with 50.78 per cent accuracy for semi-productive (65/128 correct) and 58.4 per cent for non-productive (111/190), but higher 71.2 per cent for mixed (141/198) and lower 64 per cent for productive. This validates model discrimination beyond pseudo-R^2, supporting its use for understanding preference drivers.

5. Fractional Logit Model Results

Key findings offer mixed hypothesis support. A one-SD rise in financial literacy increases productive share by 0.019 points but decreases semi-productive by 0.019 points, backing H1 for productive shifts. Herding behaviour reduces share by 0.021 points and reduces productive log-odds more sharply (coefficient −0.320, the largest main-effect coefficient in the productive-share equation), supporting H3, but boosts consumption by 0.014 points, a pattern consistent with herding favouring tangible, immediately-held assets over productive deployment of capital. Social pressure increases non-productive by 0.030 points and reduces productive by 0.024 points, supporting H2 family push to land. Quality of life boosts productive by 0.017 points and reduces non-productive by 0.016 points, supporting H5, while institutional support cuts semi-productive by 0.019 points and policy restriction shows weak, statistically insignificant effects on revealed shares, giving only partial support to H6 relative to the stronger stated preference. Business owners show interactions like a semi-productive reduction from literacy by 0.878 points, indicating group-specific biases.

The results provide partial to strong support for our hypotheses, thereby achieving our research objectives by linking behavioural and urban factors to investment shifts. H1 is supported, as literacy raises productive shares by 0.019 points overall. H2 is supported, as social pressure increases non-productive share by 0.030 points. H3 is supported, as herding reduces productive share by 0.021 points and is the strongest main-effect coefficient in the productive-share equation. H4 is supported by the stated-preference, where herding effects are concentrated among youth; the present fractional-logit sample, restricted to employees and business owners, cannot independently test this group contrast. H5 is strongly supported, as quality of life boosts productive share by 0.017 points. H6 receives only partial support: institutional support significantly affects semi-productive allocation, but policy restriction does not significantly affect revealed shares, in contrast to its stronger and more consistent effect on stated preferences.

Heterogeneity (e.g., stronger in youth) validates the framework on misallocation from sprawl/norms, informing policies for productive urban growth in Lahore.

6. Comparison across Models

Comparing stated preferences with revealed allocations shows partial alignment but notable gaps, highlighting behavioural biases. In MNL, financial literacy strongly favors productive choices (e.g., AME 0.029 for productive, baseline model), matching fractional's boost to productive shares (AME 0.019), jointly supporting H1 across both stated and revealed measures Risk/herding reduces productive intentions (−0.074 AME, baseline model) and actual productive shares (-0.021), aligning with herding toward safe assets, jointly supporting H3. Social pressure pushes stated semi-productive (0.070 AME, baseline model) and revealed non-productive (0.030 AME), consistent with family norms favouring land and supporting H2 across both measures; quality of life enhances both stated productive (0.060 AME) and revealed productive (0.017 AME) shares, supporting H5 in both models. Institutional support and policy restriction (H6) show a similar pattern of stated/revealed divergence: both significantly shift stated preferences toward productive allocation, but only institutional support carries through to a significant effect on revealed shares, though this operates through a reduction in semi-productive allocation rather than a direct increase in the productive share. However, intentions differ from behaviour where respondents state more productive/mixed preferences (e.g., youth 38.27 per cent productive stated) but reveal higher consumption/non-productive shares, possibly due to present bias overvaluing immediate rewards or loss aversion avoiding risky productive investments in reality (Laibson, 1997; Kahneman & Tversky, 1979).

XI. Discussion and Conclusion

1. Policy Implications and Practical Insights

The findings suggest that policy should focus on redirecting capital away from speculative land banking and toward productive economic activities in Lahore, particularly where urban sprawl and capital misallocation reinforce one another. On the demand side, improving financial capability among youth and early-career workers may strengthen preferences for productive investment, while family- and community-level awareness initiatives could mitigate social pressures that encourage households to favour land and property accumulation. On the urban-policy side, improvements in public transport, neighbourhood livability, and a gradual shift away from car-oriented planning may enhance the relative attractiveness of productive investments by increasing the everyday returns to living and working in the city. Separately, because institutional support and perceived policy restriction shift stated preferences toward productive

allocation but show weaker effects on realised portfolio shares, policy measures aimed at improving real (not merely perceived) access to finance, business registration, and high-rise/commercial permitting may be needed before institutional improvements translate into actual behaviour change rather than only stated intent. The results also point to the importance of differentiated policy design: youth and employees appear more responsive to financial and social factors, whereas business owners are more sensitive to quality-of-life and institutional conditions. Taken together, these findings support a policy mix combining behavioural interventions, regulatory simplification, and incentives for compact, mixed-use urban development. Although the estimates should be interpreted as associations rather than causal effects, they provide a useful evidence base for designing targeted interventions that encourage productive urban growth and reduce speculative pressures in land markets.

These recommendations, however, must be interpreted within Pakistan's institutional and political-economy context, which shapes both the feasibility and sequencing of reform. Urban development authorities are partially financed through plot sales, land conversion charges, and commercialisation fees, creating fiscal incentives that may conflict with anti-speculation and compact-development objectives. Likewise, concentrated landownership patterns and documented instances of regulatory capture can reinforce existing development trajectories and increase resistance to reform. Consequently, implementation is likely to be more effective if pursued through incremental, politically feasible entry points rather than through comprehensive institutional restructuring. Such measures may include improving transparency and digitisation in public land allocation to reduce rent-seeking opportunities; introducing gradual and well-communicated property valuation and recurrent taxation reforms that increase the carrying cost of idle land while minimising distributional backlash; piloting higher-density and mixed-use zoning initiatives in a limited number of well-served corridors before wider scaling; and delivering financial capability and enterprise-support programmes through existing institutional networks, including universities, employer and SECP-registered firm networks, and market and trade associations. Framing these interventions around fiscal neutrality, improved service delivery, and visible local benefits is likely to increase their political acceptability and prospects for sustained implementation. Accordingly, behavioural measures should be viewed as complements rather than substitutes for institutional reform, as changes in individual preferences alone are unlikely to alter investment patterns when the underlying incentive structure continues to favour speculative land development.

2.. Limitations

This study is confined to Lahore, so the findings should be generalised to other Pakistani cities with caution, as land markets, planning regimes, and household investment norms may differ across urban contexts. Although the overall sample is reasonably

large, subgroup sizes remain uneven, which may reduce precision in some interaction estimates. The study also relies partly on self-reported preferences and allocations, so recall error and social-desirability bias cannot be ruled out. Institutional support and policy restriction are measured as self-reported perceptions rather than objective policy indicators, which may partly explain why their effects are significant for stated preferences but weaker for revealed portfolio shares. Revealed preferences are estimated primarily for employees and business owners because their monthly allocation patterns are directly comparable; a youth-inclusive robustness check is reported separately, but it uses harmonised categories and should therefore be interpreted cautiously. Although formal IIA diagnostics are mixed, the IIA-free multinomial probit and the mixed-category exclusion confirm that the substantive findings do not depend on the IIA assumption. Future research could extend the analysis to other cities, use panel data, and compare mixed logit, multinomial probit, or alternative fractional response models.

c. Conclusion

In summary, this study on land banking, investment behaviors, and urban sprawl in Lahore reveals that financial literacy and improved urban quality of life strongly encourage productive investments like business expansion and skills development, while social pressures, risk aversion, and herding behaviors drive non-productive choices such as speculative plots and gold, particularly among youth, and weaker institutional support combined with greater perceived policy restriction further reinforce this speculative tilt, although these institutional effects are more consistent for stated intentions than for realized portfolio allocations, with notable group differences across employees and business owners. These findings align with our objectives by linking individual drivers such as demographics, financial knowledge, family influences, institutional perceptions, and urban burdens to broader outcomes like congestion and underperformance, validating most hypotheses and highlighting how behavioural biases exacerbate horizontal expansion. By integrating behavioural economics with urban agglomeration theory and institutional/public-choice perspectives, and by triangulating stated choices with revealed portfolio behaviour across youth, employees, and business owners in a spatially structured sample, the analysis offers novel, micro-level evidence on how individual and institutional drivers translate into land-banking and sprawl, contributing to the literature on capital misallocation in developing cities.

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