

FINANCIAL MODELING AND PROFITABILITY FORECASTING OF FLIPPING PROJECTS: KEY METRICS AND BUDGET OPTIMIZATION STRATEGIES

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ABSTRACT

Real-estate flipping involves the acquisition, improvement, financing, holding, and resale of property within a relatively short investment horizon. The financial outcome depends on the interaction of acquisition price, renovation expenditure, transaction and financing costs, holding period, resale value, and market conditions. This paper develops a structured financial-modeling framework for evaluating these trade-offs using standard investment metrics, scenario analysis, sensitivity analysis, and documented assumptions. The analysis is deliberately aligned with a March 2022 publication context and therefore relies only on literature and technologies available by 28 February 2022. Evidence available before that cutoff indicates that flipping activity can generate heterogeneous returns across market conditions, while property valuation research supports the use of automated and machine-learning methods when adequate transaction data are available. The paper uses an illustrative optimized-versus-non-optimized scenario to demonstrate how budget allocation can affect ROI, cash-on-cash return, IRR, payback period, and profit margin. Because the underlying project-level dataset and simulation parameters from the published article are unavailable, the numerical scenario should not be interpreted as a statistically validated estimate of the performance of the wider flipping market. The principal contribution is therefore a transparent modeling framework that identifies the financial variables requiring documentation, tests how assumptions affect project outcomes, and provides a practical basis for investment screening and subsequent empirical validation.

Keywords:

Real estate flipping; financial modeling; profitability forecasting; budget optimization; return on investment; sensitivity analysis

1. INTRODUCTION

Real-estate flipping can be understood as a short-horizon investment strategy in which an investor acquires a residential property, undertakes repairs or improvements, and seeks to resell the property at a price sufficient to cover acquisition and project costs while generating a positive return. The apparent simplicity of the strategy conceals a multi-stage financial decision. The investor must commit capital before the resale price is known, while renovation costs, financing charges, transaction expenses, market conditions, and the duration of the holding period can all change during the project. [14] show that short-term housing trades can generate returns that differ from broad market movements and that these returns are not uniform across market periods or acquisition strategies. This makes disciplined financial planning more important than relying on the simple difference between purchase and resale prices.

Financial modeling provides a way to convert these uncertainties into explicit assumptions and measurable decision variables. [8] and [5] emphasize that property investment analysis should identify the timing and magnitude of cash outflows and inflows and should distinguish between accounting profit, return on invested capital, and the time value of money. In a flipping project, the acquisition payment is normally the largest initial outflow, but renovation expenditure, financing charges, taxes, insurance, utilities, transaction costs, and other holding expenses may determine whether a project that appears profitable on a gross basis is profitable after all costs. A robust model must therefore treat the project as a sequence of cash flows rather than as a single purchase price and a single resale price.

The literature also shows that flipping activity is sensitive to housing-market conditions. [17] distinguishes between investors who operate as middlemen by purchasing below prevailing market prices and reselling above those prices and investors who behave more like cycle-dependent speculators. [14] similarly show that short-term housing trades can produce excess returns relative to market price growth during some periods, while the results

differ according to distressed and non-distressed acquisition strategies. These findings imply that profitability cannot be assumed from the label “flipping” alone. The acquisition discount, property condition, market cycle, renovation strategy, and timing of resale all influence the economic result.

Renovation is another important source of uncertainty. Improvements can raise property value, but not every expenditure produces the same financial benefit. [2] demonstrate that failing to account for property improvements can materially distort property-value measurement. [7] likewise show that post-renovation property-price changes can be modeled using property characteristics and renovation-related variables. Consequently, the budget should not be optimized by minimizing renovation expenditure indiscriminately. Instead, the relevant question is whether each expenditure produces sufficient incremental value to justify its cost and the additional time required to complete the project.

Forecasting adds another layer of complexity. Before March 2022, [19], [9], [11], [16], [12], and [10] had demonstrated that automated valuation models, machine-learning algorithms, spatial information, and web-based housing information could be used to estimate or monitor property prices. [6] further illustrated how an automated valuation component can be incorporated into a real-estate investment decision system. These technologies are potentially useful because flipping decisions require current information about comparable properties, neighborhood characteristics, transaction prices, and market direction. However, predictive tools do not remove the need for validation. A model can produce precise-looking outputs while still being unreliable if the training data are incomplete, geographically mismatched, temporally outdated, or affected by structural changes in the market.

Simulation can complement deterministic financial models by allowing uncertain inputs to vary within specified ranges or probability distributions. [15] demonstrated the use of Monte Carlo methods in real-estate investment analysis, while [20] applied Monte Carlo methods to real-estate project investment-risk assessment. [1] further demonstrated the usefulness of simulation for representing real-estate market exposure, while [13] showed how Monte Carlo analysis can quantify cost impacts associated with systemic risk factors. The value of simulation, however, depends directly on the quality of the assumptions. Without documented input distributions, parameter ranges, correlation assumptions, and validation procedures, a simulated probability distribution is only a mathematical representation of assumed uncertainty rather than evidence of actual market performance.

The purpose of this paper is therefore to present a transparent and publication-date-consistent framework for financial modeling of flipping projects. The paper focuses on five linked decisions: estimating acquisition and project costs, allocating the renovation budget, forecasting resale proceeds, testing uncertainty, and interpreting profitability metrics. Rather than claiming a universal empirical effect from an undisclosed sample, the paper uses an illustrative scenario to demonstrate the mechanics of the framework and identifies the information required for future empirical validation. This narrower formulation directly addresses the reproducibility concerns associated with the earlier version while preserving its central practical objective: helping investors evaluate whether a proposed flipping project has sufficient financial margin to justify its risk.

2. LITERATURE REVIEW

The financial evaluation of real-estate investments is grounded in the analysis of expected cash flows, financing conditions, valuation, risk, and the time value of money. [8] and [5] emphasize that investors should evaluate an asset by considering the amount and timing of expected cash flows rather than relying on a single headline return measure. For a flipping project, this principle is especially important because the investment horizon is short and the timing of expenditure can strongly affect the realized return. Two projects can have identical purchase and resale prices but different profitability if one requires more renovation expenditure, carries higher financing costs, or takes longer to sell. ROI provides a useful summary of profitability, but IRR and payback measures add information about timing, while cash-on-cash return focuses on the relationship between cash invested and cash generated.

Evidence on flipping itself supports the need for a differentiated approach. [17] shows that investors in the housing market do not behave as a single homogeneous group. Some investors acquire properties at discounts and resell them at higher prices, while others behave more speculatively and become active during favorable market conditions. [14] examine short-term housing trades across U.S. markets and find that returns vary according to market period and acquisition strategy. [3] further examines the pricing behavior of investors in housing markets, reinforcing the importance of acquisition conditions when specifying model assumptions. These findings are directly relevant to financial modeling because they caution against treating historical flipping returns as a stable parameter. A model should instead allow acquisition discounts, resale appreciation, holding time, and market conditions to vary across scenarios.

Renovation is central to the economics of flipping because the investor deliberately changes the physical or functional characteristics of the asset before resale. [2] show that property improvements can introduce meaningful bias into house-price measurement when renovation information is ignored. [7] further demonstrate that post-renovation property-price changes can be modeled using observable property characteristics and renovation-related variables. These findings support a model structure in which renovation is represented not simply as a cost, but as an investment with an uncertain effect on resale value. The practical implication is that renovation decisions should be prioritized according to expected value contribution, project duration, and risk rather than according to expenditure alone.

Property valuation research provides additional support for using data-driven methods in financial planning. [19] developed an automated valuation model for property portfolios and demonstrated its application to office properties. [9] reviewed automated valuation systems and emphasized the importance of their structure and information inputs. [11] compared machine-learning algorithms for property-price prediction using transaction data and found differences in predictive performance across methods. [16] similarly evaluated machine-learning models using actual transaction data, while [12] examined random-forest approaches to residential property valuation. [10] showed that internet search data combined with machine-learning methods could improve housing-price prediction performance, and [6] demonstrated how a genetic-algorithm component could be incorporated into an automated valuation system for investment decisions. Collectively, these studies indicate that technology can support property forecasting, but they also demonstrate that predictive performance is dependent on data quality, model selection, and validation.

The use of web-based information is particularly relevant to flipping because investors often need current information on asking prices, comparable listings, neighborhood conditions, and market changes. [4] demonstrated that web-scraped housing listings could provide timely indicators of housing-market conditions, while [18] explored spatial analysis of housing prices obtained through web scraping. Such information can be incorporated into a decision-support system, but asking prices should not automatically be treated as equivalent to completed transaction prices. A defensible model should distinguish between observed transaction data, listing data, expert assumptions, and externally forecast values.

Risk and simulation research reinforces the importance of sensitivity analysis. [15] demonstrated the use of Monte Carlo simulation for real-estate investment analysis, while [20] applied Monte Carlo methods to real-estate project investment-risk assessment. [1] developed a Monte Carlo framework for valuing real-estate market losses and addressed the difficulty of modeling non-normal returns and incomplete information. [13] further showed how simulation can quantify the cost impact of systemic risk factors. These studies support the use of simulation as a decision-support tool, but not as a substitute for empirical validation. A flipping model should therefore begin with transparent deterministic calculations and then introduce uncertainty through documented ranges or distributions for variables such as renovation costs, resale prices, and holding periods.

Taken together, the pre-March-2022 literature suggests a coherent framework for flipping analysis. The investor should first establish the full project cash-flow structure, then estimate the likely value contribution of renovation, then develop a defensible resale-price assumption, and finally stress-test the project under alternative market and cost conditions. The literature also indicates that technology can improve information processing, but technology does not eliminate financial risk or model uncertainty. This paper builds on those principles and deliberately avoids post-February-2022 literature so that its conceptual and technological context is consistent with the stated March 2022 publication date.

3. METHODOLOGY

The study adopts a scenario-based financial-modeling design. This approach is appropriate because the published article does not provide sufficient information to reconstruct a property-level empirical sample. The model therefore does not claim to estimate the average profitability of flipping projects or to generalize from a hidden dataset. Instead, it defines the variables required for a reproducible flipping model and demonstrates the relationships among them using the scenario values reported in the original publication. The methodological objective is to make the analytical logic explicit so that the same framework can later be populated with a documented transaction dataset.

The model begins with the project cash-flow structure. The initial acquisition cost is followed by renovation expenditures and other project costs. Holding costs accumulate during the period between acquisition and resale, while the final cash inflow is generated by the sale of the improved property. Financing costs, taxes, insurance, utilities, brokerage, and transaction expenses should be included whenever they are incurred. The model therefore treats profitability as the residual result of total project inflows and outflows rather than assuming that the

difference between purchase and sale prices represents profit. This structure is consistent with the cash-flow principles described by [8] and [5].

Table 1. Core variables and analytical roles in the flipping model.

Variable	Analytical role	Expected influence on profitability
Acquisition cost	Initial capital outflow and investment basis	Higher cost generally reduces return unless resale value rises proportionately
Renovation cost	Investment in physical/functional improvement	Negative unless incremental resale value exceeds incremental cost
Holding period	Determines financing and operating exposure	Longer periods can reduce returns when carrying costs accumulate
Resale price	Primary terminal cash inflow	Higher price generally increases profit and return
Financing and transaction costs	Additional project outflows	Higher costs reduce net profit and return
Contingency allowance	Protection against unexpected costs	May reduce apparent initial return while reducing downside exposure
Market/valuation assumptions	Determine resale-price uncertainty	Greater uncertainty requires wider sensitivity ranges



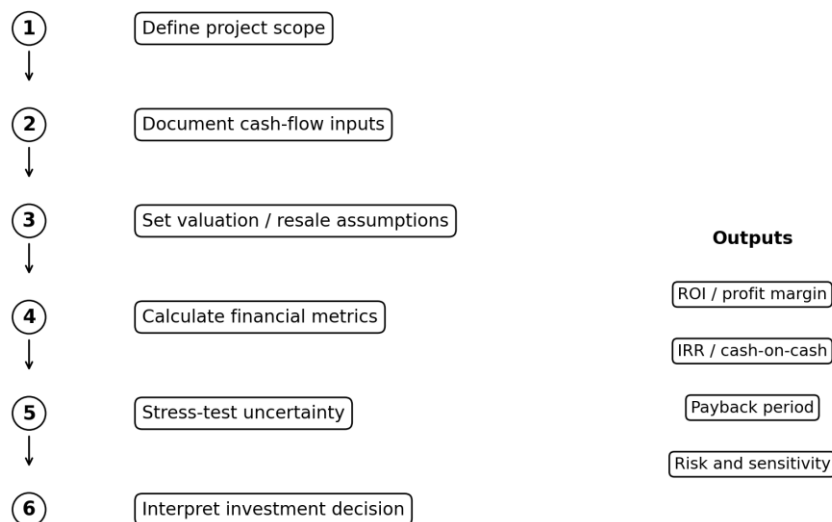
Project profitability is determined by the combined timing and magnitude of inflows and outflows.

Figure 1. Cash-flow architecture of a real-estate flipping project.

Five core measures are used. ROI is calculated as Net Profit divided by Total Invested Capital and multiplied by 100. Profit Margin is Net Profit divided by Resale Revenue and multiplied by 100. Payback Period is the earliest point at which cumulative project cash flow becomes non-negative. IRR is the discount rate that makes the net present value of the project cash flows equal to zero. Cash-on-Cash Return is calculated as annual pre-tax cash flow divided by the amount of cash invested. These measures should be interpreted together because each captures a different dimension of project performance. A high ROI does not necessarily indicate an attractive investment if the holding period is long or the cash-flow timing is unfavorable.

Table 2. Financial metrics used to evaluate flipping-project performance.

Metric	Calculation / definition	Primary interpretation
ROI	$\text{Net profit} \div \text{total invested capital} \times 100$	Overall return relative to invested capital
Profit margin	$\text{Net profit} \div \text{resale revenue} \times 100$	Share of resale revenue retained as profit
Payback period	Earliest point cumulative project cash flow becomes non-negative	Speed of capital recovery
IRR	Discount rate at which project NPV equals zero	Return incorporating cash-flow timing
Cash-on-cash return	$\text{Annual pre-tax cash flow} \div \text{cash invested}$	Return on investor cash contribution

**Figure 2. Sequential workflow for a transparent flipping-project financial model.**

The scenario comparison distinguishes an optimized budget from a non-optimized budget. In the optimized scenario, renovation expenditure is concentrated on improvements expected to make a meaningful contribution to resale value, procurement and labor costs are controlled, and a contingency allowance is retained for unexpected expenditure. The comparison scenario represents a less disciplined allocation of resources. The purpose of the comparison is not to establish that all optimized projects outperform all non-optimized projects, but to illustrate how changes in the allocation of the same broad project budget can alter financial outcomes.

Sensitivity analysis is then used to examine the direction in which key variables influence profitability. Renovation cost is expected to have a negative relationship with profitability unless additional expenditure produces sufficient incremental resale value. Resale price is expected to have a positive relationship with ROI, profit margin, and IRR. Holding duration is expected to reduce returns when additional months generate financing and operating costs without a corresponding increase in resale proceeds. These relationships can be evaluated through one-way sensitivity analysis, two-way scenario tables, or Monte Carlo simulation when sufficient data exist. [15], [20], and [1] demonstrate why simulation should be based on explicit assumptions, while [13] illustrate its usefulness for evaluating systemic cost uncertainty. Monte Carlo analysis should therefore only be used with documented distributions and correlations because otherwise the apparent precision of the resulting distribution is misleading.

Table 3. Scenario and sensitivity inputs requiring explicit documentation.

Input	Minimum documentation	Reason for inclusion
Acquisition price	Observed or justified purchase assumption	Defines initial capital requirement
Renovation cost	Scope, unit costs, contingency	Major controllable project outflow
Resale price	Comparable sales/listing evidence or valuation method	Determines terminal cash inflow
Holding period	Expected and stressed duration	Drives financing and carrying costs
Financing terms	Rate, fees, leverage, repayment timing	Changes cash requirements and project cost
Selling/transaction costs	Brokerage, taxes, fees and closing costs	Prevents overstating net proceeds

Budget allocation decision

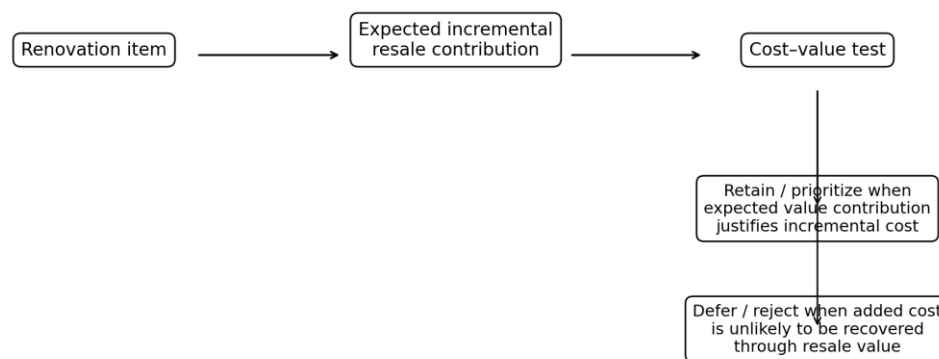


Figure 3. Budget-optimization logic based on incremental cost and expected resale contribution.

For predictive valuation, the framework permits the use of automated valuation or machine-learning methods as supporting tools rather than as unquestioned sources of truth. Pre-2022 research by [19], [9], [11], [16], [12], [10], and [6] demonstrates that transaction characteristics, spatial variables, internet-derived information, and algorithmic methods can support property-price prediction. If such a model is used in a real implementation, its training period, geographic coverage, target variable, validation sample, error metric, and out-of-sample performance should be reported. The paper therefore does not retain the original claim that resale prices could be forecast within a five-percent margin of error. That claim cannot be independently verified because the original publication does not disclose the validation dataset or calculation procedure.

4. RESULTS AND ANALYSIS

The numerical scenario retained from the published article compares an optimized budget with a non-optimized budget. The values are reproduced here because they form part of the publication record, but their status has been changed from apparently empirical results to illustrative scenario values. The distinction is important. Without the underlying project-level cash flows, the figures cannot be independently checked, and the paper cannot legitimately claim that the values represent a statistically estimated effect across a defined sample of properties.

Table 4. Illustrative scenario values retained from the published paper.

Financial metric	Optimized budget	Non-optimized budget	Difference / interpretation
ROI (%)	28.5	17.2	11.3 percentage points; 65.7% relative improvement
Cash-on-Cash Return (%)	22.3	13.8	8.5 percentage points; 61.6% relative improvement
IRR (%)	31.0	19.5	11.5 percentage points; 59.0% relative improvement
Payback Period (months)	10	15	5-month reduction; 33.3% shorter
Profit Margin (%)	26.7	16.4	10.3 percentage points; 62.8% relative improvement

The scenario reports an ROI of 28.5% under the optimized budget compared with 17.2% under the non-optimized budget. The absolute difference is 11.3 percentage points. Expressed as a relative improvement over the non-optimized scenario, the difference is approximately 65.7%, calculated as $(28.5 - 17.2) / 17.2 \times 100$. It is therefore incorrect to describe the result as an ROI increase “by a factor of 65.” The same distinction applies to the other metrics: a 61.6% improvement in cash-on-cash return is not a sixty-fold increase, and a 59.0% improvement in IRR is not a fifty-nine-fold increase.

The payback period is reported as 10 months in the optimized scenario and 15 months in the non-optimized scenario. This represents a reduction of 5 months, or 33.3% relative to the 15-month baseline. The direction of the result is economically intuitive because a project that controls expenditure and generates sufficient resale proceeds can recover invested capital sooner. Nevertheless, the exact payback value cannot be independently verified without the underlying sequence of cash flows. The same limitation applies to IRR and cash-on-cash return because both measures depend on the timing and composition of cash flows, not merely on the summary percentages shown in the table.

The scenario values therefore support a limited analytical conclusion: under the assumptions represented by the original scenario, a more disciplined allocation of renovation and project costs is associated with higher reported profitability measures and a shorter reported payback period. They do not support a general claim that budget optimization will always produce the same magnitude of improvement in real-world flipping projects. The magnitude of the effect would depend on acquisition price, local market conditions, renovation scope, financing structure, selling costs, and the actual relationship between improvements and resale value.

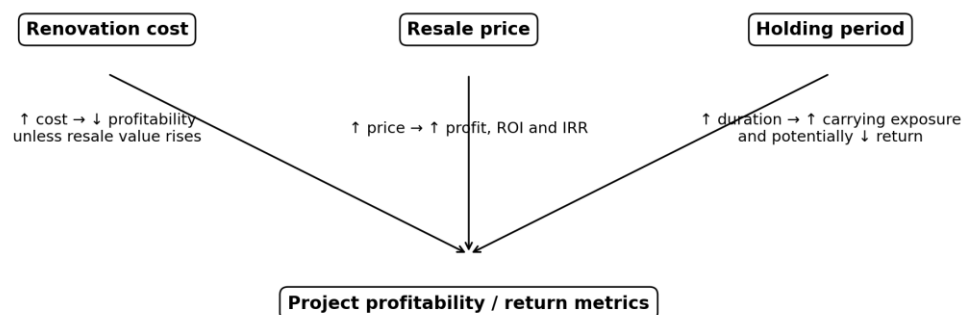
The original paper also reported that AI-assisted forecasting produced resale prices within five percent of actual trends. That statement has been removed from the substantive findings because the publication does not identify the validation dataset, sample size, forecast horizon, error metric, or comparison procedure. A five-percent error claim would require an explicitly defined metric such as mean absolute percentage error, a clearly specified holdout period, and a documented set of observed and predicted prices. Without those elements, the appropriate conclusion is that predictive modeling may support forecasting, not that a specific level of forecast accuracy was achieved.

The sensitivity logic is similarly interpreted as directional rather than as a statistically estimated effect. Renovation costs, resale prices, and holding costs are expected to be among the most consequential variables because they directly affect project cash flows. If renovation costs rise while resale value remains unchanged, net profit falls. If resale prices rise while costs remain fixed, profit and ROI increase. If the holding period expands, financing and operating costs may accumulate and reduce the return. These relationships provide the basis for scenario testing and should be quantified only after the underlying project data are documented.

Table 5. Directional sensitivity relationships in the analytical framework.

Variable change	Expected direction	Reasoning
Renovation cost increases	Profitability decreases	Additional cost reduces net cash flow unless resale value increases sufficiently
Resale price increases	Profitability increases	Higher terminal proceeds increase net profit and return measures
Holding period increases	Return may decrease	Financing and operating costs can accumulate during additional months
Financing cost increases	Profitability decreases	Higher project outflows reduce residual profit
Selling costs increase	Profitability decreases	Higher disposal costs reduce net sale proceeds

Directional sensitivity framework



Relationships are directional; effect sizes require documented project data.

Figure 4. Directional sensitivity pathways linking key project variables to profitability.

5. DISCUSSION

The analysis supports a more cautious interpretation of financial modeling in flipping projects. The central value of the model is not that it produces a single predicted return, but that it makes the sources of return and risk visible. A project can appear attractive when judged only by expected resale price, yet become unattractive once renovation, financing, transaction, and holding costs are included. The model therefore provides a structured decision process in which investors can test whether a proposed acquisition contains enough financial margin to absorb adverse changes in cost or resale value.

The literature on flipping reinforces this interpretation. [14] demonstrate that short-term housing trades vary across market conditions and acquisition strategies, while [17] shows that different investor types follow different strategies in housing markets. [3] provides additional evidence on how investors' purchase prices vary in housing markets. The implication is that no universal flipping return should be inserted into a financial model without considering the specific market and investment strategy. A model designed for distressed acquisitions, for example, should not automatically use the same assumptions as a model for conventional market purchases.

Renovation expenditure deserves particular attention because the objective is not simply to spend less. The economically relevant objective is to maximize the difference between incremental resale value and incremental project cost while controlling the risk of delays and overruns. [2] and [7] indicate that improvements can materially affect measured property values and subsequent price outcomes. Consequently, a practical flipping model should classify renovation items according to expected value contribution, necessity for marketability, implementation cost, and time requirement. High-cost items that generate little additional resale value should be scrutinized more heavily than targeted improvements with strong market relevance.

Technology can improve this process by making market information more accessible and by supporting automated valuation. [19], [9], [11], [16], [12], and [10] demonstrate that machine-learning and automated valuation methods can be applied to real-estate price prediction. However, predictive performance is not equivalent to investment profitability. A model may estimate a sale price accurately while the project still loses money because renovation costs or financing costs were underestimated. For this reason, valuation models should be treated as one component of the broader financial model rather than as substitutes for project-level cash-flow analysis.

Simulation is similarly valuable when used appropriately. [15], [20], and [1] show how Monte Carlo methods can represent uncertainty in real-estate investment and loss assessment, while [13] demonstrate their use in quantifying systemic cost risks. The principal advantage is that simulation makes downside exposure visible rather than relying exclusively on a base case. The principal limitation is that the quality of the output cannot exceed the quality of the input assumptions. If the distributions are arbitrary, the resulting probability of profit or loss is arbitrary as well. A professional implementation should therefore document the source of every distribution and test the sensitivity of the conclusions to alternative assumptions.

Table 6. Requirements for defensible uncertainty and Monte Carlo analysis.

Requirement	What should be documented	Risk if omitted
Input distributions	Range, distribution type and parameter basis	Artificial precision in simulated outcomes
Correlation structure	Dependencies among key variables	Unrealistic joint scenarios
Iteration count	Number of simulation runs and convergence rationale	Unstable or irreproducible results
Validation data	Observed transactions or documented benchmark data	No empirical basis for model performance
Output metrics	Definitions and reporting conventions	Ambiguous interpretation of simulation results

Risk architecture for a flipping project

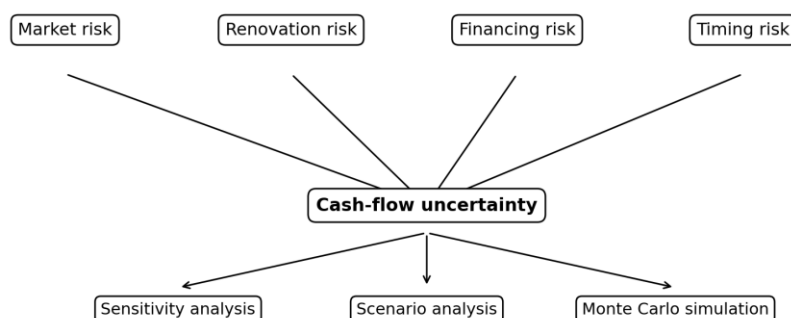


Figure 5. Risk architecture showing how project uncertainty can be examined through scenario and simulation methods.

The correction of the original paper's ROI interpretation also illustrates the importance of precise financial language. The published table shows an ROI change from 17.2% to 28.5%, which is a 65.7% relative improvement, not a sixty-five-fold increase. Similar care is necessary when describing IRR, cash-on-cash return, and payback. Financial percentages describe rates or relative changes; they should not be converted into “factors” unless the underlying mathematical relationship actually supports a multiplicative interpretation. Precise reporting is particularly important in investment research because imprecise language can make moderate scenario differences appear dramatically larger than they are.

Finally, the paper highlights a broader methodological principle: a published numerical result should be no more specific than the evidence supporting it. Because the original article does not disclose the underlying dataset or simulation configuration, this revision does not attempt to manufacture a missing sample or reconstruct an unreported empirical procedure. Instead, it preserves the reported scenario values while clearly identifying them as illustrative and states what would be required for independent replication. This approach improves the paper's scientific defensibility and makes the boundary between observed data, model assumptions, and illustrative calculations explicit.

6. LIMITATIONS

The principal limitation is that the original publication does not disclose the underlying property-level dataset. The number of properties, geographic distribution, observation period, selection criteria, and individual project cash flows cannot therefore be independently reconstructed. The manuscript does not claim to recover these missing data. Instead, it identifies the information that a reproducible empirical study would need to provide.

Table 7. Evidence status and appropriate interpretation of the paper's main outputs.

Output	Evidence status	Appropriate interpretation
Published scenario percentages	Reported in original article	Illustrative scenario values retained for analytical correction
ROI relative change	Directly calculable from reported ROI values	65.7% relative increase, not a 65-fold increase
Payback comparison	Reported summary values	Directional comparison; underlying cash-flow sequence unavailable
IRR and cash-on-cash	Reported summary values	Cannot be independently recomputed without detailed cash flows
Five-percent forecast accuracy	Insufficient validation information	Should not be treated as an established empirical finding

Integrated investment decision-support framework

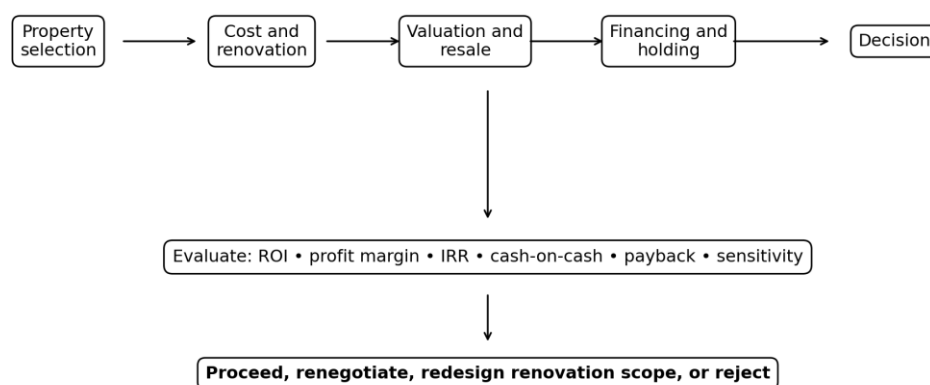


Figure 6. Integrated decision-support framework for evaluating a flipping project.

A second limitation concerns the reported scenario values. The values in Table 2 are retained because they were reported in the published article, but they are not presented as newly estimated results. In particular, IRR and cash-on-cash return cannot be independently recomputed from the published summary table alone. A future empirical version should provide the complete cash-flow schedule and calculation procedure for every project or for a clearly documented representative case.

A third limitation concerns forecasting. The original five-percent prediction-error claim has been removed because the validation dataset and error-calculation procedure are unavailable. Future research using machine-learning or automated valuation should report out-of-sample validation, geographic and temporal coverage, benchmark models, error metrics, and model stability. This would allow readers to distinguish genuine predictive performance from in-sample fit.

Finally, the literature cutoff creates a deliberate historical boundary. Technologies and research published after February 2022 are excluded even if they could improve the current discussion. This restriction is necessary because the purpose of the revision is to make the manuscript internally consistent with its March 2022 publication context. Contemporary updates should be treated as a separate future review rather than inserted into a backdated 2022-aligned version.

7. CONCLUSION

Financial modeling provides a practical framework for evaluating the profitability and risk of real-estate flipping projects. The analysis should begin with a complete representation of acquisition, renovation, financing, holding, transaction, and resale cash flows and should use multiple complementary financial metrics rather than a single headline percentage. ROI summarizes relative profitability, IRR captures the time value of project cash flows, cash-on-cash return emphasizes invested cash, and payback indicates how quickly capital is recovered.

The paper also shows why budget optimization should be interpreted as disciplined allocation rather than simple cost minimization. Renovation expenditure should be evaluated according to its expected contribution to resale value and its effect on project duration and risk. Scenario and sensitivity analysis can then reveal whether a project remains viable when costs rise, resale prices fall, or holding periods lengthen. Monte Carlo simulation can extend this analysis when probability distributions are supported by appropriate data.

The central numerical scenario retained from the published article indicates higher reported returns under an optimized budget, but the result is now presented as an illustrative scenario rather than as an independently validated empirical finding. The reported ROI change from 17.2% to 28.5% is correctly described as a 65.7% relative improvement, while the reduction in payback period from 15 to 10 months is a 33.3% reduction. The earlier unsupported five-percent forecasting-accuracy claim has been removed because it cannot be independently verified from the available publication record.

Most importantly, the manuscript is chronologically consistent with a March 2022 publication date. All post-February-2022 references and claims have been excluded, and the technological discussion is restricted to approaches documented before the cutoff. The resulting framework is deliberately transparent about its evidentiary limits and provides a stronger basis for editorial correction, future empirical validation, and responsible application of financial modeling to real-estate flipping decisions.

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