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Beyond traditional valuation: A performance-based approach to hotel asset valuation in Italy

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Introduction

Hotels sit at the intersection of real estate and business operations. Unlike "pure" property assets whose value is primarily anchored to location, replacement cost, and leasing fundamentals, hospitality assets embed a continuously evolving operating component: revenues and margins are shaped by demand composition, pricing power, distribution strategy, seasonality, service standards, and the quality of management. This hybrid nature makes hotel valuation both highly relevant and inherently complex. In practice, investors and valuers need clear benchmarks to compare destinations and segments, screen opportunities, and communicate pricing logic; at the same time, the mechanisms through which operational performance translates into value are not instantaneous and interact with capitalization assumptions, risk premia, and market expectations that often move more slowly than annual operating metrics.

This gap is particularly salient in upscale and luxury hospitality. In these segments, differentiation is frequently driven by brand strength, reputation, service depth, and experiential quality, all of which affect pricing power and demand resilience but are only imperfectly observed in standard datasets. The underlying real estate component remains central: micro-location, room inventory, product quality, and refurbishment cycles shape long-run competitiveness and risk. As a result, market participants rely on a combination of operating KPIs (such as RevPAR, TRevPAR, and GOPPAR) and valuation benchmarks (such as transaction multiples, cap rates, and price-per-key metrics) to form investment views, but the mapping between these two layers is rarely one-to-one, especially when markets are adjusting to shocks or when investors price assets on the basis of medium-term stabilization rather than short-run volatility.

Within this context, the central research question of this thesis is: to what extent, and in what way, are operational performance indicators associated with hotel valuation benchmarks in the Italian upscale and luxury market? More specifically, the thesis investigates whether destinations and segments that exhibit stronger

operating performance also display materially higher valuation benchmarks, and whether changes in operating performance within the same destination–segment over time are reflected in corresponding changes in benchmark values. This distinction matters because it separates a cross-sectional benchmarking interpretation (stronger markets are priced higher) from a short-run capitalization interpretation (year-to-year KPI movements are rapidly embedded into benchmark valuations).

To address the research question, the empirical strategy relies on a pragmatic and market-relevant outcome variable: price per key (EUR/key) as a benchmark proxy for hotel asset value. Price per key is widely used in professional practice because it is intuitive, comparable across heterogeneous assets, and directly linked to the scale of hospitality capacity. It also aligns with how market participants communicate pricing when full transaction terms and asset-level cash flow models are not publicly observable. At the same time, EUR/key is a simplified proxy: it compresses differences in asset quality, brand affiliation, risk, and financing conditions into a single figure. For this reason, the analysis treats EUR/key not as a substitute for asset-level valuation, but as a disciplined empirical bridge between operating performance and market pricing that can support peer comparisons, screening decisions, and valuation narratives.

Operating performance is captured through core hospitality KPIs that reflect complementary dimensions of the hotel profit engine. Revenue generation and pricing capacity are represented by metrics such as RevPAR and TRevPAR, while profitability and operational efficiency are proxied by measures such as GOPPAR and related indicators. Conceptually, these KPIs summarize the ability of a destination–segment to monetize its room inventory through occupancy and rate, to generate and diversify total revenues beyond rooms, and to translate revenues into operating profit given a specific cost structure. In equilibrium, markets with stronger and more resilient operating performance should be able to sustain higher cash flows, which, under reasonable capitalization assumptions, would translate into higher benchmark values. Yet hospitality markets rarely operate in short-run equilibrium, and valuation benchmarks can be influenced by discount rates, financing conditions, and investor sentiment that do not necessarily move in lockstep with operating metrics.

The empirical analysis is implemented using a destination–segment–year panel for the Italian market over 2022–2024, with a focus on upscale and luxury positioning. This design reflects both data realities and analytical intent. Asset-level transac-

tion datasets with consistent coverage are often limited, and true comparability across individual hotels is complicated by differences in physical characteristics, service models, brand standards, and renovation cycles that do not map cleanly into uniform quantitative controls. A destination–segment lens captures the market dimension that is central to many investment decisions: investors often reason in terms of where an asset operates and what positioning it serves when forming expectations about pricing power, demand resilience, and the plausibility of achieving stabilized performance.

Methodologically, the thesis adopts specifications that separate two complementary sources of variation. Pooled models exploit cross-sectional dispersion across destinations and segments and address whether structurally stronger markets tend to be priced higher in benchmark terms. Fixed-effects models, by absorbing time-invariant destination–segment heterogeneity and common time shocks, isolate within-entity variation and test whether year-to-year changes in operating performance are mirrored by changes in price per key. Working in logarithms for key variables supports an elasticity interpretation, allowing estimated coefficients to be read as proportional relationships that are more readily interpretable for benchmarking purposes. The empirical evidence points to a clear pattern. Across pooled specifications, operating performance aligns strongly with benchmark valuation levels, indicating that destinations and segments characterized by stronger KPI profiles tend to display materially higher price-per-key benchmarks. When fixed effects are introduced, the relationship weakens substantially, suggesting that within a short horizon such as 2022–2024, benchmark valuation signals at the destination–segment level may move more slowly than short-run operational fluctuations once persistent heterogeneity and common shocks are controlled for. These findings have direct implications for valuation practice: KPI-consistent benchmarking appears informative for screening and comparative valuation discussions across markets and segments, improving the transparency of pricing narratives and peer comparisons; at the same time, the limited within-entity evidence cautions against mechanically translating short-run KPI movements into immediate benchmark value adjustments, particularly when required returns, risk premia, and capitalization assumptions can dominate pricing in the short term.

Chapter 1

Hotel Valuation, Operational KPIs, and Market Dynamics

1.1 Hotel Asset Valuation: Theoretical Approaches and Alternative Models

Valuing hotel assets is a complex exercise that must account for the hybrid nature of hotels as both real estate and operating businesses. The value of a hotel comprises not only the physical property (land and improvements), but also the personal property (furniture, equipment) and the business value generated by hotel operations. Traditional real estate valuation approaches, income capitalization, sales comparison, and cost replacement, are all applied in hotel valuation, but each has limitations when faced with the unique characteristics of hospitality assets.

Income Approach (DCF/Capitalization): The income capitalization approach is generally regarded as the most persuasive method for hotels, since hotels are income-producing properties and investors focus on future cash flows. In practice, this usually involves a discounted cash flow (DCF) analysis projecting the hotel's net income over a holding period (often 10 years) and a reversion value at sale. The DCF captures the present worth of future benefits (cash flows and resale proceeds) and thus aligns with how typical hotel buyers underwrite deals by focusing on leveraged yield and ROI. An alternative income method is direct capitalization using a stabilized single-year net operating income (NOI) and market cap rate, but this is less common for hotels given the difficulty of determining a reliable cap rate and the volatility in hotel earnings. In all cases,

the income approach must be applied carefully for hotels: appraisers often deduct management and franchise fees pro forma to isolate income attributed to real estate, thus excluding portions of cash flow attributed to the business's intangible assets. This so-called "Rushmore approach" is widely used to separate the cost of living (business) from the pure value of real estate in hotel valuations. The strength of the income approach is that it directly reflects the hotel's earning power; however, it depends on accurate forecasting of revenues, expenses, and market conditions. Hotels' cash flows can be highly cyclical and sensitive to management effectiveness, making forecasts and discount rate selection challenging. However, research suggests that among valuation techniques, a well-executed DCF tends to produce the most realistic estimates of hotel value, underlining the importance of income-based analysis for this asset class.

Sales Comparison Approach: The sales comparison (market) approach attempts to value a hotel by comparing it to recent sales of similar hotel properties, adjusting for differences in location, size, brand, performance, etc. In theory, this approach grounds the valuation on actual market pricing. In practice, it is often of limited usefulness for hotels. Hotels are highly heterogeneous assets – two properties can differ on a multitude of factors (quality, segment, amenities, operating performance, lease/management contract terms, etc.), and truly comparable sales are scarce. Furthermore, comparable transactions may be limited or not fully transparent (prices may not reflect seller concessions or specific motivations). As a result, many subjective adjustments are needed to comparables, reducing the reliability of this approach. Hotel investors certainly consider sales metrics like price per room and may benchmark a target against recent trades, but rarely will they rely solely on a sales comparison to make an investment decision. At best, this approach can indicate broad value ranges or price trends. For example, it may reveal pricing momentum in a market (e.g. rising price per key trends) or serve as a reasonableness check on a DCF result. Overall, the sales comparison method plays a secondary role – informative for context but typically not definitive in hotel valuation, given the paucity of truly comparable sales and the primacy of income considerations in buyers' analyses.

Cost (Replacement) Approach: The cost approach values the hotel based on the cost to replace it with a similar new property, combining land value plus current construction costs minus depreciation. This approach is grounded in the principle that an informed buyer would not pay more for an asset than the cost to build a new one. It can sometimes provide an upper benchmark of value or be useful for insurable value calculations. However, for hotels it is rarely the

controlling approach except in specific cases (e.g. brand-new hotels or unique situations). As hotels age, physical and functional depreciation, as well as changing market preferences, make it difficult to accurately quantify depreciation and obsolescence. Moreover, cost approach ignores the property's ability to generate income – a critical factor since a well-run hotel can have value far above or below replacement cost depending on its earnings. Because knowledgeable hotel investors focus on returns and cash flow, the cost approach is generally given minimal weight in practice. It mainly serves as a check for development decisions (i.e. "buy versus build" analyses) or in markets where few sales occur. If the cost approach yields a value much lower than the income approach, it may signal an overprojection of income (or conversely, if cost greatly exceeds income value, the market may not support new development). In summary, while conceptually straightforward, the cost approach by itself does not capture the going-concern value of an operating hotel and thus is of limited utility in valuation except for new properties or when other approaches lack data.

Hybrid and Alternative Models: Recognizing the limitations of the three classic approaches, appraisers and researchers have developed hybrid methods tailored to hotels. One widely used technique in hotel appraisal is the "Management Fee and Franchise Fee Deduction" method (often associated with Stephen Rushmore) to handle the business enterprise component of value. By deducting a market-rate management fee and franchise fee in the pro forma, the valuation effectively treats those as the remuneration for the intangible assets (the management expertise, brand, and goodwill). The remaining NOI is then capitalized to value the real estate alone. This method is a practical hybrid of the income approach and cost of intangible assets, and is widely accepted in property tax assessment cases and appraisals to avoid over-taxing the intangible (non-taxable) value of hotels. An alternative view, sometimes called the Business Enterprise Approach, explicitly models separate components (valuing the business and personal property separately and subtracting them), but this approach can yield a relatively low real estate value and is debated among professionals.

Another set of alternative models are **statistical and AI-driven valuation models**. Researchers have explored hedonic pricing models and automated valuation models (AVMs) that use large datasets of hotel sales to regress sale price on characteristics like location, size, chain scale, and performance metrics (ADR, RevPAR, occupancy). The idea is to derive an equation that can predict market value based on a hotel's attributes and KPIs. While academically interesting, such models face data limitations and have not replaced traditional DCF in prac-

tice. A study by Fu et al. (2013) tested an AVM alongside traditional methods and found the AVM's estimates differed significantly from income-based methods, concluding that a detailed DCF was more reliable for the sample analyzed. Nonetheless, as data availability and machine learning techniques improve, AVMs may play a growing role in high-level valuation estimates or portfolio valuation where individual appraisal is impractical.

Investors in the marketplace also often use short-hand valuation multiples as an alternative or complement to formal appraisal methods. A common metric is the EBITDA multiple (or EBITDAR multiple, adding rent) – essentially the inverse of a capitalization rate. For instance, if similar hotel assets trade around 12× EBITDA, an investor might estimate value by applying that multiple to a subject hotel's stabilized EBITDA. Simpler yet, some use price per room benchmarks, especially for limited-service hotels, and adjust up or down based on RevPAR index or quality. These rules of thumb, while not "valuation methods" in the academic sense, are part of the alternative toolkit that market participants use for quick assessments. They are, however, blunt instruments: for example, a RevPAR multiple ignores cost structure differences, and a price-per-key heuristic fails to account for profitability. Thus, professional investors may use them only in preliminary screening and always corroborate them with a full income analysis.

Limitations in Applying Traditional Methods to Hotels: Each valuation approach must be interpreted in light of hotels' hybrid real estate–business nature. The primary challenge is that a hotel's value depends not just on its physical attributes or location (as with most real estate) but also on how well it is operated and marketed. Two identical hotels can have vastly different values if one is professionally managed under a strong brand and the other is poorly run – a reflection of intangible assets like brand name, management quality, workforce, and customer loyalty. Traditional methods struggle with this: the sales comparison approach can't easily adjust for operational prowess, and the cost approach certainly cannot capture it. Even the income approach needs adjustments (as noted, subtracting management/franchise fees) to avoid attributing all the cash flow to the bricks and mortar. Additionally, hotels have high fixed costs and operating leverage, meaning small swings in occupancy or rate cause amplified changes in NOI. This volatility makes valuation sensitive to assumptions. Unlike a leased office building with locked-in tenants, a hotel "re-leases" its rooms nightly – its future income is highly uncertain and can drop sharply in downturns. Thus, establishing a stabilized NOI for capitalization or a reliable terminal value for DCF is more difficult. Analysts often have to normalize financials for cyclicality,

removing one-time events and considering long-term trends in demand.

Another limitation is the **market data availability**. The hotel investment market is less liquid and transparent than, say, office or multifamily sectors. Many hotel transactions are private, and details on NOI, cap rates, or brand performance may not be disclosed. This opacity limits the efficacy of the sales comparison approach and even the derivation of cap rates for the income approach (often, appraisers must rely on investor surveys and experience). The uniqueness of hotels also means fewer direct comparables. For example, a luxury boutique hotel in a historic city center is one of a kind – its sale prices might not be replicable elsewhere, and adjustments are inherently subjective.

Ultimately, the hybrid nature of hotels implies that valuation depends on both asset-level characteristics and operating performance, making model assumptions, normalization choices, and fee structures particularly consequential.

1.2 Performance Indicators in Hospitality: Definitions and Role in Valuation

A hotel's performance is commonly assessed through a set of specialized Key Performance Indicators (KPIs) that gauge various aspects of revenue, occupancy, and profitability. The most widely used metrics include occupancy rate, ADR (Average Daily Rate), RevPAR (Revenue per Available Room), as well as broader measures like TRevPAR (Total RevPAR) and profitability metrics such as GOPPAR (Gross Operating Profit per Available Room), NOI, and EBITDA margin. This section defines the main hospitality KPIs and explains their significance for valuation, including how investors and valuers utilize these metrics in practice.

Occupancy Rate: Although not explicitly listed in the section title, occupancy is a fundamental metric underpinning several other KPIs. Occupancy rate is the percentage of available rooms that are occupied over a given period. It is calculated as room nights sold divided by room nights available. For example, a hotel that sold 18,000 room nights in a year out of 24,000 available room nights has a 75% annual occupancy. Occupancy reflects demand for the hotel's rooms; it tells owners how well they are filling capacity. High occupancy suggests strong demand (though it can also indicate pricing that might be too low), whereas low occupancy signals under-utilization of the asset. In valuation, occupancy matters because it directly affects revenue – an empty room yields zero revenue. However,

occupancy must be interpreted alongside ADR, as selling out rooms only creates value if rates (and consequently revenues) are sufficient.

ADR (Average Daily Rate: ADR represents the average room revenue earned per occupied room, typically reported on a daily or monthly basis. It is computed as total rooms revenue divided by the number of rooms sold. For instance, if a hotel earned €200,000 in room revenue in a month with 5,000 room nights sold, the ADR is €40.00. ADR is an indicator of pricing power and market positioning – it reflects what rate, on average, the hotel is able to charge for its rooms. A higher ADR, holding other factors constant, means the hotel is capturing more revenue per stay (often by delivering a higher-quality or more distinctive product that guests are willing to pay for). In the context of valuation, ADR is critical because it drives top-line potential: all else equal, increases in ADR contribute directly to revenue growth and often flow through to profit (since fixed costs don't rise with ADR). In fact, industry analyses have noted that ADR growth "truly powers profits" in hotels. However, ADR cannot be looked at in isolation – a high ADR might come at the expense of lower occupancy if rates are pushed too high. Investors will examine ADR trends to evaluate whether a hotel is effectively yielding rates, and compare ADR to competitors or market averages to gauge positioning (e.g., a hotel with ADR 20% above its competitive set might be a luxury or upper-upscale property in that market).

RevPAR (Revenue per Available Room): RevPAR is perhaps the single most cited metric in the hotel industry. It is defined as the total rooms revenue divided by the total number of available room nights in the period. Equivalently, RevPAR can be calculated as ADR $\times$ Occupancy. For example, if our hypothetical hotel had €200,000 in room revenue and 8,000 available room nights in a month, its RevPAR is €25. RevPAR encapsulates two critical dimensions: occupancy and rate. Thus, it is a convenient indicator of overall rooms revenue productivity. Hoteliers favor RevPAR because it allows comparisons across properties of different sizes and across time periods, normalizing for room count and days. A RevPAR of €50 means that each available room (whether occupied or not) generated €50 of room revenue on average over the period. This metric is widely used by operators, owners, and analysts as a proxy for the health of a hotel's rooms business. A rising RevPAR generally signals improving performance – either higher occupancy, higher ADR, or both – whereas a declining RevPAR is a red flag of deteriorating performance or market conditions.

However, RevPAR has important limitations when used as a measure of financial

success. Firstly, RevPAR captures only rooms revenue. For hotels with significant other revenue streams (food & beverage, spa, conference, etc.), focusing solely on RevPAR gives an incomplete picture. In full-service hotels or resorts, rooms might be just 50% of total revenue; a RevPAR-centric view would ignore the contribution of restaurants, bars, and other departments. Secondly, RevPAR alone doesn't reveal profitability – two hotels could have identical RevPAR, but if one has much higher expenses, its bottom line will be weaker despite equal rooms revenue. Thirdly, RevPAR can be skewed by hotel size: as HVS consultants have pointed out, a large hotel often has lower occupancy (and thus lower RevPAR) than a smaller hotel in the same market, simply because filling a greater number of rooms is harder. A 100-room hotel might achieve 80% occupancy while a 500-room hotel in the same market achieves 70%; the smaller hotel's RevPAR will look higher, but the larger hotel may actually earn more total profit due to economies of scale. Moreover, investors ultimately care about cash flow, not just revenue – "hoteliers do not take RevPAR or percentages to the bank!" as one industry veteran quipped. Empirical studies confirm that while RevPAR is correlated with hotel values, it is not as tightly linked as profit-based metrics. Changes in RevPAR and changes in hotel asset values often move in tandem (indicative of an elastic relationship), but the absolute level of RevPAR is not a perfect predictor of value. Because of these nuances, RevPAR is best viewed as a top-line performance indicator and a quick benchmarking tool (e.g., to compare a hotel's RevPAR to its market or to track year-over-year growth). It is not by itself a measure of investment return, though sustained RevPAR growth usually signals improving value, and investors certainly monitor RevPAR trends closely.

TRevPAR (Total Revenue per Available Room): TRevPAR expands the RevPAR concept to include all hotel revenue, not just rooms. It is calculated as total hotel revenue (rooms plus F&B, spa, and any other operated departments) divided by available rooms. For example, if a resort has significant food and beverage and spa income, its TRevPAR captures the efficiency of generating revenue from each room across all sources. The addition of non-rooms revenue is particularly important for full-service hotels, luxury resorts, and convention hotels where ancillary spend is high. TRevPAR provides a more holistic view of revenue generation. If RevPAR and TRevPAR are widely different, it indicates the hotel has substantial non-rooms revenues. Limited-service or select-service hotels will have TRevPAR only slightly above RevPAR (since rooms are their primary income), whereas a large convention hotel might have a TRevPAR far higher than its RevPAR due to banquet, catering, and other revenues. Investors

use TRevPAR to gauge how well a hotel is utilizing its space and capturing wallet share from guests beyond just the room rate. For instance, two resorts with the same RevPAR might have different TRevPARs if one aggressively upsells dining, activities, or spa services. The higher TRevPAR resort is extracting more total revenue per guest. That said, TRevPAR, like RevPAR, is still a revenue metric; it doesn't account for the cost of generating those revenues. It also doesn't indicate the mix of revenue (rooms revenue has a higher profit margin than food & beverage typically). So while TRevPAR is a valuable metric for comparing total revenue performance, it too must be paired with profitability metrics for valuation work.

GOPPAR (Gross Operating Profit per Available Room): GOPPAR is a key performance indicator that brings profitability into focus. It is defined as gross operating profit (GOP) divided by available room nights. Gross operating profit is essentially the hotel's total revenue minus all operating expenses (departmental expenses and undistributed expenses), before fixed costs like depreciation, rent, interest, and taxes. In essence, GOP is the operating income after running the hotel – often equivalent to EBITDA for property-level operations (if management fees are included as an expense). Thus, GOPPAR measures how much profit a hotel is generating per available room. A simple formula is:

$$\text{GOPPAR} = \frac{\text{Total Revenue} - \text{Total Operating Expenses}}{\text{Rooms Available}}$$

This metric directly indicates the hotel's operational efficiency in converting revenue to profit. GOPPAR is highly informative for owners and investors because it links revenue and cost control. Two hotels with the same RevPAR might have different GOPPAR if one has leaner operations or a more profitable revenue mix. GOPPAR thus captures the combined effect of occupancy, rate, ancillary revenues, and expense management. Industry analysts note that GOPPAR, used in tandem with RevPAR or TRevPAR, can reveal flow-through, i.e. the percentage of incremental revenue that is converted to profit. If RevPAR is rising but GOPPAR is flat, it means costs are eroding the additional revenue, a red flag for operators.

From an investor's standpoint, GOPPAR is arguably one of the most crucial metrics because hotel values are fundamentally based on profit, not just revenue. In fact, studies have shown GOPPAR has a much higher correlation with hotel property values than RevPAR does. One HVS analysis found GOPPAR could have an 85–90% correlation with value, compared to roughly 70–75% for RevPAR. The

intuition is clear: a hotel's ability to generate profit per room directly drives its NOI and thus its valuation via income capitalization. For this reason, seasoned hotel investors often prioritize GOPPAR when evaluating an asset's performance. As early as the 2000s, experts like Kett (HVS) advocated for GOPPAR to complement RevPAR in assessing hotels' success. GOPPAR tells investors about management efficiency and operational health: it answers "how much profit do we make per room, and is that in line with expectations or benchmarks?" A rising GOPPAR usually signals improved cost control or higher-margin revenues, which bodes well for valuation. Conversely, if GOPPAR is lagging while RevPAR is growing, investors will question why profits aren't materializing (perhaps expenses are outpacing revenue gains). In summary, GOPPAR is a critical link between operations and valuation, marrying top-line and expense factors into one metric.

NOI (Net Operating Income): Net Operating Income in hotel context typically refers to the income after all operating expenses and fixed charges that are necessary to keep the hotel running, before debt service and taxes. There is sometimes confusion between GOP and NOI terminology in hospitality. In many cases, what hoteliers call "GOP" is before management fees and fixed costs, whereas "NOI" might be after a management fee, property taxes, insurance, and reserves. For the purpose of valuation, NOI is usually taken as the stabilized annual cash flow that the property produces for the owner after paying for operating expenses, a reserve for replacement (CapEx fund), management/franchise fees, and any other expenses that a new owner would incur. This NOI is the figure that gets capitalized in a direct cap approach or that is used in DCF projections as the cash flow before financing. NOI is not a "per available room" metric, but rather an absolute annual or monthly figure. However, owners might also express it on a per-room basis (e.g. "NOI per available room" or NOI yield per key) for benchmarking. The significance of NOI for valuation cannot be overstated: it is the driver of value in the income approach. A common valuation formula is Value = NOI / Cap Rate. Thus, improving NOI increases value, and investors are keenly interested in both the current NOI and the potential NOI (through better revenue or cost changes). Many industry participants consider NOI the bottom-line KPI (short of actual profit after debt, which is more about the investor's financing structure). They monitor NOI margins (NOI as a percentage of total revenue) to compare efficiency across properties. NOI is essentially the translation of all the above metrics (occupancy, ADR, RevPAR, GOPPAR, etc.) into a single dollar amount that an investor can capitalize. Notably, O'Neill and

Mattila (2006) found that ADR had a surprisingly strong relationship with sale prices, even more so than NOI in their dataset but this finding highlights that buyers often view strong ADR (which usually yields higher NOI potential) very favorably. Generally, though, NOI is the key output of all operational metrics and the basis for determining how much a hotel is worth in financial terms.

EBITDA Margin (and related profitability ratios): EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) in hotel context is often similar or equal to the GOP or NOI figure, depending on definition (if we consider EBITDA at the property level, it's essentially GOP minus management fees and fixed costs, akin to NOI). The EBITDA margin is the percentage of total revenue that is left as EBITDA profit. For example, if a hotel's total revenues are €10 million and its EBITDA (operating profit before the owner's financing costs) is €3 million, the EBITDA margin is 30%. This metric shows overall profitability as a proportion of revenue, it reflects how efficiently the hotel converts revenue into profit. A higher EBITDA margin means better operational efficiency or a higher-margin business mix. Luxury hotels might have lower EBITDA margins (due to extensive service and amenities driving higher costs), whereas limited-service hotels often have high EBITDA margins (they have fewer expenses relative to revenue). Investors compare EBITDA margins across deals to judge if a hotel is a strong performer. For instance, if one hotel has a 40% EBITDA margin and another similar hotel has 30%, the first is generating more profit from each euro of revenue – potentially indicating superior management or economies of scale. In valuation, EBITDA margin is used to sanity-check pro formas. If an appraisal assumes a 45% EBITDA margin for a full-service hotel, one might question its realism by comparing to industry averages. Furthermore, investors looking to improve an asset's value will analyze which levers can increase the EBITDA margin (reducing costs, outsourcing services, increasing ancillary revenue with minimal cost, etc.).

EBITDA-based multiples in hotel transactions (e.g. a hotel selling for 12 $\times$ EBITDA) implicitly incorporate the EBITDA margin and growth expectations. A hotel with a higher sustainable EBITDA margin might command a better multiple (lower cap rate) because it's seen as a more efficient generator of cash per dollar of revenue. Additionally, flow-through ratios (the percentage of incremental revenue that becomes incremental EBITDA) are tracked, essentially a short-term version of margin improvement, to ensure that when revenue grows, profit grows nearly as much. This is especially pertinent in recovery periods: for example, after a downturn, hotels aim to "flow" a high percentage of returning

revenue to the bottom line by holding costs down. A strong flow-through will boost the EBITDA margin and thus value.

Use of KPIs by Investors and in Valuation: Hotel investors and appraisers use these KPIs both in evaluating ongoing performance and in building valuation models:

- **Benchmarking and Diligence**: Before acquisition, investors compare a target hotel's KPIs to its competitors and market. RevPAR index (the hotel's RevPAR divided by the market average) is a quick gauge of whether the hotel is underperforming or outperforming the market. If a hotel has an 80% RevPAR index, the investor sees upside potential (through better revenue management or brand change); a 120% index means the hotel is a market leader, but the investor will ask whether that premium is sustainable. Similarly, investors look at historical occupancy and ADR trends to judge volatility and pricing strategy. A due diligence checklist often includes reviewing the past 3-5 years of occupancy, ADR, RevPAR, TRevPAR, and profit margins. They may also compare the hotel's GOP margin or EBITDA margin to industry averages for that chain scale; significant deviations can indicate either an opportunity (if margins are below average due to inefficiencies that can be fixed) or a risk (if margins are above average, maybe the current owner deferred maintenance or under-staffed, implying costs might rise).

- **Valuation Modeling**: In underwriting a hotel, investors typically project future occupancy, ADR, and resulting RevPAR as the starting point of a DCF model. These projections are grounded in market research (e.g. expectations for demand growth, new supply entering, and the hotel's competitive dynamics). The projected RevPAR drives total room revenues, which then feed into total revenue (via assumptions on ancillary revenue capture, often using TRevPAR ratios). Key cost line items are often modeled as percentages of revenues or per-occupied-room figures, which relate back to these KPIs. For instance, rooms department expenses may be budgeted based on cost per occupied room, meaning if occupancy changes, the model adjusts costs in tandem. As a result, operational KPIs are tightly woven into the financial model that yields NOI and value. The capitalization rate or discount rate applied is also informed by the risk associated with those KPIs – e.g., a hotel in volatile market with very seasonal occupancy might be assigned a higher cap rate (lower valuation multiple) due to risk.

- **Quick Valuation Rules**: As mentioned, some investors use shorthand multiples that implicitly involve KPIs. A well-known rule of thumb used historically is the "$1 per $1,000" rule (mostly in U.S. context) – roughly, each $1 increase in ADR translates to about $1,000 increase in value per room for a stabilized select-service hotel (assuming a 10% cap rate). O'Neill and Mattila's research (2006) lending support to ADR's role aligns with this industry heuristic. Similarly, investors might say, "Hotels in this market trade at X times EBITDA or at Y per key, which given the hotel's RevPAR implies a cap rate of Z%." These shortcuts all boil down to revenue and profit metrics.

- **Performance Monitoring**: Post-acquisition, owners closely monitor monthly KPIs, especially occupancy, ADR, RevPAR and GOPPAR, to ensure the asset is meeting underwritten expectations. Management agreements often include performance clauses based on RevPAR index or GOP margins. For instance, an operator might be required to achieve at least a fair market RevPAR index; failure could lead to owner's right to terminate the management contract. Investors thus care about these KPIs not just at purchase but throughout the holding period as indicators of whether the hotel is creating the expected value. If RevPAR or GOPPAR stagnate or decline, the hotel's appraised value likely falls, affecting loan covenants or investment returns.

- **Industry Reporting and Sentiment**: Aggregated KPIs also drive market sentiment and capital flows. Industry reports frequently cite RevPAR growth as a metric for market performance. For example, Italy's hotel market saw RevPAR exceed 2019 levels in 2024 after the pandemic recovery, which signaled robust performance and attracted investor interest. In H1 2024, Italy's RevPAR was noted to be the second highest in Europe (after Switzerland), with a 5.2% increase over the previous year driven by a 5.7% ADR rise. Such statistics, drawn from STR data and others, are used by investors to decide which markets to invest in. A market with strong RevPAR and ADR growth and improving GOP margins is likely to see more acquisition activity as investors expect rising incomes (and thus rising property values). Conversely, if industry reports show RevPAR declines or margin compression in a market, investors may become cautious or demand higher cap rates.

1.3 Literature Review and Research Gaps

Hotel valuation has been studied extensively at the intersection of real estate finance and hospitality management, reflecting the idea that hotel prices are ultimately anchored to cash-flow generation while remaining highly exposed to operating dynamics. The earliest academic contributions largely framed hotels as income-producing real estate and relied on traditional appraisal logic, where stabilized operating income and market yields determine value. Within this stream, net operating income (NOI) is treated as the core driver of pricing and the main link between operational performance and valuation outcomes.

In line with standard income-capitalization theory, Walsh and Staley (1993) emphasize the central role of stabilized NOI in lodging valuations, consistent with the canonical relationship that hotel value can be expressed as **stabilized NOI divided by the capitalization rate**. Practitioner-oriented work from the same period echoes this view, stressing that transaction pricing in the lodging market is fundamentally anchored to how NOI is translated into value through market yields. Egan (1996) captures this appraisal intuition succinctly by noting that "NOI divided by the capitalization rate equals value," reinforcing NOI's role as a key determinant of observed selling prices.

In the early 2000s, researchers like O'Neill (2004) further reinforced that NOI is a key driver in hotel asset pricing and investment decisions. However, the hospitality literature also began to explore how operational metrics (occupancy, ADR, RevPAR, etc.) relate to profitability and property value. John W. O'Neill and Anna S. Mattila produced a series of influential studies mid-2000s examining these relationships. In one notable study, O'Neill and Mattila (2006) analyzed hotel sales and found that top-line metrics could be surprisingly powerful indicators of value. They reported that a hotel's ADR had a **stronger correlation** with its market sale price than even its NOI did. This counterintuitive result (since valuation theory would point to NOI as primary) suggested that investors may implicitly capitalize revenue assuming typical margins, or that ADR is a proxy for a hotel's quality and competitive positioning that investors highly value. Essentially, a higher ADR may signal a luxury or high-quality asset with potential for high cash flows, which the market prices in even if current NOI is modest. O'Neill and Mattila's work challenged the sole focus on bottom-line metrics and indicated the need to consider the dynamic interplay between occupancy, ADR, and profit.

Another significant strand of research has focused on **RevPAR's role as a performance and valuation metric**. RevPAR's "relevance in assessing hotel performance and property value is well-established in hospitality research". Empirical studies consistently show that hotels with higher RevPAR (relative to their peers or to prior years) tend to have higher values and better financial outcomes. For example, a study on hotel sales by Quan, Li, and Butler (2011) found that RevPAR was a statistically significant predictor of sale price per room. Similarly, an Iowa State University dissertation (2018) on the impact of branding on hotel sale prices noted that RevPAR was a **significant predictor** of hotel sale prices across the board, and in the luxury segment both RevPAR and GOP (profit) were significant. This indicates that for higher-end hotels, investors consider both revenue and profit metrics when determining value – possibly because luxury hotels can have widely varying cost structures and profit conversion, so revenue alone doesn't tell the full story. Indeed, in that study, "for chain scale luxury sector hotels, GOPAR and RevPAR were both significant predictors of sale price", underlining that in upscale properties, a high revenue hotel that doesn't efficiently convert to profit may not be as valuable as one with slightly lower revenue but much higher profit margins.

The introduction of GOPPAR into industry practice (around the 2000s by HVS and others) has been mirrored by academic interest in comparing revenue versus profit metrics. Recent research by scholars like Scott Smith and Ozdemir (2020) looked at RevPAR vs. GOPPAR as performance indicators. One study published in *Journal of Hospitality Financial Management* found that at a firm level (portfolio of hotels), RevPAR was generally more useful for benchmarking performance than GOPPAR, but at the individual property level, the results were mixed. This reflects that publicly traded hotel firms often report RevPAR as a key metric (since it's easily comparable across brands and markets), whereas property-level analysis, especially for valuation, benefits from GOPPAR insight. Another thesis by Chatziantoniou et al. (2017) examined the use of RevPAR and GOPPAR together and suggested that analyzing both provides a more complete picture of performance, since RevPAR alone might mislead if cost structures differ.

Academic research has also explored factors beyond basic KPIs that influence hotel value, highlighting gaps in traditional analyses. Brand affiliation is one such factor. A study by O'Neill and Xiao (2006) titled "The Role of Brand Affiliation in Hotel Market Value" found that being part of a major brand can add significant incremental value to a hotel, above and beyond what metrics like

NOI and RevPAR would predict. This implies that investors value the flag and loyalty network as an intangible asset – something not captured in standard financial metrics. The finding underscores that two hotels with identical NOI and RevPAR might sell for different prices if one has a prestigious brand. This insight dovetails with the hybrid nature of hotels: the brand is part of the going-concern value. Similarly, studies on management companies, guest satisfaction scores, and even online ratings have emerged, examining whether those softer metrics translate into better performance and higher values. For example, research by Prof. Chekitan Dev and colleagues investigated how guest satisfaction and online reputation correlate with RevPAR premiums, thereby potentially affecting valuations (a hotel with strong reviews may achieve higher ADRs and RevPAR, which investors factor into future earnings potential).

In terms of valuation methodology research, academics have evaluated how well different valuation approaches work for hotels. As mentioned in Section 1.1, Rushmore (1992) was a seminal figure who articulated the conventional appraisal approaches for hotels and introduced methods for separating intangible value. Later, Chen and Kim (2010) expanded on Rushmore's techniques, and Fu, Sheel, and Lang (2013) conducted a systematic comparison of valuation methods (income capitalizations including DCF, band-of-investment models, sales comparison, cost approach, and an automated valuation model). Their research, published in *Journal of Hospitality Financial Management*, concluded that the 10-year DCF method provided the most robust estimates of hotel value among those tested. Notably, their study included an Automated Valuation Model (AVM) which did not perform as well, suggesting that while mass appraisal models can be developed, they may lack property-specific nuance. These findings reinforce industry practice that careful income analysis is paramount. However, such research also points out an area for further exploration: as more real-time data become available (for example, STR performance data, online pricing, etc.), could machine learning models one day augment or improve hotel valuations? This remains a relatively open question: currently, academic literature has not fully resolved how to integrate big data and AI into hotel valuation models, representing a modern research gap.

Despite the breadth of prior work, several conceptual and empirical gaps remain, which motivate the research developed in this thesis:

- **Integration of Operational Metrics into Valuation Models**: While it's established that KPIs like RevPAR and GOPPAR correlate with value,

there is less guidance on how exactly to integrate these metrics into valuation beyond traditional methods. Most appraisals still rely on NOI and cap rates, with KPIs as supporting indicators. The literature has pointed out the correlation, but hasn't fully developed a new valuation model that, for instance, directly uses RevPAR and profit margins to estimate value. There is room for research to create or refine hybrid models that explicitly link operational benchmarks (e.g., RevPAR indices, ADR growth rates, EBITDA margins) to cap rate determination or risk assessment. In other words, bridging the gap between hospitality management metrics and real estate valuation techniques is an ongoing challenge. This thesis addresses this gap by testing whether widely used market valuation benchmarks (e.g., price per key) systematically relate to operating performance metrics. In addition, it complements the market-based approach with an income-based valuation robustness check.

- **Focus on Profitability vs. Revenue in Analysis**: Much of the industry still trumpets RevPAR as the primary metric, and indeed many researchers have used RevPAR as an independent variable in studies of value. However, fewer studies explicitly focus on GOPPAR or NOI variability as a predictor of market value. One gap is the need for more empirical evidence on whether investors are increasingly favoring profit-based metrics over revenue metrics in pricing decisions. The HVS findings that GOPPAR better explains value need further validation across different markets and time periods. This thesis aims to contribute by analyzing market-level valuation benchmarks in relation to both RevPAR and GOPPAR (and other profit measures), to assess which has greater explanatory power in today's market, particularly in the post-COVID environment when cost structures have changed.

- **Market-specific and Segment-specific Research**: A significant gap in the literature is the relative scarcity of research focusing on European hotel markets and especially the Italian hotel market in terms of valuation. The bulk of hotel valuation research has been U.S.-centric (given data availability from sources like STR and public REIT filings in the U.S.). Concepts like cap rates, ADR-value relationships, and the efficacy of certain metrics may not directly transpose to Europe, where market dynamics and investor behavior can differ. For example, Italy's hotel sector has a much larger share of unbranded, family-owned hotels and historically lower average profitability margins than the U.S. This thesis addresses this gap by concentrating

on Europe (with a deep dive into Italy), applying the lens of operational KPIs to valuation in these markets. It will review whether findings like O'Neill's ADR vs. NOI result hold true in Italy, or whether different factors (perhaps tourism flows, or presence of international operators) play a bigger role in value formation here. Early indications from industry reports suggest Italy's market has unique traits, e.g., very low chain penetration but high RevPAR in luxury segment, warranting focused study.

- **Luxury Segment and High-End Assets**: Another gap is in segmentation, particularly the luxury hotel segment. As mentioned, one study hinted that in luxury hotels, both revenue and profit metrics need to be high for value maximization. But academic literature has not deeply explored how valuation models might need adjustment for luxury resorts vs. budget hotels. Luxury hotels often have large ancillary revenues and expenses (e.g., fine dining, spas, extensive staff) which could mean RevPAR is a less sufficient indicator of performance. There is room for more research on which KPIs best predict the value of luxury properties and whether traditional valuation (which often assumes an average margin or expense ratio) might undervalue or overvalue these assets. With the luxury segment gaining attention (as seen in industry reports of record ADRs at luxury hotels post-2021), this thesis will specifically examine the luxury hotel subset to see if the valuation drivers differ from the general hotel population.

- **Post-Pandemic Dynamics and New Variables**: The hospitality industry has gone through a tumultuous period with COVID-19, and recovery has been uneven across segments. A gap in the literature is understanding how the pandemic has altered the relationships between KPIs and value. For example, have investors changed how they evaluate hotels, placing more weight on certain metrics like breakeven occupancy or cash burn rate during crises? Are lenders now looking at different covenants (perhaps requiring minimum GOPPAR levels or DSCR linked to performance metrics)? The thesis will explore the recent literature and data to identify if the pandemic created new considerations, a topic not fully covered yet, as academic studies often lag real-world events by a couple years.

- **Intangible Asset Valuation**: Finally, although brand affiliation and management quality are widely recognized as value-relevant, their quantification remains underdeveloped in both appraisal practice and academic research. The debate on business enterprise value (e.g., the Rushmore approach versus

alternative decompositions) highlights the difficulty of separating non-real-estate components such as brand goodwill, distribution reach, and managerial know-how—from the cash flows of an operating hotel. Yet, there is limited consensus on robust and transferable methods to allocate value across tangible real estate, personal property, and intangibles. This thesis contributes to this gap by discussing and testing practical allocation logics (e.g., fee-based deductions, benchmarking approaches, and sensitivity analyses) that help interpret how intangible drivers may be reflected in observed valuation outcomes.

1.4 The European and Italian Hotel Market: Evolution, Segmentation, and Luxury Focus

The hotel industry in Europe, and in Italy in particular, has evolved markedly over the past decades, shaped by shifts in demand, the gradual entry of international brands, and, more recently, the shock and subsequent recovery triggered by the COVID-19 pandemic. This section provides an overview of the European and Italian hotel markets, highlighting key trends in their evolution, the segmentation of supply (especially the mix of independent versus chain-affiliated hotels and the distribution across service levels), and a focus on the luxury segment, which has become a major area of growth and investment. The discussion draws on industry reports and market data, with special attention to Italy and its luxury hospitality sector.

Europe remains one of the world's most mature and diverse hotel markets, spanning capital cities, cultural destinations, and resort areas. Prior to 2020, tourism and hotel performance followed a long-term upswing, with 2019 representing a peak year for many countries, including Italy. In that year, Italy recorded 97.8 million tourist arrivals, an all-time high, and—alongside Spain, France, and Germany, consistently ranked among Europe's top destinations by international arrivals. The pandemic caused an unprecedented disruption in 2020: international travel collapsed and occupancies across Europe fell to historic lows, with Italy among the countries hit earliest and hardest. Recovery since 2021–2022 has nonetheless been robust, particularly in leisure-driven markets. Tourist flows in Italy rebounded strongly by 2022, although they remained slightly below the 2019 record. The Horwath HTL Italy Hotels Chains Report 2024 notes that in 2023 Italy's tourist arrivals were still a few percentage points below 2019 (2.8% versus

2019, improving from 5.2% in 2022). Despite this residual volume gap, performance indicators in 2023 registered double-digit growth compared with 2022, reflecting strong pricing dynamics and pent-up travel demand.

At the European level, Italy's recovery has been somewhat slower than certain peers in pure volume terms, countries such as Spain and France benefited from faster domestic rebounds, yet Italy's revenue performance has been particularly strong, supported by higher spending per guest and a marked rate repositioning. By the first half of 2024, Italy recorded one of the highest performance levels in Europe. According to Cushman & Wakefield, Italy's RevPAR in H1 2024 was the second highest in Europe (after Switzerland) and increased by 5.2% relative to H1 2023, driven by a 5.7% rise in ADR. Notably, Italy's ADR in H1 2024 stood nearly 48% above the same period in 2019, indicating that the post-pandemic cycle has been characterized more by pricing power than by purely volume-driven growth. Occupancy by H1 2024 was only marginally below 2019 (roughly one percentage point lower), suggesting that demand has largely normalized, while higher rates have pushed revenues to new highs. This rate-led recovery has placed Italy "front and center" in investors' attention, particularly in segments such as luxury where ADR gains have been most pronounced.

Investment market data reinforce this shift in positioning. While European hotel investment volumes have fluctuated with the macroeconomic cycle, Southern Europe, including Italy, has attracted increasing focus in recent years. In H1 2024, hotel investment volumes in Italy reached approximately €807 million (over 30 properties and 4,477 rooms), representing a 90% increase relative to H1 2023. For the first time, Italy ranked as the fourth-largest hotel investment market in Europe during that period, behind only the UK, Spain, and France—an important development given Italy's historically lower institutional participation compared with some peers. The composition of capital also signals a broader deepening of the market, with domestic and European investors accounting for roughly 85% of volumes. Although higher interest rates have put upward pressure on European yields, prime yields in Italy remained broadly stable in H1 2024, and market commentary points to stabilization or mild sharpening as debt markets normalize. In combination, strong trading performance and a supportive investment backdrop have underpinned hotel values in Italy during the recent recovery phase.

On the supply side, Italy is characterized by an exceptionally large number of hotels, typically with small average size, and a historically low penetration of branded chains. Horwath HTL (2024) reports that Italy counts around 32,000

hotels nationwide across all categories, one of the largest totals in Europe, yet only a small fraction are affiliated with international or domestic chains. As of 2023, approximately 6–7% of Italian hotels by number are chain-affiliated, while chains account for roughly 21% of total rooms. This chain penetration rate (CPR) remains the lowest among major Western European markets; by comparison, Spain and the UK exhibit substantially higher chain presence, particularly in urban and resort submarkets. The structure is rooted in historical patterns: Italy's accommodation sector has long been dominated by family-owned hotels and small regional operators, with more aggressive expansion by global groups occurring only over the last two decades.

Nevertheless, chain presence has been rising steadily. THRENDS data indicate that between 2013 and 2024 the number of chain hotels in Italy increased by 79% (to 2,414 hotels), while chain rooms rose by 53% (to approximately 226,000). Growth has occurred both through conversions of independent properties to branded affiliations and through new developments by chains. Yet, given the very large overall base, penetration by property count has moved only gradually—from roughly 5% to about 7.5% over the period—whereas the increase is more visible in room share, now exceeding 20%. This divergence is consistent with the fact that branded hotels tend to be larger than the typical independent property: many Italian hotels have fewer than 50 rooms, whereas chain-affiliated hotels are frequently mid-sized or large, often exceeding 100 rooms.

The segmentation of Italy's supply by service level also reveals a meaningful shift in quality mix. Historically, the market included a large proportion of economy and midscale hotels (one- to three-star), aligned with mass tourism and domestic demand. In recent years, however, the upper-upscale and luxury category (five-star and five-star-luxury) has expanded more rapidly than other segments. Horwath HTL documents that from 2019 to 2023 this tier recorded a 5.3% increase in room supply, adding around 4,800 new luxury rooms. Upscale (four-star) and economy segments also grew, though at slightly lower rates, while midscale growth was comparatively modest. This pattern points to a gradual qualitative upgrading of Italian supply, driven by both new developments and repositioning/-conversions—often involving luxury brands and international operators. Within the branded universe specifically, the high-end skew is even more apparent: 32% of chain hotel rooms in Italy are classified within the upper-upscale and luxury tier.

Chain penetration also differs sharply by segment, with the luxury tier showing

a materially higher degree of branding than the market average. As of 2024, around 39% of Italy's luxury hotels (by number) are chain-affiliated, compared with roughly 7.5% across the overall hotel population. In terms of rooms, branded presence is even more pronounced at the top end: Horwath notes that 61% of five-star keys in Italy are part of brands. This reflects the strategic focus of global operators and luxury collections on Italy's trophy assets and prime destinations—an outcome that is economically intuitive, since high ADRs can support both brand fees and the costs associated with professional management and global distribution. By contrast, the midscale and lower tiers remain overwhelmingly independent, with many three-star properties still family-run or embedded in local groups; chain penetration in these segments remains in the single digits, even as franchising and standardized midscale formats (e.g., Best Western affiliations, B&B Hotels expansion) gradually expand.

Geographic segmentation further differentiates performance and pipeline dynamics. Italy comprises multiple submarkets, including major art cities such as Rome, Florence, Venice, and Milan; business hubs such as Milan, Turin, and Bologna; coastal and alpine resort destinations; and rural tourism formats such as agriturismi. In the recent cycle, art cities—particularly Rome—have exhibited strong recovery. Horwath HTL highlights Rome as the best performer among leading destinations in 2023, citing a "remarkable recovery" supported by the rebound in international demand and potential event-related boosts. Milan, Florence, and Venice also recovered, although Venice faces idiosyncratic constraints linked to overtourism management. At the same time, investor and operator attention has increasingly extended toward Southern and secondary destinations. Looking ahead, the development pipeline for 2025–2028 remains concentrated in traditional regions such as Lombardy (Milan) and Lazio (Rome), which together account for roughly 35% of planned projects, but Sicily, Puglia, and Sardinia also feature meaningfully. THRENDS reports that around 20% of upcoming projects are located in "Sun & Beach" destinations and 23% in broader leisure destinations, consistent with the rising international appeal of Southern Italy and policy efforts to broaden tourism beyond the most established northern and gateway-city circuits.

Against this backdrop, the luxury segment warrants particular attention given both its structural prominence in Italy and its outsized contribution to recent performance. Italy's cultural heritage, iconic landscapes, and lifestyle appeal have long attracted high-end travelers, with destinations such as the Amalfi Coast, Capri, Lake Como, Tuscany, and the cities of Rome, Venice, and Florence forming

core nodes of global luxury itineraries. The luxury product spans historic grand hotels (e.g., Venice's Gritti Palace and Rome's Hotel Hassler), destination resorts, and modern design-led city properties. In the post-pandemic cycle, luxury hotels have been at the forefront of the recovery, with industry sources highlighting the segment's ability to push rates aggressively as travel resumed. A THRENDS report using HotStats data emphasizes that luxury rooms performance, propelled by ADR increases, has placed the luxury tier "front and centre of investors' interest." Many luxury properties not only recovered but exceeded pre-pandemic ADR levels, with some ultra-luxury coastal assets reportedly achieving record suite rates in 2022–2023 as affluent travelers sought exclusive experiences. The same demand shift supported strong ancillary revenue growth; in some cases, wellness, spa, and leisure activities grew by more than 50% relative to pre-pandemic averages. Moreover, Italy appeared to diverge from a broader European pattern of weaker food-and-beverage profitability: while many markets experienced margin compression in F&B, Italy's food and beverage culture contributed to F&B profits in 2023 rising above 2022 and returning to 2019 levels, supporting healthy operating profitability even amid inflationary pressure on labor and utilities.

Investment and development signals are consistent with this performance narrative. Several high-profile transactions and brand entries have reinforced the perception of Italy, particularly Rome and other prime destinations, as a priority market for global luxury hospitality. Rome has seen notable activity and pipeline momentum: the Hotel Eden (Dorchester Collection) traded in 2022, the Bulgari Hotel opened in 2023, and further entries are expected from brands such as Six Senses and Orient Express. Milan similarly has continued to attract top-end flags, with brands such as Mandarin Oriental already present and an Edition planned. Beyond major cities, Belmond (LVMH) has been active in acquiring or refurbishing trophy assets, including properties in the Amalfi Coast and Tuscany. The scale of the pipeline underscores the luxury emphasis: out of approximately 409 planned hotel projects through 2028, 127 are classified in the luxury segment, representing roughly 31% of total pipeline. THRENDS further notes that 55% of new hotel openings in Italy in coming years are expected to operate under international brands, led predominantly by American, French, and UK hotel chains, and that a substantial share of these openings sits in the upscale and luxury tiers.

The luxury segment's structural positioning is reinforced by branding dynamics. Upper-upscale and luxury hotels not only expanded faster than other segments but also exhibit materially higher chain affiliation, suggesting an ongoing consolidation of trophy assets under global operators. Horwath HTL reports that 61% of

five-star and five-star-luxury rooms in Italy are branded, the highest brand penetration across Italian segments. This reflects both demand-side dynamics—luxury travelers' trust in established brands and loyalty ecosystems—and owner-side incentives to secure international distribution and professional management. In performance terms, luxury has contributed meaningfully to Italy's broader RevPAR leadership within Europe. Italy's second-highest RevPAR ranking in Europe in 2024 is partly consistent with a luxury segment that commands exceptionally high ADRs, similar in direction to Switzerland's top ranking as another market with many luxury destinations. In peak season, destinations such as the Amalfi Coast and Capri now exhibit ADR levels among the highest globally. At the same time, industry commentary raises a natural question regarding sustainability: the Luxury Hospitality Report 2023 by THRENDS asks whether the segment can maintain an "unprecedented pace" of ADR and revenue growth, given the potential for normalization in travel patterns and increased competitive supply in certain markets. Nonetheless, evidence from HotStats cited by THRENDS indicates that by late 2023 some Italian luxury hotels had achieved GOPPAR above pre-pandemic levels, whereas profitability in several other European markets was still catching up.

Within Italy, luxury performance and risk characteristics also differ materially between city and resort assets. City luxury in Rome, Milan, Florence, and Venice benefits from diversified demand drivers, high-end leisure, corporate travel, diplomatic and institutional flows, and event-related peaks, particularly in Rome and Milan. Resort luxury in destinations such as Sardinia's Costa Smeralda or Tuscan countryside estates remains more seasonal and leisure-dependent, often tied to ultra-wealthy clientele. Post-pandemic, resort luxury surged as travelers prioritized privacy and exclusive getaways; destinations such as Capri and Costa Smeralda reportedly experienced demand outstripping supply in summer 2022, supporting double-digit ADR increases. City luxury similarly rebounded once long-haul connectivity normalized: Rome's luxury market reportedly sold out around major events such as the 2023 Ryder Cup, and Milan's luxury inventory during Fashion Weeks, at ADR levels exceeding €1,000. A related development has been the rise of luxury "lifestyle" formats and large-scale refurbishments, expanding the luxury offer beyond traditional grand hotels. Brands such as Marriott's EDITION and Hyatt's Andaz illustrate this shift, as do hybrid concepts combining hotels with branded residences. For example, in 2025 the first Orient Express Hotel (Accor) is planned to open in Rome in the historic Palazzo Banchi, blending heritage positioning with contemporary luxury, an emblematic signal of

Italy's attractiveness for globally recognized premium concepts.

Industry data also provide quantitative support for the demand–supply backdrop that has enabled strong KPI outcomes. Cushman & Wakefield's Italy Marketbeat 2024 reports modest supply growth (approximately +1.7% in rooms in H1 2024 versus the prior year), implying that rising demand translated primarily into stronger occupancy and higher ADR rather than being diluted by rapid new supply additions. This is particularly relevant in historic city centers, where development constraints structurally limit new inventory. On the demand side, 2023–24 performance has been supported by international tourism. Bank of Italy data cited indicate 168 million foreign visitor nights in H1 2024, up 4% year-on-year, alongside 129 million domestic nights, up 9% year-on-year. The return of American travelers has been especially supportive for luxury, given their historically high spending propensity in Italy and the tailwind from a strong dollar in 2022–2023. The domestic market also expanded meaningfully, with a higher percentage increase, even if average spending per night typically remains lower than for international guests. The combination of high-spend international demand and constrained new supply has therefore played a key role in driving KPI improvements and supporting value expectations.

Finally, Italy's low chain penetration is widely interpreted not as a structural weakness but as a strategic opportunity. With only about 21% of rooms affiliated to chains, Italy remains "under-branded" relative to markets such as Spain, where branded operators dominate many resort areas. This has attracted interest from large international groups, several of which have announced growth plans, including Minor Hotels (Anantara), Accor, and Hilton. Domestic chains such as Gruppo UNA and Starhotels continue to expand as well, albeit at a more gradual pace. The breadth of brand entry illustrates the market's increasing segmentation: by end-2024, 84 international hotel chains with 178 brands were operating in Italy, more than double the number recorded in 2013. This proliferation reflects both competition and differentiation, as Italy's luxury landscape shifts from being dominated by a handful of iconic independent hotels to a broader spectrum of branded luxury propositions, classic, boutique, and lifestyle.

Public–private initiatives further shape the sector's evolution, particularly in the context of quality upgrading and major international events. National and regional authorities have recognized the need to modernize and renovate hotel infrastructure, including in preparation for the 2026 Winter Olympics in Milan–Cortina. Renovation incentives and related funding mechanisms have thus

become part of the broader market narrative. Horwath HTL highlights expectations for stronger public–private collaboration in emerging regions to support the qualification of hotel supply, a theme that is especially relevant for Southern Italy where improvements in airports and transport infrastructure can unlock additional high-end development potential.

Taken together, the European and Italian hotel markets have emerged from the pandemic with renewed strength, with performance particularly concentrated in upscale and luxury segments. Italy exhibits a clear evolution toward higher-quality and more branded supply while retaining a large independent base, and the current cycle has been shaped by strong international leisure demand, constrained supply growth in many submarkets, and a strategic push by luxury operators. The luxury segment, in particular, has expanded faster than other tiers, captured outsized revenue gains, and attracted substantial investment into trophy assets across prime urban and resort destinations. Although an open question concerns the sustainability of extraordinary ADR levels as travel patterns normalize and additional luxury supply enters certain markets, current evidence points to a segment that is still delivering record performance and strong profitability outcomes.

From a valuation perspective, these market characteristics, rising RevPAR and GOPPAR, quality upgrading, and intensified investor focus on luxury—provide a fertile setting for the empirical analysis developed in this thesis. Recent performance trends offer tangible evidence that operating outcomes (notably higher ADR and RevPAR) are influencing investment behavior and valuation expectations in real time. Italy's combination of low chain penetration, rapid luxury expansion, and pronounced destination differentiation therefore constitutes a compelling context in which to study how KPIs and market dynamics interact with valuation benchmarks, and the subsequent chapters build on this overview by focusing on the Italian upscale and luxury market as the empirical setting to test how operational performance and market structure relate to hotel valuation outcomes.

Chapter 2

Methodology and empirical analysis

2.1 Research Design and Scope of the Analysis

The empirical investigation developed in this thesis aims to rigorously assess the relationship between operational performance indicators and the value of hotel assets in the Italian market, with particular emphasis on the upscale and luxury segments. As established in Chapter 1, hotels represent a hybrid asset class that combines real estate characteristics with the operational dynamics of a service-intensive business. This dual nature complicates traditional valuation approaches, which often struggle to fully capture the contribution of operating performance to asset value. Consequently, a performance-based perspective is required to adequately reflect the economic fundamentals of hotel assets. Accordingly, the analysis adopts a market-based value proxy (€/key) as the main outcome, while income-based measures are used as robustness checks.

This section outlines the research design and scope of the empirical analysis, defining the analytical framework that guides the construction of the dataset, the selection of variables, and the econometric methodology adopted in subsequent sections. The research design is explicitly grounded in the theoretical insights and market evidence discussed in Chapter 1, ensuring consistency between the conceptual framework and the empirical investigation.

The thesis adopts a quantitative panel data approach, which allows for the simultaneous exploitation of cross-sectional and temporal variation in the data. This methodological choice is particularly appropriate for the hospitality sector, where both asset values and operating performance evolve over time in response to market cycles, demand fluctuations, and pricing strategies. By analyzing mul-

tiple destinations and hotel segments over several years, the panel structure helps to explore systematic associations, rather than relying on purely cross-sectional correlations.

The empirical scope of the analysis is deliberately focused on the Italian hotel market. Italy represents one of Europe's leading tourism destinations and exhibits a heterogeneous hospitality landscape characterized by strong international demand, significant regional differentiation, and a relatively low penetration of international hotel chains. These features make Italy a particularly suitable case study for examining valuation models that incorporate operational performance indicators. Within this context, the analysis concentrates on the upscale and luxury segments, which are more capital-intensive, attract a higher level of institutional investment, and display more complex revenue structures due to the relevance of non-room revenues.

From a temporal perspective, the study covers the period 2022–2024, capturing the post-pandemic recovery phase of the hospitality sector. This period is marked by substantial changes in occupancy levels, pricing strategies, and profitability, particularly in prime urban and resort destinations. Focusing on this timeframe allows the analysis to capture valuation-performance relationships in a dynamic market environment shaped by recovery-driven demand and evolving investor expectations. Given the short time window, the empirical evidence should be interpreted as primarily associational and indicative, rather than as causal estimates.

The empirical strategy is structured in sequential steps. First, a dataset is constructed by integrating operational performance indicators and valuation benchmarks from multiple industry sources. Second, hotel asset values are proxied primarily using a market-based measure, while income-based measures commonly employed in professional valuation practice are used as robustness checks. Third, econometric models are specified to examine the association between operational KPIs and asset values while controlling for location-specific and time-specific effects. Finally, the results are interpreted in light of existing literature to assess their theoretical and practical implications.

By clearly defining the research design and scope of the analysis, this section provides the conceptual bridge between the theoretical foundations developed in Chapter 1 and the empirical results presented in the subsequent sections. The next section focuses on the selection of the sample and the data sources employed, laying the groundwork for the construction of the empirical dataset.

2.2 Sample Selection and Data Sources

The empirical analysis conducted in this thesis is based on a carefully defined sample and on the integration of multiple industry data sources. The selection of the sample and the identification of appropriate data providers are guided by the overarching research objective of assessing how operational performance indicators are associated with hotel asset values within a consistent empirical framework.

The analysis focuses on the Italian hotel market, with particular attention to the upscale and luxury segments. This focus is motivated by several interrelated considerations. First, these segments are characterized by higher capital intensity and greater exposure to institutional investment, making valuation issues particularly relevant from a real estate finance perspective. Second, upscale and luxury hotels typically exhibit more complex revenue structures, with a significant contribution from non-room revenues such as food and beverage, wellness, and ancillary services. As discussed in Chapter 1, this complexity strengthens the rationale for adopting a performance-based valuation approach that goes beyond traditional real estate metrics. Third, these segments are more consistently covered by professional data providers, which enhances data availability and comparability across markets.

From a geographic standpoint, the sample includes the main Italian urban and resort destinations that concentrate the majority of hotel investment activity and international demand. These markets generally include major cities such as Rome, Milan, Florence, and Venice, alongside selected leisure destinations with a strong upscale or luxury positioning. Focusing on these locations allows the analysis to capture heterogeneous market conditions—such as differences in demand drivers, seasonality, and pricing power—while maintaining a coherent investment context in which valuation benchmarks and performance indicators are meaningfully comparable.

The temporal scope of the analysis covers the period 2022–2024, corresponding to the post-pandemic recovery phase of the hospitality sector. This timeframe is particularly relevant for empirical investigation, as it reflects a period of rapid adjustment in operating performance, pricing strategies, and investor expectations. During these years, key indicators such as occupancy, Average Daily Rate (ADR), and Revenue per Available Room (RevPAR) experienced substantial changes, especially in prime destinations. By focusing on this interval, the study avoids

distortions associated with the exceptional market conditions observed during the height of the COVID-19 crisis, while still capturing a dynamic and economically meaningful environment. At the same time, the limited time span implies that findings should be interpreted as indicative evidence rather than as causal estimates.

Data used in the empirical analysis are drawn from a combination of industry reports and market intelligence sources widely recognized in both academic research and professional hospitality practice. Operational performance indicators are sourced from reports that systematically monitor hotel KPIs by destination and segment, providing consistent measures of pricing, occupancy, revenue, and profitability. These data are complemented by market-level information on hotel investment benchmarks, including price per room and capitalization rates, which are commonly employed as proxies for asset values when transaction-level data are not publicly available.

The integration of multiple data sources serves several methodological purposes. First, it allows for the combination of operational and financial dimensions of hotel performance, which is central to the research question of this thesis. Second, it facilitates cross-validation of information across different reports, reducing the risk of measurement error and enhancing the overall reliability of the dataset. Where data are reported in aggregated form or as value ranges, consistent criteria are applied to ensure comparability across observations and over time.

The unit of observation adopted in the analysis is defined at an aggregated market level, combining information by destination, hotel segment, and year. This choice reflects the structure of the available data and aligns with common practices in hospitality real estate research when property-level transaction data are unavailable. While this level of aggregation limits the ability to capture idiosyncratic characteristics of individual assets, it allows the analysis to explore systematic associations between performance indicators and valuation benchmarks across markets and segments. This also implies that the empirical results should be interpreted as market-level evidence and may not directly translate to property-level valuation dynamics.

Overall, the sample selection and data sourcing strategy are designed to balance empirical rigor, data availability, and practical relevance. By focusing on well-defined market segments, a coherent geographic scope, and a recent yet economically significant time horizon, the dataset provides a solid foundation for the definition of variables and the construction of the empirical models developed in

the following section.

2.3 Variable Definition and Dataset Construction

This section provides a structured overview of the variables employed in the empirical analysis and outlines the process through which the dataset is constructed and prepared for econometric estimation. Building on the research design and data sources discussed in the previous sections, the purpose of this section is to formally define the analytical components of the empirical framework while ensuring transparency and replicability.

In line with the research objectives of the thesis, the empirical framework distinguishes between variables capturing hotel asset value and variables reflecting operational performance. Given the hybrid nature of hotel assets, as discussed in Chapter 1, the definition of variables follows a performance-based valuation logic, whereby operating outcomes are explicitly linked to asset value proxies. To mitigate mechanical overlap between constructed valuation measures and operating KPIs, the empirical analysis primarily relies on a market-based value proxy (€/key), while income-based proxies are used as robustness checks. This approach is consistent with both academic literature and professional valuation practice in hospitality real estate.

The construction of the dataset involves the integration of operational performance indicators and market-based valuation benchmarks sourced from multiple industry reports. Due to the absence of publicly available transaction-level data for individual hotel assets, the dataset is assembled at an aggregated market level, combining information by destination, hotel segment, and year. This level of aggregation reflects the structure of the available data and allows for meaningful cross-sectional and temporal comparisons across markets.

Special attention is devoted to the definition and measurement of each variable, including units of measurement, transformation procedures, and consistency across data sources. Where necessary, standardized definitions and harmonization criteria are applied to ensure comparability across destinations and over time. These methodological choices are intended to minimize measurement inconsistencies and improve the comparability of the empirical results. The section is organized as follows. Subsection 2.3.1 introduces the dependent variable, focusing on the proxies used to represent hotel asset value and the rationale behind their selection. Subsection 2.3.2 defines the independent variables, namely the

key operational performance indicators employed to explain asset values. Finally, Subsection 2.3.3 describes the structure of the dataset and presents descriptive statistics that provide an initial overview of the data used in the empirical analysis.

By clearly defining the variables and outlining the dataset construction process, this section establishes the foundation for the econometric models specified in the subsequent section. The careful articulation of variable definitions and data structure ensures that the empirical results presented later can be interpreted within a well-defined and transparent analytical framework.

2.3.1 Dependent Variable: Hotel Asset Value

The dependent variable in the empirical analysis captures **hotel asset value**, the main outcome of interest of this study. Valuing hotels poses well-known empirical challenges because hotels are hybrid assets: they combine the characteristics of income-producing real estate with those of an operating business. As a result, hotel values reflect not only location and physical attributes, but also operating performance and market conditions.

A key limitation in hospitality real estate research is the scarcity of publicly available transaction-level prices at the individual property level. Hotel deals are relatively infrequent, often confidential, and heterogeneous in terms of asset quality and contract structure. To address this constraint and enable cross-sectional and time-series analysis, the study relies on market-level valuation benchmarks sourced from professional industry reports.

Main dependent variable (market-based). The baseline specification uses the market price per key (EUR per room) as the primary proxy for hotel asset value. This measure is widely used in investment practice as a standardized benchmark of pricing dynamics across destinations. In the dataset, price-per-key observations are available at the destination–year level and therefore reflect market-wide valuation conditions rather than individual asset-level prices. For econometric estimation, the dependent variable is expressed in logarithms, i.e. ln(price per key), so that coefficients can be interpreted as elasticities.

Alternative dependent variable (income-implied, robustness). As an additional valuation perspective, the analysis constructs an income-based proxy based on a capitalization approach. Specifically, an income-implied value per key is computed using a market cap rate and an estimate of Net Operating Income (NOI),

consistent with standard real estate valuation logic. This measure is used only as a robustness check to assess whether the empirical relationship between operating performance and market value is qualitatively consistent under an alternative valuation framework.

All dependent-variable measures are aligned with the structure of the available data and are defined at an aggregated market level. While this aggregation limits the ability to capture asset-specific heterogeneity, it is consistent with established empirical approaches in hospitality real estate when transaction-level prices are unavailable and ensures comparability across destinations and over time.

Table 2.1: Variable definitions and transformations

Variable (dataset)	**Definition**	**Unit**	**Transformation used in regressions**
`price_per_key_market`	Market-based hotel asset value proxy (price per key) at destination–year level	EUR per key	`ln_price_per_key_market = ln(price_per_key_market)`
`income_value_per_key_adj`	Income-implied hotel asset value proxy (NOI / cap rate), adjusted, aggregated to destination–year (rooms-weighted)	EUR per key	`ln_income_value_per_key_adj = ln(income_value_per_key_adj)`
`trevpar`	Total Revenue per Available Room	EUR	`ln_trevpar = ln(trevpar)`
`goppar`	Gross Operating Profit per Available Room	EUR	`ln_goppar = ln(goppar)`
`revpar`	Revenue per Available Room	EUR	`ln_revpar = ln(revpar)`
`adr`	Average Daily Rate	EUR	Level (not used as main regressor in baseline models)
`occupancy`	Occupancy rate	% (0–100)	Level (not used as main regressor in baseline models)
`rooms_supply`	Total room supply (market size); used for weighting segment-level aggregation	Number of rooms	Used as weights to aggregate segment data to destination–year
`cap_rate`	Market capitalization rate used in the income-implied valuation	%	Level (input to income-implied DV construction)

2.3.2 Independent Variables: Operational Performance Indicators

The independent variables in the empirical analysis consist of a set of operational performance indicators (Key Performance Indicators, KPIs) commonly used in the hospitality industry to assess revenue generation, pricing power, and operating profitability. These indicators are selected to capture the main channels through which hotel operations are expected to translate into asset value, consistent with the performance-based valuation perspective discussed in Chapter 1. In the hotel sector, valuation benchmarks such as price per key are ultimately linked to the market's ability to generate sustainable revenues and operating profits, adjusted for risk and perceived stability of cash flows. Accordingly, the KPI set is designed to measure the operating fundamentals that investors and valuers routinely monitor when forming expectations about value.

The KPI selection is guided by both conceptual relevance and data structure. First, the variables reflect distinct economic mechanisms: (i) the strength of demand and room-revenue monetization; (ii) the contribution of ancillary revenues (particularly relevant for upscale and luxury markets); and (iii) the ability to convert revenues into operating profit through cost efficiency and operating leverage. Second, the dataset is constructed at an aggregated market level (destination–year), meaning that the indicators represent market-wide operating conditions rather than property-level performance. This aggregation is consistent with the objective of explaining variation in market valuation benchmarks across destinations and over time. A central empirical issue in hospitality data is that several KPIs are mechanically related. For example, RevPAR is defined by the interaction of ADR and occupancy, and TRevPAR includes revenue components that overlap with room-revenue indicators. Estimating models that include multiple closely related KPIs simultaneously would raise multicollinearity concerns and complicate interpretation. For this reason, the baseline econometric design adopts three separate specifications, each focusing on one core KPI at a time. This approach preserves transparency and allows the analysis to compare how different dimensions of operating performance relate to market asset values.

Baseline KPI set (main regressors). The three KPIs used as the primary explanatory variables are:

- **Revenue per Available Room (RevPAR)**: RevPAR is a standard measure of room-revenue performance per unit of available capacity and sum-

marizes the combined effect of demand intensity and pricing effectiveness in the accommodation business. Higher RevPAR is expected to be associated with higher asset values because it signals stronger revenue-generating potential in the core operating activity of hotels.

- **Total Revenue per Available Room (TRevPAR)**: TRevPAR extends RevPAR by incorporating all operating revenue streams, including food and beverage, meetings and events, wellness services, and other ancillary activities. This indicator is particularly relevant for upscale and luxury destinations, where non-room revenues can represent a substantial share of total income and may enhance resilience through revenue diversification. Higher TRevPAR is therefore expected to be positively related to market valuations by capturing broader monetization capacity beyond room sales.

- **Gross Operating Profit per Available Room (GOPPAR)**: GOPPAR measures gross operating profitability per unit of available capacity and reflects both revenue generation and cost control. From a valuation standpoint, GOPPAR is closely linked to the market's ability to convert revenues into operating profits, thereby supporting higher and more sustainable cash flows. It is therefore expected to exhibit a strong positive relationship with asset values, particularly when investors emphasize profitability and operating efficiency.

All baseline KPI regressors enter the econometric models in logarithmic form (ln). Log-transformations improve comparability across destinations, mitigate scale effects, and enable interpretation of coefficients in elasticity terms. In addition to these core regressors, the dataset includes other operational indicators such as Average Daily Rate (ADR) and occupancy, which are useful for descriptive analysis and contextual interpretation of market conditions. However, given their definitional overlap with RevPAR-based metrics, these variables are not included as simultaneous regressors in the baseline specifications.

Table 2.2: Operational performance indicators (KPIs): definitions, units, and transformations

Variable (dataset)	**Definition / interpretation**	**Unit**	**Transformation used**	**Sign**
`revpar`	Revenue per Available Room; summary measure of room-revenue performance (captures demand and pricing). Often defined as ADR × Occupancy.	EUR	`ln_revpar = ln(revpar)`	+
`trevpar`	Total Revenue per Available Room; extends RevPAR by including all revenue streams (rooms + ancillary revenues such as F&B, meetings, wellness).	EUR	`ln_trevpar = ln(trevpar)`	+
`goppar`	Gross Operating Profit per Available Room; operating profitability per unit of available capacity (reflects revenue generation and cost efficiency).	EUR	`ln_goppar = ln(goppar)`	+
`adr`	Average Daily Rate; average achieved room price (pricing power / positioning). Used for descriptive context.	EUR	Level	+*
`occupancy`	Occupancy rate; rooms sold as a share of rooms available (demand intensity). Used for descriptive context.	%	Level	+*

*Notes:*Baseline regressions estimate three separate specifications, each including one core KPI (RevPAR, TRevPAR, or GOPPAR) to avoid mechanical overlap and multicollinearity (e.g., RevPAR depends on ADR and occupancy).

The independent variables are designed to capture complementary dimensions of hotel market performance, top-line monetization (RevPAR and TRevPAR) and bottom-line operating profitability (GOPPAR). The use of separate model specifications reflects the need to avoid mechanical overlap among KPIs while maintaining interpretability and empirical robustness.

2.3.3 Dataset Structure and Descriptive Statistics

The empirical analysis relies on a purpose-built dataset constructed at an aggregated market level, reflecting the limited availability of publicly accessible hotel-level transaction prices and financial statements. This approach is consistent with established practices in hospitality real estate research, where destination-level benchmarks are commonly employed to study how operating performance and valuation dynamics co-move across markets and segments over time.

The raw dataset is initially organized at the **destination–segment–year** level. Each observation captures the average operational performance, profitability, and valuation characteristics of a specific hotel segment (upscale or luxury) within a given destination and year. The dataset covers five major Italian hotel markets, **Milan, Rome, Florence, Venice, and the Amalfi Coast**, over the period **2022–2024**, resulting in a balanced panel of **30 observations** (5 destinations $\times$ 2 segments $\times$ 3 years). The balanced configuration enhances comparability across observations and avoids the need for imputation or corrections related to missing values, ensuring consistency across variables and years.

For the econometric analysis, the unit of observation is the **destination–segment–year**. Each observation captures average performance and valuation conditions for a given segment (upscale or luxury) within a destination and year. The resulting dataset forms a balanced panel of 30 observations (5 destinations $\times$ 2 segments $\times$ 3 years), which allows the empirical models to exploit both cross-sectional differences across destinations and segments and within-entity variation over time.

The dataset includes a comprehensive set of variables capturing operating performance, profitability, valuation outcomes, and structural market characteristics. Operational performance is measured through standard hospitality KPIs widely adopted in both professional practice and academic research, including **Average Daily Rate (ADR)**, **occupancy rate**, **Revenue per Available Room (RevPAR)**, **Total Revenue per Available Room (TRevPAR)**, and **Gross Operating Profit per Available Room (GOPPAR)**. In line with the econometric strategy, the baseline specifications use these KPIs in **logarithmic form** when appropriate, allowing estimated coefficients to be interpreted as elasticities and reducing the sensitivity of results to scale differences across markets.

Two valuation measures are available in the dataset framework: an income-based proxy derived from capitalization logic and a market-based benchmark.

Consistent with the final empirical strategy, the baseline regressions use the **market-based price per key** as the primary valuation proxy, operationalized as ln(Price per Key Market). This choice strengthens identification by anchoring the dependent variable to an external market benchmark, rather than relying on valuation measures mechanically derived from operating variables included on the right-hand side of the regression. Income-based valuation measures remain informative for validation and interpretation but are not treated as the main dependent variable in the baseline models.

Structural market characteristics are captured through controls that proxy for destination size and institutionalization. In particular, the dataset includes room supply as an indicator of market scale and chain penetration as a proxy for the degree of brand presence and institutional development in each destination. These variables are expected to capture persistent cross-market differences that may influence both performance and valuation conditions. Consistent with their slow-moving nature, these structural indicators exhibit limited year-to-year variation over the short 2022–2024 horizon and are therefore interpreted primarily as cross-sectional controls rather than short-run drivers of valuation changes.

For clarity, Table 2.3 reports destination-year averages (N = 15), while the regression sample is defined at the destination-segment-year level (N = 30).

Table 2.3: Descriptive statistics (destination–year regression sample)

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**
Price per key (market)	243387.33	150441.61	113636.00	693277.00	15
ADR	218.83	16.15	185.86	239.93	15
Occupancy	64.09	4.73	53.85	69.55	15
RevPAR	139.71	13.64	115.74	157.87	15
TRevPAR	194.45	18.13	163.90	217.38	15
GOPPAR	44.66	5.59	36.12	51.65	15
Income value per key (income-based)	848.22	49.35	761.21	913.72	15
Room supply	19060	10082	7300	34000	15
Chain penetration	0.631	0.078	0.508	0.717	15
Cap rate	0.0417	0.0032	0.0375	0.0450	15

Notes: Statistics are computed on the destination–year aggregation used in the baseline regressions (5 destinations × 3 years = 15 observations). Destination-level KPIs are constructed as room-supply-weighted averages across segments (upscale and luxury). Price per key (market) is the market-based valuation benchmark used to compute `ln_price_per_key_market`.

Table 2.3 provides an overview of the empirical variation in the key operational, profitability, valuation, and structural variables used in the regression analysis. The summary statistics highlight meaningful dispersion across destinations and years, consistent with the heterogeneity of performance and market conditions characterizing Italian upscale and luxury hotel markets during the post-pandemic recovery period.

The operating environment exhibits clear differences between markets. **ADR** averages approximately **218.8 €**, with a variation ranging from about 185.9 € to 239.9 €, reflecting differences in positioning and pricing power between destinations. **Occupancy** averages roughly **64.1%**, with a range between 53.9% and 69.6%, indicating heterogeneous demand recovery patterns across markets. Con-

sistent with these patterns, room revenue performance, captured by **RevPAR**, shows a mean of approximately **139.7 €**, while **TRevPAR** averages about **194.4 €**, underlining the relevance of ancillary revenue streams for higher-end destinations and segments. Profitability conditions also vary substantially: **GOPPAR** averages around **44.7 €**, with values ranging from roughly 36.1 € to 51.7 €, suggesting that destinations differ not only in revenue generation but also in their ability to translate revenues into operating profits.

Valuation benchmarks display particularly pronounced dispersion. The market-based **Price per Key Market** shows substantial variation between destinations and years, with values ranging from approximately **113,636 €** to **693,277 €** per key. This wide range is consistent with strong differences in perceived risk, demand depth, and investor appetite across Italian hotel markets, especially between prime urban destinations and leisure-oriented markets. Finally, structural variables confirm meaningful heterogeneity in market scale and institutionalization: **room supply** ranges widely between destinations, and **chain penetration** exhibits variation consistent with differences in branded presence across Italian markets.

Taken together, the dataset structure and descriptive statistics provide a coherent and empirically meaningful setting for the econometric analysis developed in the following section. The combination of cross-sectional dispersion between destinations and time variation over the 2022–2024 period generates sufficient identifying variation to study how operational performance indicators relate to market-based hotel asset valuation benchmarks within a consistent analytical framework.

2.4 Econometric Model Specification and Estimation Method

This section outlines the econometric framework adopted to investigate the relationship between hotel operating performance and asset valuation in the Italian upscale and luxury hotel markets. The objective is to formally test whether and to what extent variation in destination-level performance indicators translates into variation in market-based valuation benchmarks across destinations and over time.

The empirical analysis is conducted using a balanced panel dataset constructed at the destination–segment–year level. The panel includes five Italian hotel des-

tinations (Milan, Rome, Florence, Venice and the Amalfi Coast), two segments (upscale and luxury), and three years (2022–2024), resulting in a total of 30 observations ($5 \times 2 \times 3$). Segment-level information (upscale and luxury) is incorporated in the construction of destination-level indicators through **room-supply weighted aggregation**, ensuring that the resulting series reflect destination-wide market conditions rather than segment-specific fluctuations.

Although the time dimension is short, the dataset displays meaningful cross-sectional dispersion across destinations, as well as time variation associated with the post-pandemic recovery phase. The empirical strategy therefore focuses on identifying systematic associations between operating performance and valuation benchmarks in a compact but economically relevant panel setting.

The baseline dependent variable is the **market-based price per key benchmark**, expressed in logarithmic terms:

$$Y_{d,s,t} = \ln\big(\text{Price per Key}_{d,s,t}^{Market}\big)$$

where d indexes destinations, s indexes segments, and t indexes years. Using a market-based benchmark strengthens the empirical design by anchoring the outcome variable to an external valuation proxy rather than to a measure mechanically derived from operating performance. This is particularly important in hospitality markets, where income-based valuations may embed assumptions that are closely related to operating metrics included among regressors.

Hotel operational performance is captured through standard hospitality KPIs. A central modelling issue is that several KPIs are mechanically related (e.g., RevPAR depends on ADR and occupancy), which can introduce multicollinearity and blur economic interpretation. For this reason, the baseline empirical strategy estimates **three separate specifications**, each focusing on one core KPI that represents a different dimension of operating performance.

The baseline models are specified as:

$$\ln\big(\text{Price per Key}_{d,s,t}^{Market}\big) = \alpha + \beta \ln(\text{KPI}_{d,s,t}) + \delta_t + \varepsilon_{d,s,t}$$

where δ_t denotes **year fixed effects** that absorb common macroeconomic and industry-wide shocks (e.g., inflation, travel demand normalization, financing conditions) affecting all destinations in a given year, and $\varepsilon_{d,s,t}$ is the idiosyncratic error term.

The three baseline models are:

1. **Revenue diversification and total top-line performance**

$$\ln\big(\text{Price per Key}_{d,s,t}^{Market}\big) = \alpha + \beta \ln(\text{TRevPAR}_{d,s,t}) + \delta_t + \varepsilon_{d,s,t}$$

   TRevPAR captures the ability of destinations to generate revenues beyond rooms (e.g., food & beverage, meetings, wellness), which is particularly relevant for upscale and luxury markets.

2. **Operating profitability and efficiency**

$$\ln\big(\text{Price per Key}_{d,s,t}^{Market}\big) = \alpha + \beta \ln(\text{GOPPAR}_{d,s,t}) + \delta_t + \varepsilon_{d,s,t}$$

   GOPPAR reflects the capacity to translate revenues into operating profit and is therefore expected to be closely linked to valuation through the cash-flow channel.

3. **Room-driven revenue performance**

$$\ln\big(\text{Price per Key}_{d,s,t}^{Market}\big) = \alpha + \beta \ln(\text{RevPAR}_{d,s,t}) + \delta_t + \varepsilon_{d,s,t}$$

   RevPAR provides a synthetic measure of room revenue generation, combining pricing power and demand intensity.

All three KPIs are modelled in logarithms to improve comparability across destinations, reduce scale effects, and allow estimated coefficients to be interpreted as elasticities.

To account for persistent differences across destinations that may influence valuation benchmarks, extended specifications incorporate structural market controls:

$$\ln\big(\text{Price per Key}_{d,t}^{Market}\big) = \alpha + \beta \ln(\text{KPI}_{d,s,t}) + \gamma_1 \ln(\text{RS}_d) + \gamma_2 \,(\text{CP}_d) + \delta_t + \varepsilon_{d,s,t}$$

where RS_d denotes Room Supply and CP_d denotes Chain Penetration. Room supply proxies market scale and depth, while chain penetration captures institutionalization and brand presence. Over a short horizon such as 2022–2024, these variables exhibit limited within-destination variation and are therefore interpreted primarily as structural controls.

Models are estimated using *Ordinary Least Squares* with year fixed effects. Given the small sample size and the limited number of destinations, inference is conducted using **heteroskedasticity-robust standard errors**, and where appropriate results are also reported using **destination-clustered standard errors** as a sensitivity check. Because the number of clusters is small, clustered inference should be interpreted with caution and results are discussed primarily in terms of economic magnitude, sign consistency across specifications, and robustness to alternative modelling choices.

Finally, to assess the stability of the estimated relationships, the empirical analysis includes robustness exercises designed to verify that findings are not driven by a single destination. In particular, a **leave-one-destination-out** procedure re-estimates the baseline models repeatedly excluding one destination at a time, allowing the analysis to evaluate whether estimated effects remain qualitatively stable across subsamples.

Overall, the econometric framework described in this section provides the foundation for the empirical results presented in the following chapter, where coefficient estimates are interpreted considering hospitality valuation theory and the institutional features of the Italian upscale and luxury hotel market.

2.5 Empirical Results and Interpretation

This section presents and discusses the empirical evidence on the relationship between hotel operating performance and asset valuation in the Italian upscale and luxury segments. The analysis is conducted on the balanced destination–segment–year panel described in Section 2.3, and it is designed to separate (i) **cross-sectional differences** across markets and segments from (ii) **within-entity variation** over time.

Consistent with the econometric framework outlined in Section 2.4, the empirical strategy proceeds in two steps. First, **pooled specifications** with year and segment fixed effects provide a benchmark description of the overall association between valuation and performance across the sample. Second, **entity fixed effects models** (destination–segment fixed effects) exploit within-entity changes over time and therefore deliver a more conservative identification of the relationship, net of time-invariant market characteristics. Throughout, standard errors are computed using heteroskedasticity-robust (HC1) procedures to mitigate small-sample sensitivity, and results are interpreted as associations consistent

with valuation mechanisms, rather than as strict causal estimates.

Table 2.4: Pooled OLS Results (log-log specifications)

	(1) TRevPAR	**(2) GOPPAR**	**(3) RevPAR**
`ln_trevpar`	4.3440***		
	(1.2096)		
`ln_goppar`		4.0019***	
		(1.1387)	
`ln_revpar`			4.3440***
			(1.2096)
Intercept	-10.7299*	-2.9170	-8.9685
	(6.3808)	(4.2921)	(5.8907)
C(year_cat)[T.2023]	-0.7967***	-0.9371***	-0.7967***
	(0.3037)	(0.3355)	(0.3037)
C(year_cat)[T.2024]	-1.0039***	-1.2508***	-1.0039***
	(0.3453)	(0.4055)	(0.3453)
C(segment)[T.Upscale]	1.0350***	1.0630***	0.5773***
	(0.3010)	(0.3013)	(0.2037)
R-squared	0.2781	0.2585	0.2781
Adjusted R-squared	0.1626	0.1398	0.1626
Observations	30	30	30
SE	HC1 robust	HC1 robust	HC1 robust
Segment FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 2.4 reports pooled estimates in which the dependent variable is the logarithm of market-based hotel valuation (**ln(Price per Key)**) , regressed on alternative operational performance indicators. Year indicators are interpreted relative to 2022 (omitted base category). Each model includes **year fixed effects** and **segment fixed effects** to net out common macro shocks and systematic differences between upscale and luxury. Because several KPIs are mechanically related

(e.g., RevPAR derives from ADR and occupancy), performance measures are introduced **one at a time** (or in limited combinations) to avoid multicollinearity and to allow a clean interpretation of each coefficient.

Across pooled specifications, the estimated coefficients confirm a strong positive association between operating performance and valuation. In economic terms, the log-log formulation implies that coefficients can be interpreted as **elasticities**: a one-percent increase in the KPI is associated with an approximate percentage change in valuation. This transformation improves interpretability and attenuates scale effects that would otherwise make comparisons across destinations less transparent. Coefficients on dummy variables (year indicators and the segment dummy) are semi-elasticities and can be interpreted as approximate percentage differences relative to the omitted base category.

To complement the regression evidence, Figure 2.1 provides a visual representation of the baseline relationship between valuation and total revenue generation capacity.

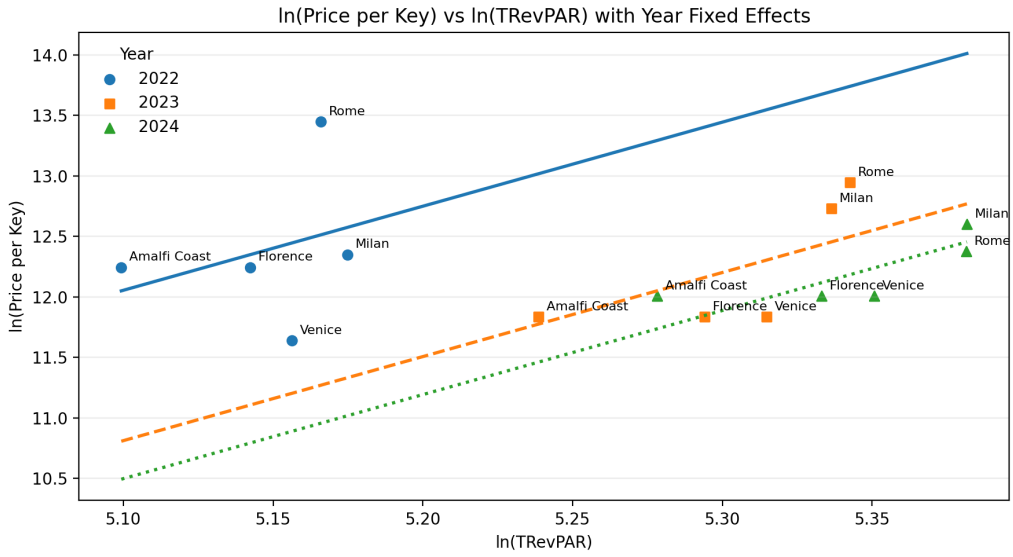

Figure 2.1: ln(Price per Key) vs ln(TRevPAR), by year (2022–2024)

The figure depicts a clear positive relationship consistent with the pooled regression results, and suggests that the association is broadly stable across years.

Importantly, TRevPAR captures not only room revenues but also non-room income streams (e.g., food & beverage and ancillary services), which are particularly relevant in upscale and luxury positioning. This feature makes TRevPAR a natural performance metric for valuation analysis in hospitality assets where a

material share of value is generated beyond room revenues.

While pooled regressions summarize broad cross-sectional relationships, they may partly reflect persistent unobserved differences across markets—such as destination attractiveness, long-run tourism intensity, or structural positioning. Entity fixed effects specifications control for these time-invariant characteristics by introducing destination–segment fixed effects, so that identification comes from **within-entity changes over time** (2022–2024). This is a demanding specification given the short time dimension, but it is appropriate for assessing which KPIs retain explanatory content once unobserved heterogeneity is absorbed.

Table 2.5: Entity Fixed Effects Results (log-log specifications)

Variable	**(1)** ln(**TRevPAR**)	**(2)** ln(**GOPPAR**)	**(3)** ln(**RevPAR**)
ln(TRevPAR)	-3.1958		
	(5.3626)		
ln(GOPPAR)		-1.0627	
		(3.1970)	
ln(RevPAR)			-3.1958
			(5.3626)
Intercept	29.0180	16.1619	27.7222
	(28.3474)	(12.1114)	(26.1731)
Year 2023	0.3285	0.0610	0.3285
	(0.7760)	(0.6257)	(0.7760)
Year 2024	0.4150	0.0963	0.4150
	(0.9630)	(0.8333)	(0.9630)
Entity FE (destination×segment)	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	30	30	30
R^2	0.7703	0.7664	0.7703
Adj. R^2	0.6081	0.6016	0.6081
SE	HC1 robust	HC1 robust	HC1 robust

Notes: Dependent variable is $\ln\left(\text{Price per Key}^{Market}\right)$. Standard errors in parentheses. Entity fixed effects coefficients are included but not reported for brevity.

The entity fixed effects estimates provide a within-destination–segment interpretation of the valuation–performance link. Once time-invariant heterogeneity is

absorbed by destination × segment fixed effects, the KPI coefficients become negative and statistically imprecise in this short panel. This indicates that the strong positive pooled association is primarily driven by cross-sectional differences across destinations and segments (levels), while within-entity year-to-year co-movement is limited and noisily estimated over 2022–2024. Therefore, the fixed effects evidence should be interpreted cautiously as suggestive rather than conclusive about within-entity dynamics.

A complementary visualization of within-entity variation is provided in Figure 2.2. The plot de-means variables by destination to remove time-invariant destination components and emphasize short-run deviations around each destination's mean (a descriptive complement to the destination–segment fixed-effects regressions).

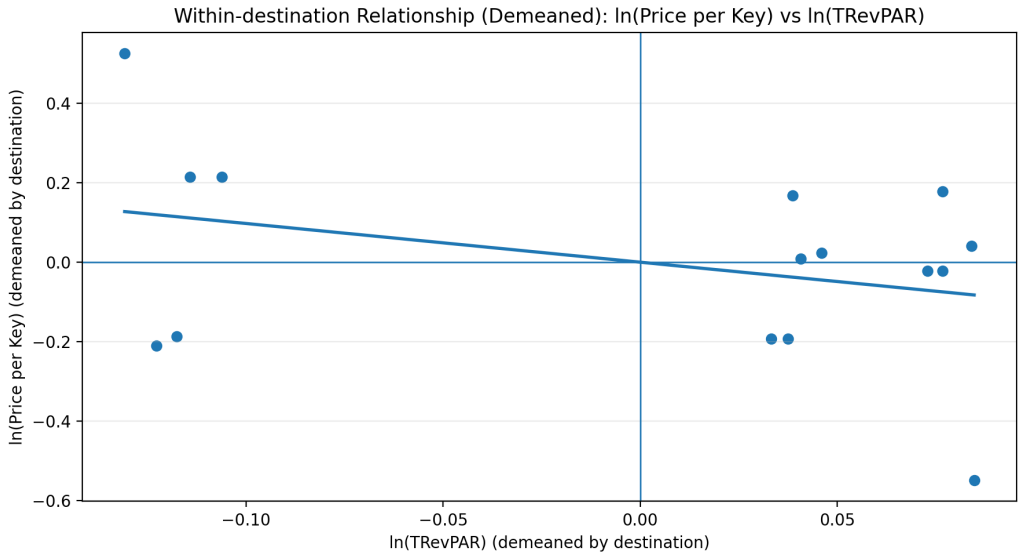

Figure 2.2: Within-entity variation (demeaned by destination): ln(Price per Key) and ln(TRevPAR)

By construction, the figure removes the average destination component and therefore emphasizes within-entity fluctuations. The slightly negative slope should not be interpreted as evidence of a negative causal relationship; rather, it is consistent with the fixed-effects estimates being imprecise in a very short panel, indicating limited and noisy within-destination co-movement between valuation and comprehensive revenue generation over 2022–2024.

To complement the fixed-effects interpretation, it is helpful, given the short 2022–2024 panel, to visually inspect how valuations move within each destination over time. Figure 2.3 plots the evolution of ln(Price per Key) by destination over 2022–2024 and summarizes the main valuation trajectories across markets.

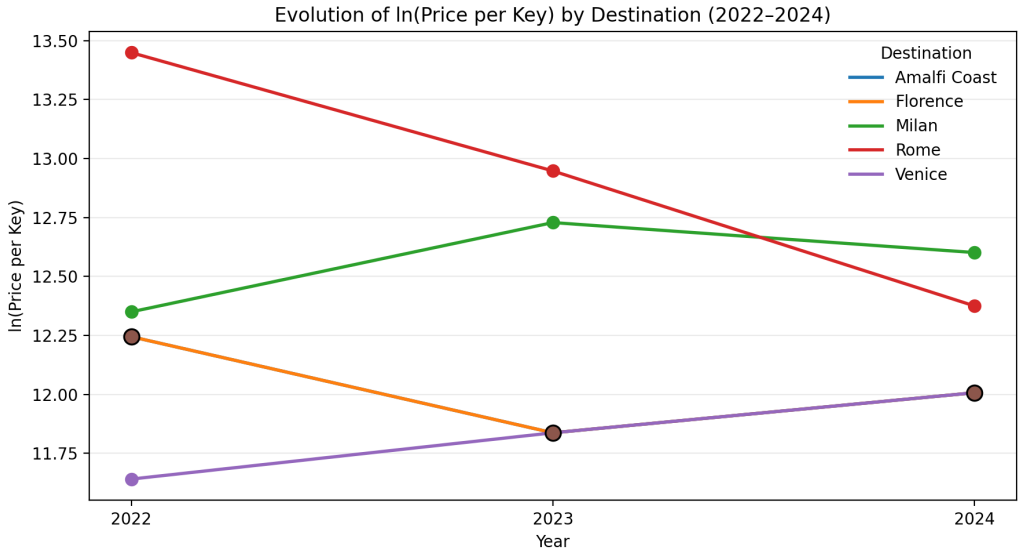

Figure 2.3: Evolution of ln(Price per Key) by destination, 2022–2024

The figure highlights meaningful heterogeneity in valuation trajectories across Italian destinations over 2022-2024. This heterogeneity supports the econometric approach: the presence of both cross-sectional differences (levels) and within-entity changes (dynamics) provides the necessary variation to estimate performance–valuation relationships. The plot also reinforces the conceptual rationale for fixed effects: destinations differ persistently in valuation level, and isolating within-entity movements helps avoid conflating structural positioning with performance-driven movements.

To complement the baseline results, the analysis performs an additional leave-one-destination-out robustness check. A key concern in small samples is that results might be overly influenced by one destination. To address this, the analysis implements a leave-one-destination-out (LOO) exercise: the regressions are re-estimated repeatedly, each time excluding one destination from the sample. This check assesses whether the baseline relationship is stable across alternative subsamples.

Table 2.6: Leave-one-destination-out robustness (log-log specifications)

Excluded destination (left out)	**TRevPAR**	**GOPPAR**	**RevPAR**
Amalfi Coast	17.482***	16.472***	15.719***
	(4.334)	(3.942)	(3.879)
Florence	6.555***	6.572***	5.710***
	(2.053)	(2.075)	(1.734)
Milan	6.248*	6.063*	5.566*
	(3.524)	(3.637)	(2.856)
Rome	4.183	4.358	3.641*
	(2.556)	(2.711)	(1.998)
Venice	7.841***	8.328***	6.066***
	(2.122)	(2.221)	(1.678)

Notes: Each row reports the KPI coefficient from re-estimating the model after excluding the destination in the first column. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The LOO exercise indicates that the main findings are not driven by any single destination. While coefficient magnitudes may vary across exclusions, reflecting the natural heterogeneity of Italian hotel markets, the direction and overall interpretation remain consistent. This strengthens confidence that the observed association between valuation and performance reflects a systematic pattern in the data rather than an idiosyncratic outlier.

Taken together, the results provide consistent evidence that hotel asset valuation is closely linked to operating performance, with the strongest associations emerging in the pooled specifications for comprehensive revenue measures. However, once destination–segment fixed effects are introduced, the KPI coefficients become statistically imprecise in this short panel, indicating that much of the positive relationship is driven by persistent cross-sectional differences across markets and segments rather than by tightly estimated within-entity year-to-year co-movement.

More specifically, the pooled estimates indicate a strong positive association between valuation (**ln(Price per Key)**) and each of the operating KPIs, with eco-

nomically meaningful magnitudes in a log–log setting. In this framework, coefficients can be interpreted as elasticities: a 1% increase in the KPI is associated with an approximate percentage change in Price per Key, holding year and segment effects constant.

The entity fixed effects results provide a more conservative within-entity benchmark and reinforce the interpretation that the most informative signal for valuation is related to comprehensive revenue generation capacity, rather than purely room-centric metrics. The graphical evidence is consistent with this pattern: Figure 2.1 visualizes a clear positive cross-sectional relationship, while Figure 2.2 provides a within-destination visualization and shows no clear positive co-movement over 2022–2024; if anything, the fitted slope is slightly negative and should be read as imprecise evidence in a very short panel rather than as a structural relationship. Finally, the leave-one-destination-out exercise supports the stability of the main findings and reduces concerns that the results are driven by a single market.

At the same time, the analysis should not be interpreted as establishing a causal mechanism. Hotel valuation proxies and performance indicators are intrinsically linked through income-based valuation logic (cash-flow generation and capitalization), which implies that part of the relationship is structural rather than purely statistical. The contribution of the econometric evidence is therefore best framed as identifying which operational KPIs are **most informative, stable, and valuation-consistent** across alternative specifications.

Two limitations are worth emphasizing. First, the short time dimension (2022–2024) restricts the ability to study delayed adjustments and long-run dynamics in pricing and investment. Second, the sample size and the use of market-based valuation proxies imply that the estimates should be interpreted as descriptive evidence within the analyzed destinations and segments. Future work could extend the panel horizon, incorporate additional destinations, and test alternative valuation measures to further assess the generalizability of the results.

Overall, the empirical results support the central premise of the study: in Italian upscale and luxury hotel markets, valuation outcomes co-move with operating performance, and comprehensive revenue capacity metrics provide the most reliable and valuation-consistent signals for asset value in this setting.

2.6 Comparison with Literature and Theoretical Implications

The empirical findings presented in this chapter can be interpreted within the broader theoretical and empirical literature on hotel valuation, hospitality operating performance, and real estate investment outcomes. Overall, the results are consistent with standard income-based valuation principles, according to which asset values reflect expectations about future cash flows, while providing evidence on which operational performance indicators appear most informative in upscale and luxury hotel markets.

More specifically, the chapter's evidence contributes to the ongoing debate on whether hotel value is better explained by "price-and-occupancy" room metrics or by broader measures of revenue and operating cash-flow generation. In full-service and luxury properties, value creation is increasingly tied to diversification of demand sources and monetization beyond the room product (e.g., F&B, MICE (meetings, incentives, conferences, and exhibitions), wellness, branded experiences). This makes comprehensive KPIs especially relevant for valuation because they map more directly into the underlying cash-flow base that is capitalized into asset prices; however, in short panels the within-entity signal can be estimated imprecisely once destination–segment fixed effects absorb time-invariant positioning.

A first key result is the positive relationship between hotel valuation (ln (Price per Key)) and revenue- and profit-related performance measures in pooled specifications. This pattern aligns with the income capitalization framework underpinning hotel valuation theory, where capital values are linked to expected operating cash flows and their capitalization (Rushmore, 2002; Baum & Crosby, 2008; Damodaran, 2012). In a log–log setting, the coefficients on continuous KPIs can be interpreted as elasticities, indicating that higher operating performance is associated with higher market-based values per key, holding year and segment effects constant.

Among the considered indicators, Total Revenue per Available Room (TRevPAR) appears particularly informative in pooled models and in robustness checks. This is consistent with hospitality research emphasizing the limitations of room-only metrics, such as ADR or RevPAR, in capturing the full economic performance of upscale and luxury properties (O'Neill & Xiao, 2006; Kim & Jang, 2016). Unlike room-centric measures, TRevPAR incorporates revenues generated through food

and beverage operations, meetings and events, wellness services, and other ancillary activities. These non-room streams are structurally important in full-service and luxury business models and can represent a meaningful share of cash-flow generation and, therefore, of capitalized value.

This result is also coherent with valuation practice in hospitality appraisal, where stabilized net operating income and expectations about sustainable revenue capacity are central inputs into cap-rate and discounted cash-flow approaches. In this sense, metrics capturing the "total monetization" of the asset can be viewed as closer reduced-form proxies for the underlying cash-flow engine than metrics focused solely on the room department. The evidence therefore supports the idea that, in upscale and luxury segments, the economic performance relevant for valuation is multidimensional and cannot be fully summarized by room-only indicators.

When moving from pooled regressions to entity fixed effects models, the interpretation becomes more conservative. Pooled estimates capture cross-sectional differences across destinations and segments (levels), while entity fixed effects isolate within-entity variation over time (changes) within the same destination–segment. In a short panel such as 2022–2024, within-entity variation is limited, and fixed effects estimates may be less precisely estimated. In this sense, the fixed effects results should be read as suggestive evidence on which KPIs retain explanatory content once time-invariant market characteristics are absorbed, rather than as definitive causal estimates.

Importantly, the distinction between levels and changes helps reconcile why some variables appear strongly associated with valuation in pooled regressions but become less precisely estimated once entity fixed effects are introduced. Cross-sectional differences across destinations may reflect persistent attributes such as brand positioning, tourist appeal, accessibility, or long-run demand intensity. Fixed effects absorb these time-invariant components and shift the focus to year-to-year variation within the same destination–segment. With only three years, the identifying variation is limited, so coefficient instability or larger standard errors should be interpreted primarily as a data and design constraint rather than as evidence against the relevance of operating performance for valuation.

From a theoretical perspective, this pooled-versus-fixed-effects comparison carries an important implication: market-based hotel valuation in upscale and luxury destinations reflects both (i) persistent structural positioning across markets (captured in cross-sectional levels) and (ii) year-to-year operating dynamics

within the same market. The broader takeaway is that comprehensive revenue-generation capacity and profitability are central to valuation logic, while purely room-centric indicators may be less effective proxies for value in segments where non-room income streams materially contribute to operating cash flows.

A further link with valuation theory concerns the role of discounting and risk. In income-based approaches, the market value of a hotel reflects both (i) expected operating cash flows (proxied by revenue and profit KPIs) and (ii) the rate at which those cash flows are capitalized (cap rates or discount rates), which embeds risk, growth expectations, and liquidity conditions. Within this framework, comprehensive KPIs such as TRevPAR and profitability measures such as GOPPAR can be interpreted as reduced-form summaries of the cash-flow component, whereas purely structural market variables may matter primarily insofar as they affect expected margins, demand resilience, and operating leverage—ultimately influencing value indirectly through the income channel.

Relatedly, the results fit a broader hospitality and real estate literature emphasizing that pricing outcomes reflect both asset-specific income generation and market-level positioning. Cross-sectional differences in values across destinations are consistent with persistent heterogeneity in desirability, accessibility, brand strength, and long-run demand intensity, while within-destination movements are harder to identify in a short panel and may be dominated by short-run noise or by strategic adjustments that operate with lags. This interpretation reinforces why fixed-effects evidence should be read as conservative and why stability checks, such as the leave-one-destination-out exercise, are useful complements when sample size and time dimension are limited.

These findings are also consistent with hospitality and industrial-organization perspectives in which market structure and competitive environments shape value primarily through their effects on revenues, margins, and operating efficiency, rather than necessarily through a direct mechanical channel (Porter, 1980; Yang et al., 2018). In practical terms, the results support valuation approaches that move beyond simplified room-performance metrics and incorporate measures capturing the breadth of revenue creation in full-service and luxury hotels.

At the same time, two limitations should be emphasized. First, the short time dimension (2022–2024) limits the ability to study delayed adjustments, longer-run dynamics, and gradual strategic repositioning. Second, the sample size and the use of market-based valuation proxies imply that results should be interpreted as descriptive evidence for the analyzed destinations and segments. Future work

could extend the panel horizon, expand the set of destinations, and test alternative valuation measures to further assess external validity.

The implications for investment strategy, asset management, and valuation practice are discussed in the following chapter, where the empirical results are interpreted considering managerial decision-making and real estate investment considerations.

Chapter 3

Discussion, implications, and conclusions

3.1 Simulations and sensitivity to market and operational conditions

This chapter interprets the econometric evidence in practical terms and discusses how the findings can be used in valuation and decision-making. The empirical setting is a destination–segment–year panel for the Italian upscale and luxury hotel market over 2022–2024 (N = 30). Given the short time horizon and the limited within-entity variation, the scenario analysis below is designed to be transparent and conservative. In particular, it translates the estimated KPI–valuation relationship into implied differences in the price-per-key benchmark and clarifies which interpretations are supported by the data (between-entity benchmarking) and which are not (short-run within-entity causal effects).

To ground the simulations, the pooled estimates are interpreted within the log–log framework, where KPI coefficients can be read as elasticities: a 1% change in a KPI is associated with an approximately β% change in price per key, conditional on the included fixed effects. In the pooled OLS specifications reported in Chapter 2 (Table 2.4), these elasticities are large and statistically significant, with the KPI coefficient around 4.0–4.34 depending on the KPI used; these magnitudes provide the quantitative basis for the scenario mappings reported below.

Economically, such magnitudes are plausible in hospitality because the asset combines real estate characteristics with operating leverage. When markets price

hotels using benchmarks such as €/key, they implicitly capitalize expectations about future cash-flow generation, not merely current revenue. Therefore, destinations and segments that consistently exhibit stronger operating performance can be associated with substantially higher valuation benchmarks.

At the same time, the entity fixed effects estimates do not replicate the strong positive relationship within the same destination–segment over time. When destination–segment fixed effects and year fixed effects are included, the KPI coefficients become imprecise and statistically insignificant. This suggests that the strong pooled relationship is primarily driven by between-entity variation, while within-entity identification is limited over the 2022–2024 horizon. Accordingly, the simulations below are best interpreted as cross-sectional sensitivity benchmarks rather than as short-run causal predictions for a given entity. This interpretation is consistent with the entity fixed effects evidence in Chapter 2 (Table 2.5), where within-entity estimates are imprecise over the short 2022–2024 window.

With this interpretation in mind, the scenario analysis below provides a transparent mapping from KPI changes to implied valuation sensitivity. Consider a generic elasticity β. For a percentage change Δ in the KPI, the implied percentage change in price per key is approximately:

$$\Delta\text{Price/Key (\%)} \approx \beta \times \Delta\text{KPI (\%)}.$$

Using the pooled elasticity range ($\beta \approx 4.0$–4.34), the implied sensitivity is substantial. Figure 3.1 summarizes this mapping across plausible KPI changes.

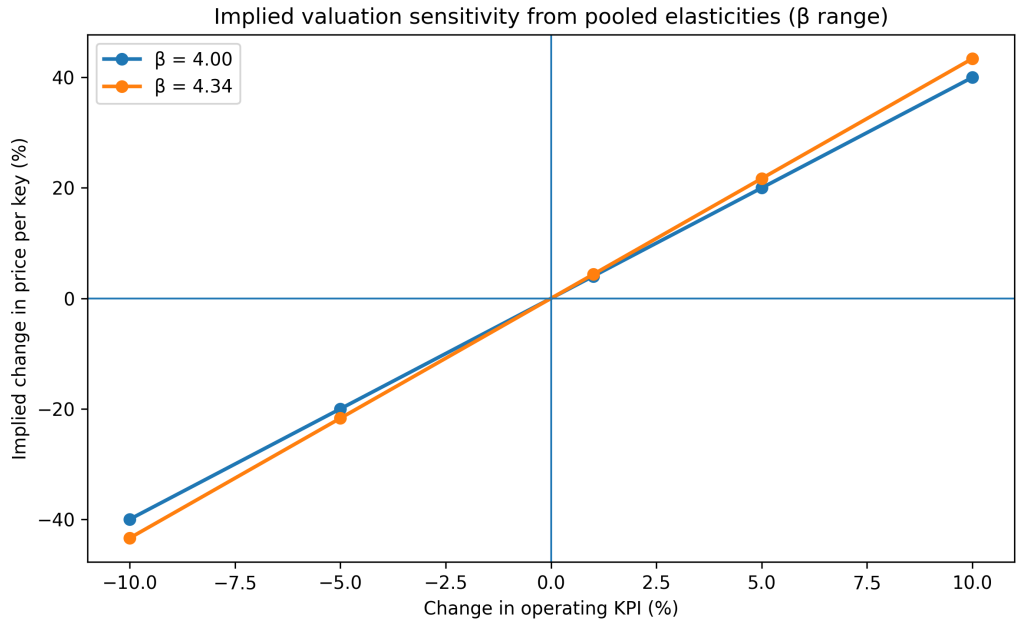

Figure 3.1: Elasticity-based mapping from KPI changes to implied changes in price per key (pooled estimates, $\beta \approx 4.0$–4.34).

Scenario A: ***Operational outperformance (KPI improvement).***

Suppose a destination–segment improves its operating KPI by +5% (e.g., through higher ADR, better occupancy management, stronger ancillary revenue capture, or tighter cost control reflected in profit-oriented KPIs). With β in the 4.0–4.34 range, the implied valuation effect is:

$$+5\%\ \text{KPI} \ \rightarrow\ \text{about}\ +20\%\ \text{to}\ +22\%\ \text{price per key.}$$

A stronger operational improvement of +10% would imply:

$$+10\%\ \text{KPI} \ \rightarrow\ \text{about}\ +40\%\ \text{to}\ +43\%\ \text{price per key.}$$

These magnitudes indicate that modest performance differences across upscale and luxury destinations can correspond to large differences in market valuation benchmarks. In practice, this provides a quantitative basis for per key benchmarking: if two destination–segment cells differ materially in RevPAR, TRevPAR, or profit metrics, it is plausible that the observed € /key benchmarks also differ substantially.

Scenario B: ***Demand softness (KPI decline).***

If operating performance deteriorates by -5% (e.g., weaker international demand, slower ADR growth, pressure on occupancy, or cost inflation reducing profit conversion), the implied change in valuation is:

$$-5\% \text{ KPI } \rightarrow \text{ about } -20\% \text{ to } -22\% \text{ price per key.}$$

For a larger shock of -10%, the implied effect becomes:

$$-10\% \text{ KPI } \rightarrow \text{ about } -40\% \text{ to } -43\% \text{ price per key.}$$

From a valuation standpoint, these downside scenarios are helpful because they translate operating stress tests into an interpretable valuation language. They can also be used to communicate risk to investment committees and lenders, provided that the user explicitly frames them as cross-sectional sensitivity benchmarks rather than as precise within-entity forecasts.

To interpret these scenarios economically, it is useful to relate KPI movements to the underlying operational and market drivers that generate them. A KPI change is a reduced-form summary of several underlying drivers. A RevPAR increase may be driven by ADR (pricing power), occupancy (demand strength), or a shift toward higher-yield segments and seasons. TRevPAR adds an additional channel: the ability to monetize ancillary services such as food and beverage, events, wellness, and other non-room revenue streams, which can be especially relevant for upscale and luxury assets where the guest proposition extends beyond rooms.

From an underwriting perspective, the scenarios are most credible when they are backed by a coherent operational narrative. For example, an ADR-led performance improvement may require investment in service quality, brand alignment, and distribution strategy; an occupancy-led improvement may hinge on destination demand recovery, events, and connectivity; and an ancillary-revenue improvement may require capex and operational execution that is consistent with the positioning of the asset.

This suggests that sensitivity analysis should be internally consistent. If KPI improvement is achieved via higher ADR, the underwriting should reflect plausible impacts on cost structure and service delivery. Conversely, if KPI improvement is achieved through cost reductions, the analysis should discuss whether these

savings are sustainable without eroding quality, particularly important in luxury hospitality where reputational effects can be persistent and may ultimately affect pricing power.

Although the empirical models focus on operating KPIs and valuation benchmarks, hotel valuation is also shaped by capitalization conditions, interest rates, risk premia, and liquidity in the transaction market. In practice, price-per-key benchmarks embed both cash-flow expectations and discount-rate assumptions. As a result, the KPI–benchmark relationship may appear stronger in stable capitalization environments and weaker when cap rates or risk premia shift materially.

A practical implication is that KPI-based valuation sensitivity should be interpreted alongside a capitalization stress test. Even if operating performance improves, an adverse shift in financing conditions or investor required returns can offset the valuation impact. Therefore, practitioners may wish to pair the KPI scenarios above with a simple cap-rate or discount-rate sensitivity in the income-based approach to demonstrate that valuation conclusions are robust to both operational and financial conditions.

Beyond generic KPI shocks, practitioners often want to understand which underlying levers are most likely to move the KPI in practice. Three lenses are particularly relevant for Italian upscale and luxury destinations: demand mix, seasonality, and competitive supply.

First, demand mix shifts, especially changes in the share of international arrivals, can alter both ADR potential and volatility. International demand is often associated with higher willingness to pay and stronger ancillary spending, but it can also be more sensitive to macro shocks and geopolitics. A useful way to operationalize this lens is to translate a change in demand mix into an implied KPI change (e.g., a $+x\%$ uplift in ADR with stable occupancy), and then map it into €/key using the elasticity benchmark.

Second, seasonality effects matter because a destination's ability to extend the shoulder season can improve capacity utilization without eroding pricing integrity. Operational initiatives (events programming, partnerships, improved airlift and connectivity) can create KPI improvements that are more durable than one-off pricing changes. When the KPI improvement comes from better seasonality smoothing, it is often perceived as higher-quality performance and may be more readily capitalized into benchmarks.

Competitive supply dynamics, such as new openings, renovations, and brand

entries, can pressure occupancy and ADR when demand does not expand proportionally. In these settings, the same KPI shock may reflect either a short-run competitive disturbance or a structural change in the competitive set. Valuation narratives should make this distinction explicit, since markets typically treat structural competitive shifts as more consequential than transient shocks.

With these channels in mind, the final step is to clarify the interpretation boundaries of the scenario results and reconcile the pooled and fixed-effects evidence. The contrast between pooled OLS and entity fixed effects estimates is central. The pooled sensitivities describe market-level pricing differences across destinations and segments, while the fixed effects estimates indicate that short-run within-entity identification is limited over the short panel.

There are at least three practical implications:

1. **Cross-sectional pricing:** destinations and segments with structurally stronger performance tend to be associated with higher valuation benchmarks.

2. **Limited within-entity variation:** over a short 2022–2024 horizon, valuation benchmarks and KPIs may not move enough within the same entity to deliver precise within-entity estimates.

3. **Role of unobserved heterogeneity:** persistent characteristics (positioning, brand mix, destination demand drivers) likely explain a large share of valuation differences, which the entity fixed effects absorb.

Accordingly, the scenario analysis should be read as "how much higher or lower valuation benchmarks are across entities when performance differs," rather than as "how much the €/key of a given entity will move next year if its KPI changes."

Using the pooled elasticities ($\beta \approx 4.0$–4.34), the implied valuation responses are:

- KPI +1% → price per key about +4.0% to +4.34%
- KPI +5% → price per key about +20% to +22%
- KPI +10% → price per key about +40% to +43%

These ranges provide an intuitive benchmark for how strongly operating performance and market valuation can be aligned in the Italian upscale and luxury hotel market, while the fixed effects evidence cautions against interpreting the

relationship as a robust within-entity causal mechanism over the short panel horizon.

Elasticity-based sensitivities are useful because they are transparent and easy to communicate. However, several practical caveats should be stated to avoid over-interpretation.

- **Non-linearity:** the KPI–benchmark relationship may not be linear for large shocks; elasticities can change across performance tiers.
- **Joint movements:** RevPAR, TRevPAR, and profit metrics often move together; scenario assumptions should specify which component changes and why.
- **Benchmark smoothing:** €/key benchmarks may incorporate appraisal smoothing or survey-based conventions that react with a lag.
- **Capitalization overlay:** changes in required returns (cap rates, discount rates) can dominate valuation even if KPIs improve.

For these reasons, the preferred use of the scenarios is as a benchmarking and communication tool. In appraisal or investment committee settings, it is often best practice to present a small set of KPI-consistent valuation ranges, and to explain what operational and market conditions would justify moving between ranges.

3.2 Practical implications

The core message is that operating performance and market valuation benchmarks are strongly aligned in the pooled cross-sectional estimates, while the within-entity evidence over 2022–2024 does not support a mechanical short-run causal interpretation. Accordingly, the implications are framed as practical guidance for benchmarking and pricing differences across destinations and segments, rather than as one-year-ahead prediction rules. In this sense, the results are most useful as a benchmarking tool across destinations and segments, while short-run within-entity forecasting should be treated with caution.

For **investors**, the results support the view that market pricing in upscale and luxury hospitality reflects expectations about operating strength. The pooled

elasticities imply that relatively small differences in operating KPIs can correspond to sizeable differences in €/key benchmarks across destination–segment cells. In practice, this reinforces the importance of underwriting that is internally consistent across ADR, occupancy, ancillary revenues, and operating cost assumptions.

A useful application is screening and relative pricing. When assessing a potential acquisition, investors can use KPI benchmarks to position the asset within a plausible €/key range for the relevant destination and segment. If the observed asking price implies a performance tier that is inconsistent with the asset's KPI profile, the valuation narrative should explain either a credible path to close the performance gap or a structural reason why the asset commands a premium (e.g., unique location, irreplaceability, brand strength, or development optionality).

At the same time, the absence of robust within-entity evidence cautions against assuming that short-run KPI improvements automatically lead to immediate repricing within the same destination–segment. Therefore, value creation strategies should be assessed over a multi-year horizon and supported by durable drivers (repositioning, brand upgrades, distribution strength, and sustained demand shifts) rather than by transitory or one-off measures.

For **operators**, the evidence provides a quantitative rationale for prioritizing strategies that improve the core drivers of operating KPIs, because cross-sectional market valuation benchmarks appear closely associated with performance differences. This is particularly relevant in upscale and luxury hospitality, where pricing power and service intensity can amplify operating leverage.

Operational initiatives that may carry valuation relevance include strengthening rate integrity, improving channel mix, enhancing ancillary revenue capture, and managing cost inflation without compromising guest experience. In luxury contexts, reputational and brand-consistency effects can be persistent; therefore, initiatives that reinforce durable positioning, such as upgrading the guest proposition or improving service quality, are more likely to be capitalized by the market than one-off cost cuts.

A practical recommendation is to adopt a KPI dashboard that mirrors how investors compare assets. RevPAR alone can be insufficient; TRevPAR captures non-room monetization, and profit-oriented metrics help validate whether top-line improvements translate into economic value. Consistent KPI tracking can improve communication between operations, owners, and capital providers.

For **valuers** and **advisors**, the findings support the use of market-based benchmarks (€/key) as a meaningful cross-sectional proxy correlated with operating performance. In appraisal practice, KPIs can strengthen the narrative by explaining why a selected benchmark multiple is consistent with the asset's observed or expected performance relative to peers.

Methodologically, the pooled-versus-fixed-effects contrast suggests that valuation benchmarks embed persistent, unobserved destination and segment characteristics. Therefore, KPI-to-value mappings should be treated as context-dependent and should not be applied mechanically to justify large valuation revisions based solely on short-run KPI changes. Corroborating evidence, such as transaction comparables, observable repositioning, or structural demand changes, should be required.

A robust implementation approach is triangulation: use KPI-consistent €/key benchmarking as a plausibility check and complement it with an income-based approach. If the market benchmark implies a cash-flow level that is inconsistent with the operating story, the assumptions should be revisited. Presenting a small set of KPI-consistent valuation ranges (rather than a single point estimate) can improve transparency and reduce the risk of over-fitting conclusions to short-run noise.

For **lenders**, operating performance remains a key signal when comparing collateral quality across destination–segment cells. If market benchmarks are aligned with KPI differences across entities, underwriting and covenant monitoring can benefit from performance-based indicators, especially for assets dependent on sustained pricing power and resilient demand.

However, the limited within-entity evidence suggests that short-term KPI fluctuations should be interpreted cautiously over a short horizon. A practical risk framework should combine structural factors (destination resilience, seasonality, demand composition), operational factors (cost inflation sensitivity, staffing constraints), and capitalization factors (refinancing risk, interest-rate environment). KPI monitoring is most informative when interpreted within this broader structure.

To translate the results into actionable practice, the following checklist summarizes how KPIs can be integrated into valuation without over-interpreting short-run movements:

- **Benchmark first:** position the asset's KPIs relative to a credible peer set (same destination and segment, comparable positioning).
- **Use KPI-consistent ranges:** map performance tiers to plausible €/key ranges rather than relying on a single multiple.
- **Triangulate:** cross-check market benchmarks with an income-based approach to validate implied cash-flow assumptions.
- **Stress test:** apply symmetric upside and downside KPI shocks to communicate valuation sensitivity transparently.
- **Avoid short-run overreaction:** require corroborating evidence before translating KPI movements into large valuation revisions.

Overall, the results imply that valuation benchmarks in the Italian upscale and luxury hotel market are closely associated with operating performance differences across destinations and segments. The most robust practical use is cross-sectional benchmarking: using KPIs to justify relative pricing and to validate where an asset should fall within an observed €/key range, while triangulating with income-based reasoning and avoiding overly mechanical short-run KPI-to-value translations within the same entity.

Although the analysis is primarily aimed at investors, operators and valuers, the results also have relevance for destination-level stakeholders. If valuation benchmarks are strongly aligned with performance differences across destinations and segments, policies and investments that improve destination competitiveness (connectivity, public realm quality, event infrastructure, and tourism management) can indirectly support hospitality valuations.

In practical terms, destination managers can use KPI benchmarking to identify performance gaps relative to peer destinations and to prioritize interventions that improve the quality of demand rather than only volume. For upscale and luxury segments, the ability to attract high-spending travelers and to support ancillary experiences is often more valuation-relevant than maximizing headcount. Future work with richer data could quantify these channels more directly, but the current evidence already supports a benchmarking-oriented policy narrative.

3.3 Limitations and future research

The limitations reflect constraints that arise when studying hospitality valuation with a short panel horizon and market-level proxies, and they also define a clear agenda for extending and strengthening the evidence base.

The analysis is based on a destination–segment–year panel with N = 30 over 2022–2024. While the design is consistent with the objective of focusing on Italian upscale and luxury destinations, it limits statistical power and the precision of estimated effects. Small samples can lead to wide confidence intervals and make within-entity relationships difficult to detect even when economically meaningful.

Moreover, with a small number of entities, inference can be sensitive to modeling choices such as the fixed effects structure and the treatment of standard errors. This reinforces the interpretation of the results as descriptive evidence of cross-sectional alignment rather than definitive causal estimates.

Future work would benefit from expanding both the cross-section (more destinations, additional segments) and the time dimension (longer pre- and post-COVID window). A longer panel would improve identification of within-entity dynamics and allow testing whether the KPI–valuation relationship strengthens in periods with greater cyclical variation.

The dependent variable is a market-based valuation benchmark (price per key) derived from industry sources rather than observed transaction prices for specific assets. This implies that the analysis captures how market benchmarks co-move with operating KPIs, not how individual hotel deals are priced. Benchmarks may embed appraisal conventions, smoothing, or methodological assumptions that differ across sources and time.

Future research could validate the benchmark-based approach by linking operating KPIs to transaction-level evidence, where available, and comparing benchmark-implied valuation changes to observed pricing in deals. Another extension is to compare multiple benchmark providers, quantify dispersion across sources, and test whether results are robust to provider choice and methodology.

The pooled-versus-fixed-effects contrast suggests that the strong KPI–benchmark relationship is driven primarily by between-entity differences, while within-entity variation is limited over the short horizon. This constrains causal interpretation. In addition, endogeneity concerns may arise: unobserved structural factors (destination attractiveness, positioning, brand mix) can affect both KPIs and valuation

benchmarks, and higher-valuation destinations may attract stronger brands and investment that in turn improves KPIs.

Future research could address these issues through stronger identification strategies, including instrumental variables, quasi-experimental shocks (transport infrastructure, major events, regulatory changes), or difference-in-differences designs with credible control groups. A further direction is to model capitalization channels explicitly, linking interest rates and risk premia to benchmark movements and testing whether the KPI–value relationship changes across rate regimes.

Operating KPIs can differ in measurement conventions across data providers, particularly for metrics beyond RevPAR. Definitions of TRevPAR, the coverage of ancillary revenues (such as food and beverage, wellness, events, and other on-property services), and the allocation of profits across departments may vary across sources and reporting systems. These differences introduce measurement error that can attenuate estimated relationships, especially in fixed effects models that rely on relatively small within-entity changes over time. Future research can improve measurement consistency by relying, where possible, on standardized reporting frameworks, carefully documenting KPI definitions and data transformations, and prioritizing harmonized metrics that are comparable across providers and destinations. In addition, because value formation in upscale and luxury hospitality is influenced by qualitative dimensions that are not fully captured by accounting metrics, future work could incorporate complementary performance proxies, such as online reputation indices, pricing and rate-positioning measures, and demand-composition indicators, to better reflect structural drivers of pricing power and perceived asset quality.

While destination–segment aggregation is appropriate for benchmarking, it may conceal meaningful heterogeneity across individual assets and business models operating within the same destination. Resort-oriented properties, for example, may be more sensitive to seasonality, airlift intensity, and international arrivals than urban assets that depend primarily on business travel and midweek demand. Differences in brand affiliation, amenity intensity, and customer mix can further shape the responsiveness of revenues and profits to the same demand shock. Future research could address this heterogeneity by adopting finer segment definitions, splitting samples by destination type, or using multi-level models that distinguish destination-level effects from asset-level dynamics. Related model extensions could test non-linearities, such as threshold effects in occupancy or

diminishing marginal returns to ADR increases, as well as interaction terms capturing how macro-financial conditions amplify or dampen the impact of operating performance on valuation benchmarks.

The empirical setting focuses on Italy and on upscale and luxury destinations over the 2022–2024 period. This narrow scope enhances contextual relevance and interpretability, but it naturally limits external validity. The KPI–valuation relationship may differ across countries, hotel segments, ownership structures, and market regimes, and the mapping from operating performance to value may vary substantially depending on regulatory frameworks, liquidity conditions, and the maturity of investment markets. A clear avenue for future work is to test generalizability by replicating the framework across multiple European countries, explicitly comparing tourism-driven versus business-travel-driven destinations, and modeling the role of macro-financial conditions in determining valuation benchmarks. Extending the time horizon would also allow the analysis to cover different phases of the cycle and to assess whether the KPI–value link is stable across regimes or changes in periods of stress.

Two further limitations are worth highlighting from an econometric perspective. First, with a small panel, results can be sensitive to multicollinearity among controls and to the inclusion of multiple fixed effects. In hospitality data, many covariates co-move, demand indicators, ADR, occupancy, and ancillary revenues often move together, so standard errors can inflate and coefficients may appear less significant in fixed effects specifications even when underlying relationships are economically meaningful. Second, benchmark construction can introduce measurement noise that is not classical. If valuation benchmarks are based on appraiser surveys, expert judgment, or appraisal processes that embed smoothing, they may adjust slowly to new information. In that case, short-run variation in KPIs may not be reflected immediately in benchmark revisions, mechanically weakening within-entity estimates and potentially biasing inference toward finding weaker relationships than the market would imply over longer horizons. Future work can mitigate these issues by increasing sample size, using higher-frequency data, and adopting designs that explicitly model dynamic adjustment (e.g., distributed lag specifications or partial-adjustment frameworks). Where transaction evidence is available, systematically comparing benchmark revisions with observed deal prices over time would help assess how quickly operating information is capitalized into values and whether appraisal-based benchmarks lag market clearing prices.

Overall, the main limitations relate to sample size and horizon, the proxy nature of valuation benchmarks, and identification constraints in a short panel. These limitations define a coherent research agenda: expanding the dataset across time and geography, validating benchmarks with transaction evidence, improving KPI comparability across reporting systems, and applying stronger identification strategies to better isolate causal mechanisms linking operating performance to hospitality valuation. Several concrete extensions follow from this agenda. First, assembling asset-level datasets that combine transaction prices, detailed operating statements, and capital expenditure histories would enable a closer mapping between performance, investment, and value, and would allow a clearer test of whether profit-oriented KPIs dominate revenue-based KPIs once accounting definitions are harmonized. Second, dynamic valuation channels can be explored by explicitly modeling how expected growth, risk premia, and financing conditions interact with KPIs. For example, a unified framework could connect operating performance to NOI, map NOI into value via cap rates, and allow cap rates to vary with macro-financial conditions, thereby separating cash-flow-driven effects from discount-rate-driven effects. Third, heterogeneity can be analyzed at a finer level by distinguishing destination type (leisure versus business), accessibility (e.g., airlift intensity and transport connectivity), and product differentiation (amenities, branded residences, brand strength), improving external validity and producing more tailored implications for practitioners and investors.

Conclusion

This thesis set out to assess how operational performance indicators are associated with hotel asset values in the Italian market, with a focus on the upscale and luxury segments. The motivation stems from the hybrid nature of hotels: they are simultaneously real estate assets and operating businesses, meaning that conventional valuation frameworks must be interpreted through the lens of operational cash-flow generation, cost structure, and market dynamics. In this context, a performance-based perspective is especially relevant because the value embedded in market pricing benchmarks reflects not only physical and locational attributes, but also the ability of a destination–segment to sustain strong revenues and operating profits over time.

Building on this motivation, the empirical analysis was designed to keep the valuation perspective closely tied to measurable operating outcomes, while remaining consistent with the data constraints that characterize hotel markets.

To maintain coherence between the conceptual framework and the empirical strategy, the analysis adopted a panel approach at the aggregated market level (destination–year, with segment focus), exploiting cross-sectional and temporal variation in the post-pandemic recovery period 2022–2024. Given the scarcity of public transaction-level data and the confidentiality and heterogeneity typical of hotel deals, the study used a market-based proxy for asset value, price per key (€/key), as the main outcome variable, expressed in logarithms to interpret coefficients as elasticities. Income-implied measures were introduced as robustness checks, while operational performance was captured via standard hospitality KPIs, estimated in separate specifications to reduce mechanical overlap.

Against this backdrop, the empirical results can be interpreted along two complementary dimensions: the strength of cross-sectional benchmarking relationships and the extent to which short-run within-market dynamics are detectable over the available time horizon.

In particular, the distinction between cross-sectional (between-entity) variation and time-series (within-entity) variation is central in hospitality market analysis. Cross-sectional differences typically reflect deep, slow-moving determinants, destination appeal, accessibility, demand composition, brand presence, and the long-run quality of the competitive set, that jointly shape both pricing power and investors' expectations of stabilized cash flows. By contrast, within-entity movements over a short horizon are often dominated by transitory shocks (seasonality, event-driven demand, macro shocks, temporary supply constraints, or post-pandemic normalization), which may not be immediately capitalized into benchmarks such as €/key.

As a consequence, a strong pooled relationship is highly informative for benchmarking and positioning across destinations and segments, while weak within-entity results should not be read as evidence that operating performance 'does not matter'. Rather, it indicates that the available panel window may be too short, or the benchmarks too smooth and influenced by discount-rate conditions, to detect rapid repricing within the same market–segment once fixed effects absorb persistent heterogeneity.

The econometric evidence highlights a strong alignment between operating KPIs and market-based valuation benchmarks in pooled specifications. Estimated elasticities range between approximately 4.0 and 4.34, implying that relatively small differences in operating performance are associated with large differences in valuation benchmarks across destinations and segments. This finding is economically intuitive in hospitality markets, where operating leverage and expectations of future cash flows play a central role in pricing.

However, once destination–segment and time fixed effects are introduced, the relationship weakens substantially. This suggests that the observed association is primarily driven by persistent cross-sectional differences rather than short-run within-entity dynamics. As a result, the findings are best interpreted as market-level benchmarking evidence rather than as a causal prediction of short-term value changes.

From a practical standpoint, these results provide useful sensitivity benchmarks that can be applied in valuation and investment discussions. Nevertheless, KPI-based valuation logic should always be complemented with explicit assumptions on capitalization conditions, financing costs, and risk premia.

The study also carries important implications for investors, operators, and valuation professionals. Investors can use KPI profiles to assess whether market

pricing benchmarks are consistent with observable operating performance, while operators can focus on strategies that translate revenue growth into sustainable profitability. For valuation practitioners, the results support the use of €/key benchmarks as a cross-sectional proxy, while cautioning against mechanical short-run adjustments.

In operational terms, the implications can be summarized as follows (consistent with the discussion above):

- From a valuation practice perspective, this supports a disciplined workflow in which operational KPIs serve as a first-pass diagnostic tool: they help define the appropriate peer set, assess whether the implied pricing tier is internally consistent, and flag cases where the investment narrative relies on assumptions that are not yet visible in operating data. When a pricing premium is observed, the premium should be justified by durable drivers (irreplaceable location, proven brand uplift, documented repositioning potential, or structural demand tailwinds) rather than by short-lived occupancy or rate spikes.
- For investors and asset managers, KPI-consistent benchmarking helps validate whether market pricing levels are aligned with observable operating performance and whether the investment thesis hinges on durable, multi-year improvements rather than short-run fluctuations.
- For operators, the results reinforce the importance of strategies that improve the conversion of revenues into sustainable profits, ensuring that top-line growth is accompanied by disciplined cost management and resilient cash-flow generation.
- For valuation professionals, the findings support the use of performance information to strengthen benchmarking narratives, while emphasizing the need to triangulate with capitalization assumptions and broader market conditions.

Several limitations must be acknowledged, including the short time horizon, the aggregated nature of the data, and the potential for mechanical relationships among performance indicators. These constraints limit causal interpretation but do not invalidate the benchmarking relevance of the findings.

For ease of reading, the key constraints embedded in the statement above can be grouped into the following points:

- the limited time horizon and sample size, which reduce statistical power and make within-market inference less precise;
- the aggregated level of observation, which may mask property-specific heterogeneity and contractual or strategic differences;
- the potential overlap between performance indicators and valuation constructs, which calls for careful interpretation;
- the role of capitalization conditions and required returns, which can shift benchmarks independently of operational changes.

Future research could extend the analysis by using longer panels, property-level data, and explicit modeling of capitalization conditions, as well as by adopting causal identification strategies.

Concretely, these extensions would be most valuable if they enabled a clearer separation between cash-flow channels and discount-rate channels, and if they improved the ability to draw inference from within-market variation over time.

Overall, this thesis contributes to the literature by clarifying the role and limits of performance-based valuation benchmarks in the Italian hotel market. By explicitly distinguishing cross-sectional benchmarking from within-entity dynamics, it provides a rigorous and practically meaningful framework for interpreting the link between hotel operating performance and asset values.

Finally, the post-pandemic period analyzed in this thesis highlights how quickly operating metrics can rebound relative to valuation benchmarks, especially when capital markets reprice risk and financing conditions evolve. For this reason, future empirical work that explicitly integrates capitalization variables, such as cap-rate proxies, financing spreads, and liquidity indicators, would be particularly valuable to practitioners: it would allow benchmark movements to be decomposed into a 'cash-flow channel' and a 'required-return channel', improving both interpretation and forecasting.

In summary, the evidence presented here provides a coherent, performance-grounded lens through which hotel values can be discussed in the Italian upscale and luxury market. By combining a clear conceptual framing with transparent empirical benchmarks, and by explicitly acknowledging identification limits, the thesis offers a robust basis for valuation narratives, investment screening, and strategic operating decisions.

Appendix: Python Code

Python code: Regression estimation and table replication (Tables 2.4 and 2.5)

```
import pandas as pd
import statsmodels.formula.api as smf
from statsmodels.iolib.summary2 import summary_col
from pathlib import Path

data_path = r"/mnt/data/Dataset .xlsx"
df = pd.read_excel(data_path)

# Treat year as categorical
df['year_cat'] = df['year'].astype(str)

def fit_ols(formula, data):
    # HC1 robust standard errors
    return smf.ols(formula, data=data).fit(cov_type='HC1')

out_dir = Path(r"/mnt/data/thesis_tables_final")
out_dir.mkdir(parents=True, exist_ok=True)

# ----------------------------
# Table 2.4: Pooled OLS
# DV: ln_price_per_key_market
# FE: Year + Segment
# ----------------------------
m1 = fit_ols('ln_price_per_key_market ~ ln_trevpar + C(year_cat) +
    ↪ C(segment)', df)
m2 = fit_ols('ln_price_per_key_market ~ ln_goppar + C(year_cat) +
    ↪ C(segment)', df)
m3 = fit_ols('ln_price_per_key_market ~ ln_revpar + C(year_cat) +
    ↪ C(segment)', df)

info_24 = {
```

```
    'Observations': lambda m: f"{int(m.nobs)}",
    'R': lambda m: f"{m.rsquared:.4f}",
    'Adj. R': lambda m: f"{m.rsquared_adj:.4f}",
    'Segment FE': lambda m: 'Yes',
    'Year FE': lambda m: 'Yes',
    'SE': lambda m: 'HC1 robust',
}

tab_24 = summary_col(
    [m1, m2, m3],
    model_names=['(1) TRevPAR', '(2) GOPPAR', '(3) RevPAR'],
    stars=True,
    float_format='%0.4f',
    info_dict=info_24,
    regressor_order=['ln_trevpar','ln_goppar','ln_revpar']
)

# ----------------------------
# Table 2.5: Entity FE
# FE: destinationsegment (entity) + Year
# ----------------------------
fe1 = fit_ols('ln_price_per_key_market ~ ln_trevpar + C(year_cat) +
    ↪ C(entity)', df)
fe2 = fit_ols('ln_price_per_key_market ~ ln_goppar + C(year_cat) +
    ↪ C(entity)', df)
fe3 = fit_ols('ln_price_per_key_market ~ ln_revpar + C(year_cat) +
    ↪ C(entity)', df)

info_25 = {
    'Observations': lambda m: f"{int(m.nobs)}",
    'R': lambda m: f"{m.rsquared:.4f}",
    'Adj. R': lambda m: f"{m.rsquared_adj:.4f}",
    'Entity FE': lambda m: 'Yes (destinationsegment)',
    'Year FE': lambda m: 'Yes',
    'SE': lambda m: 'HC1 robust',
}

tab_25 = summary_col(
    [fe1, fe2, fe3],
    model_names=['(1) TRevPAR', '(2) GOPPAR', '(3) RevPAR'],
    stars=True,
    float_format='%0.4f',
    info_dict=info_25,
    regressor_order=['ln_trevpar','ln_goppar','ln_revpar']
)
```

```
71
72 print(tab_24.as_text())
73 print('\n' + '='*80 + '\n')
74 print(tab_25.as_text())
```

Python code: Figure 2.1 (ln(Price per Key)) vs ln(TRevPAR), by year, (2022–2024)

```
1  import pandas as pd
2  import numpy as np
3  import matplotlib.pyplot as plt
4  import statsmodels.formula.api as smf
5  from pathlib import Path
6
7  # --- Load dataset ---
8  df = pd.read_excel("Dataset .xlsx")
9  out_dir = Path(".")
10
11 # --- Build destination-year market panel (rooms-weighted) ---
12 cols_to_avg = ["trevpar"]
13 def wavg(values, weights):
14     return np.average(values, weights=weights)
15
16 rows = []
17 for (dest, yr), g in df.groupby(["destination", "year"]):
18     w = g["rooms_supply"].values
19     row = {"destination": dest, "year": int(yr)}
20     row["trevpar"] = wavg(g["trevpar"].values, w)
21     row["price_per_key_market"] = float(g["price_per_key_market"].iloc[0])
22     rows.append(row)
23
24 mkt = pd.DataFrame(rows).sort_values(["destination",
       ↪ "year"]).reset_index(drop=True)
25
26 # --- Logs + categories ---
27 mkt["ln_price_per_key_market"] = np.log(mkt["price_per_key_market"])
28 mkt["ln_trevpar"] = np.log(mkt["trevpar"])
29 mkt["year_cat"] = mkt["year"].astype("category")
30
31 # --- Year FE model ---
32 model_yearFE = smf.ols(
33     "ln_price_per_key_market ~ ln_trevpar + C(year_cat)", data=mkt
34 ).fit(cov_type="HC1")
```

```
35
36 beta = model_yearFE.params["ln_trevpar"]
37 base = model_yearFE.params["Intercept"]
38 year_levels = list(mkt["year_cat"].cat.categories)
39
40 def intercept_for_year(y):
41     # baseline year is the first category
42     if y == year_levels[0]:
43         return base
44     key = f"C(year_cat)[T.{y}]"
45     return base + (model_yearFE.params[key] if key in model_yearFE.params
       ↪ else 0.0)
46
47 markers = {year_levels[0]: "o", year_levels[1]: "s", year_levels[2]: "^"}
48 linestyles = {year_levels[0]: "-", year_levels[1]: "--", year_levels[2]:
       ↪ ":"}
49
50 # --- Plot ---
51 fig, ax = plt.subplots(figsize=(9, 5))
52
53 for y in year_levels:
54     d = mkt[mkt["year"] == int(y)]
55     ax.scatter(d["ln_trevpar"], d["ln_price_per_key_market"],
56                marker=markers[y], label=str(y))
57
58 # annotate destinations
59 for _, r in mkt.iterrows():
60     ax.annotate(str(r["destination"]),
61                 (r["ln_trevpar"], r["ln_price_per_key_market"]),
62                 textcoords="offset points", xytext=(5, 4), fontsize=8)
63
64 xgrid = np.linspace(mkt["ln_trevpar"].min(), mkt["ln_trevpar"].max(), 100)
65 for y in year_levels:
66     a = intercept_for_year(y)
67     yhat = a + beta * xgrid
68     ax.plot(xgrid, yhat, linestyle=linestyles[y], linewidth=2)
69
70 ax.set_title("ln(Price per Key) vs ln(TRevPAR) with Year Fixed Effects")
71 ax.set_xlabel("ln(TRevPAR)")
72 ax.set_ylabel("ln(Price per Key)")
73 ax.legend(frameon=False, title="Year")
74 ax.grid(True, axis="y", alpha=0.25)
75 fig.tight_layout()
76
77 plt.savefig(out_dir / "plot1_lnprice_vs_lntrevpar_yearFE.png", dpi=200)
```

```
plt.show()
plt.close(fig)
```

Python code: Figure 2.2 Within-entity variation (demeaned by destination): ln(Price per Key) and ln(TRevPAR)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
from pathlib import Path

# --- Load dataset ---
df = pd.read_excel("Dataset .xlsx")
out_dir = Path(".")

# --- Build destination-year market panel (rooms-weighted) ---
def wavg(values, weights):
    return np.average(values, weights=weights)

rows = []
for (dest, yr), g in df.groupby(["destination", "year"]):
    w = g["rooms_supply"].values
    row = {"destination": dest, "year": int(yr)}
    row["trevpar"] = wavg(g["trevpar"].values, w)
    row["price_per_key_market"] = float(g["price_per_key_market"].iloc[0])
    rows.append(row)

mkt = pd.DataFrame(rows).sort_values(["destination",
    ↪ "year"]).reset_index(drop=True)

# --- Logs ---
mkt["ln_price_per_key_market"] = np.log(mkt["price_per_key_market"])
mkt["ln_trevpar"] = np.log(mkt["trevpar"])

# --- Demean by destination (within-destination variation) ---
mkt["ln_price_within_dest"] = (
    mkt["ln_price_per_key_market"]
    -
    ↪ mkt.groupby("destination")["ln_price_per_key_market"].transform("mean")
)
mkt["ln_trevpar_within_dest"] = (
    mkt["ln_trevpar"]
```

```
    - mkt.groupby("destination")["ln_trevpar"].transform("mean")
)

within_model = smf.ols(
    "ln_price_within_dest ~ ln_trevpar_within_dest", data=mkt
).fit(cov_type="HC1")

# --- Plot ---
fig, ax = plt.subplots(figsize=(9, 5))
ax.scatter(mkt["ln_trevpar_within_dest"], mkt["ln_price_within_dest"])

xgrid = np.linspace(
    mkt["ln_trevpar_within_dest"].min(),
    mkt["ln_trevpar_within_dest"].max(),
    100
)
yhat = (
    within_model.params["Intercept"]
    + within_model.params["ln_trevpar_within_dest"] * xgrid
)
ax.plot(xgrid, yhat, linewidth=2)

ax.axhline(0, linewidth=1)
ax.axvline(0, linewidth=1)
ax.set_title("Within-destination Relationship (Demeaned): ln(Price per Key)
    ↪ vs ln(TRevPAR)")
ax.set_xlabel("ln(TRevPAR) (demeaned by destination)")
ax.set_ylabel("ln(Price per Key) (demeaned by destination)")
ax.grid(True, axis="y", alpha=0.25)
fig.tight_layout()

plt.savefig(out_dir / "plot2_within_destination_demeaned.png", dpi=200)
plt.show()
plt.close(fig)
```

Python code: Figure 2.3: Evolution of ln(Price per Key) by destination, 2022–2024

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pathlib import Path

# --- Load dataset ---
df = pd.read_excel("Dataset .xlsx")  # adjust path if needed

# --- Build destination-year market panel (rooms-weighted) ---
cols_to_avg = ["adr","occupancy","revpar","trevpar","goppar"]

def wavg(values, weights):
    return np.average(values, weights=weights)

rows = []
for (dest, yr), g in df.groupby(["destination", "year"]):
    w = g["rooms_supply"].values
    row = {"destination": dest, "year": int(yr)}
    for c in cols_to_avg:
        row[c] = wavg(g[c].values, w)
    row["price_per_key_market"] = float(g["price_per_key_market"].iloc[0])
    rows.append(row)

mkt = pd.DataFrame(rows).sort_values(["destination",
    ↪ "year"]).reset_index(drop=True)
mkt["ln_price_per_key_market"] = np.log(mkt["price_per_key_market"])

out_dir = Path(".")

# --- Plot 3: Time evolution by destination (Florence highlighted) ---
fig, ax = plt.subplots(figsize=(9, 5))

# 1) Lines first (no markers)
for dest, g in mkt.groupby("destination"):
    g = g.sort_values("year")
    ax.plot(g["year"], g["ln_price_per_key_market"], linewidth=2,
    ↪ label=str(dest))

# 2) Markers for all destinations
for dest, g in mkt.groupby("destination"):
    g = g.sort_values("year")
    ax.scatter(g["year"], g["ln_price_per_key_market"], s=55, zorder=3)
```

```

# 3) Florence on top with black edge
gF = mkt[mkt["destination"] == "Florence"].sort_values("year")
ax.scatter(
    gF["year"], gF["ln_price_per_key_market"],
    s=90, zorder=5, edgecolors="black", linewidths=1.2
)

ax.set_title("Evolution of ln(Price per Key) by Destination (20222024)")
ax.set_xlabel("Year")
ax.set_ylabel("ln(Price per Key)")
ax.set_xticks(sorted(mkt["year"].unique()))
ax.legend(frameon=False, title="Destination")
ax.grid(True, axis="y", alpha=0.25)
fig.tight_layout()

plt.savefig(out_dir /
    ↪ "plot3_lnprice_time_by_destination_florence_visible.png", dpi=200)
plt.close(fig)
```

Python code: Table 2.6: Leave-one-destination-out robustness (log-log specifications)

```
import pandas as pd
import numpy as np
import statsmodels.formula.api as smf
from pathlib import Path

# -----------------------
# Inputs / outputs
# -----------------------
INPUT_XLSX = "Dataset .xlsx"   # adjust if needed
OUT_DIR = Path(".")
OUT_TXT = OUT_DIR / "robustness1_leave_one_out_TableA_summary.txt"
OUT_TEX = OUT_DIR / "robustness1_leave_one_out_TableA_summary.tex"

# -----------------------
# Helpers
# -----------------------
def wavg(values, weights):
    return np.average(values, weights=weights)

def stars(p):
```

```
    if p < 0.01:
        return "***"
    if p < 0.05:
        return "**"
    if p < 0.10:
        return "*"
    return ""

def fmt_cell(beta, se, p):
    # match your table style: 17.482*** (4.334)
    return f"{beta:0.3f}{stars(p)} ({se:0.3f})"

def build_destination_year_panel(df):
    cols_to_avg = ["adr", "occupancy", "revpar", "trevpar", "goppar"]
    rows = []
    for (dest, yr), g in df.groupby(["destination", "year"]):
        w = g["rooms_supply"].values
        row = {"destination": dest, "year": int(yr)}
        for c in cols_to_avg:
            row[c] = wavg(g[c].values, w)

        # market price per key is identical across segments by construction
        row["price_per_key_market"] =
    ↪ float(g["price_per_key_market"].iloc[0])
        rows.append(row)

    mkt = pd.DataFrame(rows).sort_values(["destination",
    ↪ "year"]).reset_index(drop=True)
    return mkt

def fit_cross_market(mkt, x_col):
    # Cross-market spec: Year FE only
    # ln(price/key) ~ ln(KPI) + Year FE
    formula = f"ln_price_per_key_market ~ {x_col} + C(year)"
    return smf.ols(formula, data=mkt).fit(cov_type="HC1")

# -----------------------
# Load & construct data
# -----------------------
df = pd.read_excel(INPUT_XLSX)
df.columns = [c.strip() for c in df.columns]

mkt = build_destination_year_panel(df)

# Logs
```

```
mkt["ln_price_per_key_market"] = np.log(mkt["price_per_key_market"])
mkt["ln_trevpar"] = np.log(mkt["trevpar"])
mkt["ln_goppar"] = np.log(mkt["goppar"])
mkt["ln_revpar"] = np.log(mkt["revpar"])

# Ensure categorical year (for clean FE)
mkt["year"] = mkt["year"].astype("category")

# -----------------------
# Leave-one-destination-out (Table 2.6)
# -----------------------
destinations = list(mkt["destination"].unique())
kpis = [("TRevPAR", "ln_trevpar"), ("GOPPAR", "ln_goppar"), ("RevPAR",
    ↪ "ln_revpar")]

table_rows = []
for d_left_out in destinations:
    sub = mkt[mkt["destination"] != d_left_out].copy()

    row = {"Excluded destination": d_left_out}
    for kpi_name, xcol in kpis:
        model = fit_cross_market(sub, xcol)
        beta = float(model.params[xcol])
        se = float(model.bse[xcol])
        p = float(model.pvalues[xcol])
        row[kpi_name] = fmt_cell(beta, se, p)

    table_rows.append(row)

out_df = pd.DataFrame(table_rows).set_index("Excluded destination")
# Keep column order
out_df = out_df[["TRevPAR", "GOPPAR", "RevPAR"]]

# -----------------------
# Write TXT (plain)
# -----------------------
lines = []
lines.append(" " * 12 + "TRevPAR".ljust(20) + "GOPPAR".ljust(20) + "RevPAR")
for idx, r in out_df.iterrows():
    lines.append(
        f"{str(idx):<12} {r['TRevPAR']:<20} {r['GOPPAR']:<20} {r['RevPAR']}"
    )
OUT_TXT.write_text("\n".join(lines), encoding="utf-8")

# -----------------------
```

```
# Write TEX (simple tabular)
# ------------------------
tex = []
tex.append(r"\begin{tabular}{lccc}")
tex.append(r"\hline")
tex.append(r"Excluded destination & TRevPAR & GOPPAR & RevPAR \\")
tex.append(r"\hline")
for idx, r in out_df.iterrows():
    tex.append(
        f"{idx} & {r['TRevPAR']} & {r['GOPPAR']} & {r['RevPAR']} \\\\"
    )
tex.append(r"\hline")
tex.append(r"\end{tabular}")
OUT_TEX.write_text("\n".join(tex), encoding="utf-8")

print(out_df)
print(f"\nSaved:\n- {OUT_TXT}\n- {OUT_TEX}")
```

Bibliography

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