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Revenue Management Delivers Significant Revenue Lift for Holiday Retirement

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Abstract. Holiday Retirement (Holiday), the second-largest senior-housing operator in the United States, has over 300 facilities and an annual revenue of approximately $1 billion. Holiday partnered with Prorize to replace its outdated pricing model with a new revenue management system to increase revenue and improve customer satisfaction. Holiday's previous inconsistent pricing structure resulted in continual price negotiations between corporate and local staff, and between local staff and customers, and led to revenue loss and negative customer experiences. By implementing an innovative revenue management system similar to those traditionally used in the travel and hospitality industries, Holiday has increased its revenue from new rentals by $88 million, or approximately nine percent, since it fully deployed the state-of-the-art system in 2014.

Keywords: revenue management • yield management • pricing • pricing science • value selling • senior living • senior housing • self-storage

The global population of people aged 65 and over is growing at a record rate, increasing from 6.9 percent in 2010 to an anticipated 16.4 percent, or approximately 1.5 billion people, by 2050. In the United States alone, people over 65 will increase from 13 percent in 2010 to 19 percent, or approximately 71 million, by 2030, primarily because of the aging baby boomer generation (U.S. Department of Commerce Economics and Statistics Administration 2010, Kochhar and Oates 2014).

Meeting the needs of and caring for this looming gray wave, especially as the proportion of working adults to retired seniors continues to shrink, is an issue of global proportions. As society grapples with this issue, demographics are driving the growth of a multibillion-dollar industry focused on building, owning, operating, buying, selling, and renting senior-living facilities. These facilities fill a key chasm between living at home and being in a hospital, and range from independent-living and assisted-living communities to nursing homes.

Investor interest in the senior-housing sector is strong, particularly in the United States. Over the past 15 years, the U.S. senior-living business has grown to be a $315 billion industry (Gottlieb 2015). This increase propelled the development of healthcare-focused real estate investment trusts (REITs) and large-scale senior-living operators. In this paper, we address only the senior-housing rental market—not the real estate investment market nor the market in which people purchase homes for their own residential use.

For senior-living facilities to succeed, they must be run efficiently and supported by a profitable business model. To accomplish this, no process is more foundational than the method an operator uses to make pricing decisions. Unfortunately, the pricing process that most senior-living operators use is archaic at best, and is inconsistent, manual, and reactive. A typical operator sets prices (rents) for its products at the beginning of each year based on budgets. If prices are too low, the operator ends up with waiting lists of interested residents, but no available apartments; if prices are too high, the operator ends up with unsustainable low occupancies. The latter often results in requests for exceptions and incentives, causing corporate management, local staff, and prospective residents to spend excessive time negotiating prices.

Holiday Retirement (Holiday), the second-largest senior-housing operator (and the largest private owner and operator of independent senior-living communities) in the United States, was the first company to use operations research and analytics to determine an optimal pricing methodology for the senior-housing industry. Holiday partnered with Prorize, an Atlanta-based revenue management firm, to analyze, develop, and implement the first revenue management (RM) system for this industry.

Revenue management is a key business discipline that balances demand and supply with the goal of maximizing revenue and profit growth. The use of RM is well established in the travel and hospitality industries and widely recognized as a critical business process by leading airlines, hotels, and car rental companies. It has also been successfully employed in real estate rental businesses to enhance the profitability of multifamily operators for over 15 years. For comprehensive treatments of RM, refer to Talluri and van Ryzin (2004) and Phillips (2005).

In general, RM in a senior-living community can be viewed as a special case of matching supply to demand. Available units (or apartments) determine supply. A senior-living product is best described by its unit size, unit location, and unit attributes; hence, each potential resident may value it differently. For example, a 500-square-foot unit close to activities and dining areas is more desirable than a similar unit farther away. Customer requests represent the demand, which is highly uncertain, based on factors such as the current economic market, community characteristics, care services, unit size, unit location, unit attributes, population density, season, number of competitor sites, proximity to competitor sites, and quality of competitor sites. In addition, industry practices typically include extensive move-in incentives, various discounts, and modifications of rents for existing residents. These and other factors make it difficult to match demand and supply in a way that maximizes long-term revenue.

In this paper, we provide a brief overview of the senior-living industry and Holiday, and present Holiday's pricing challenges along with the project's history and evolution (project phases and changing business processes). We then focus on the solution framework and discuss the managerial problem, technology infrastructure, demand forecasting, customer price-sensitivity modeling, optimization, and rent-deployment processes. Finally, we discuss the financial and business impacts of the RM system and the portability of our solution.

Overview of the Industry and Holiday Retirement

Senior-living business segments are differentiated by the care and services they provide.

- Independent living (IL) includes age-restricted rental communities that provide residents with meals and other services, such as housekeeping, linen service, transportation, and social and recreational activities as part of their monthly rent.
- Assisted living (AL) includes state-regulated rental communities with services comparable to IL communities; in addition, they provide supportive care, such as supervision of medication, bathing, dressing, toileting, and eating. Some of these types of communities also include memory care (MC) for those with failing memories (e.g., dementia).
- Skilled nursing facilities (SNF) comprise rental units that provide 24-hour skilled nursing and (or) medical care.
- Continuing-care retirement communities are age-restricted communities that provide a combination of IL, AL, MC, and SNF services at a single location.

As the second-largest senior-housing operator in the United States, Holiday has approximately $1 billion in annual revenue and operates over 300 communities comprising 40,000 apartments in 43 states. It is organized into four districts and 25 regions. The company has 12,000 employees, including a sales staff of approximately 350. Most of the Holiday communities are IL facilities, and about 10 percent also provide AL services.

Holiday IL communities resemble all-inclusive resorts, providing residents with three chef-prepared meals a day, paid cable and utilities, housekeeping, linen service, local transportation to shopping and appointments, social activities, and exercise rooms. In addition, Holiday offers travel programs that allow residents to visit other Holiday communities across the United States without charge for up to seven nights.

Pricing Challenges

As with most senior-living firms, Holiday has traditionally set its prices at the beginning of each year during its primarily manual budgeting process. The prices were then handed down to local sales people who were also given allowances for significant negotiation and incentives. The result was large gaps between asking prices and actual prices. Prior to the April 2013 pilot deployment of our RM recommendations, these gaps averaged 11 percent (see Figure 1).

In addition, for any unit type (e.g., studio), each community offers many different amenities, such as size, unit location (e.g., close to the dining area), floor level, view, and full kitchen. However, when pricing these units, Holiday did not consistently consider amenities as a key factor. This created a situation where two very different units of the same unit type could be priced equally. Our research shows that systematic consideration of amenity values is important for any RM system because the average price gap between the most valuable and least valuable units within a unit type is 12 percent. Figure 2 illustrates how different amenity values can affect pricing.

Moreover, Holiday's pricing was reactive and not granular. Customer price sensitivities and move-in forecasts were not considered when pricing. In a good month in which many residents moved in, rents increased, discounts were reduced, and incentive allowances were eliminated across the board. In a poor month, rents were reduced in an ad hoc, reactive fashion and additional discounts and incentives were allowed.

When rents were too high, local staff received frequent requests for exceptions. As a result, staff members had to spend excessive sales time negotiating rents, first between local and corporate staff, and then between local sales people and potential residents.

Figure 1. (Color online) Gaps Between the Asking Prices and the Actual Prices Were Significantly Reduced After the RM Project Implementation

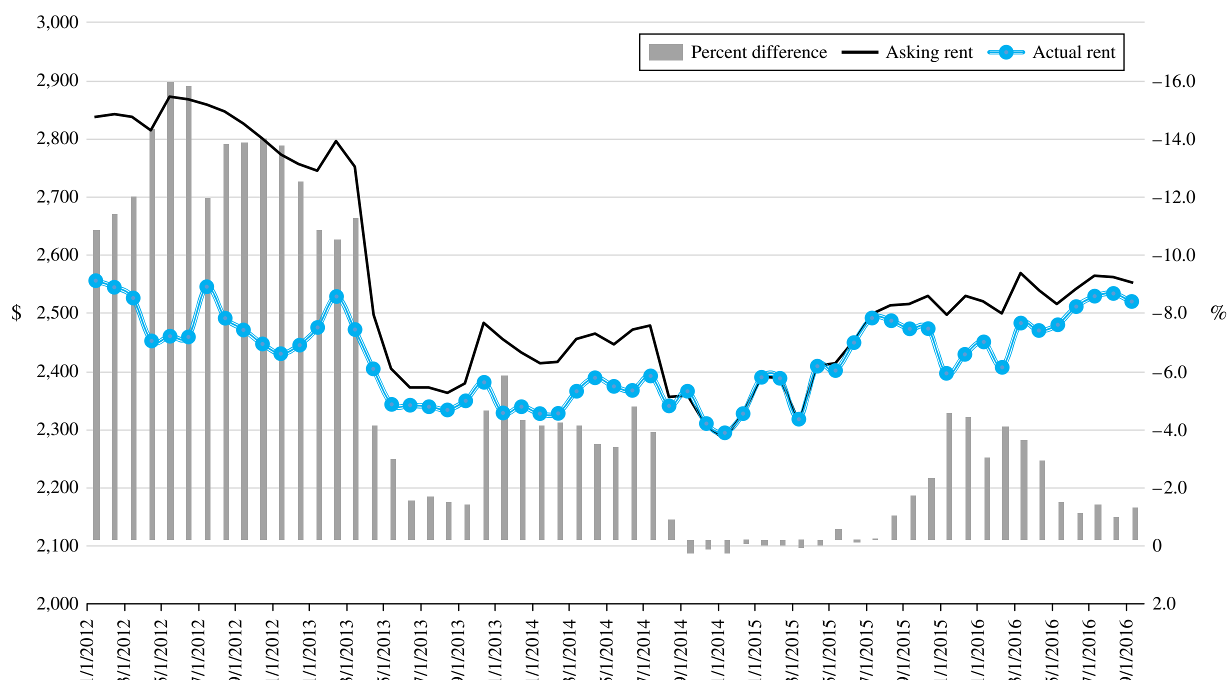
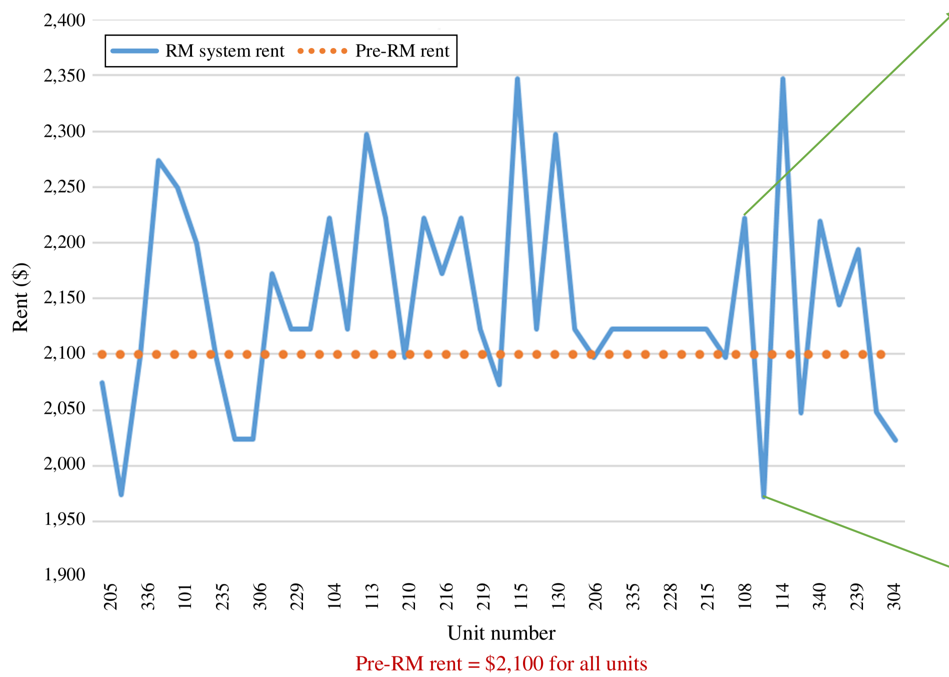


Figure 2. (Color online) RM System Ensures That Two Similar Apartments Are Priced Differently Based on Their Amenities



Amenity type	Value ($)	Description
BATHROOM	25	BATH OFF BEDROOM
BATHROOM	25	STANDUP SHOWER
LOCATION	0	1st FLOOR
LOCATION	75	DIRECT OUTDOOR ACCESS
LOCATION	100	SAME FLOOR AS DINING
PATIO/BALCONY	0	STANDARD PATIO/BALCONY
VIEW	–25	PARKING/GARAGE VIEW

Total amenity value: $200

RM rent = $2,222

Amenity type	Value ($)	Description
BATHROOM	25	BATH OFF BEDROOM
BATHROOM	25	STANDUP SHOWER
LOCATION	–75	FAR FROM CENTER
PATIO/BALCONY	0	STANDARD PATIO/BALCONY
VIEW	–25	PARKING/GARAGE VIEW
VIEW	0	RESIDENTIAL VIEW

Total amenity value: –$50

RM rent = $1,972

Note. This price differentiation allows the marketing team to promote units, and the sales team to sell each unit based on the value of its amenities.

The decision to move into a senior-living facility is an emotional one for prospects, and the sensitivity to this process is a vital contributor to creating a positive customer experience. Yet, instead of the positive anticipation of choosing a home that would be well suited to live in for the remainder of his (her) life, the potential resident often felt that the transaction was more like buying a used car.

The process was difficult for everyone involved, and Holiday management ultimately felt that it was leaving revenue on the table. The leadership at Holiday was aware that many other industry sectors (e.g., airlines, hotels, and multifamily housing) were using big data to optimize their prices. However, management also knew the senior-living industry differed from those industries; therefore, it partnered with Prorize to develop a solution that (1) addressed the unique needs of the senior-living industry, (2) delivered the best pricing for residents and their families, (3) enabled the Holiday sales staff to adapt to a new business process, and (4) used consistent and robust pricing processes to achieve revenue improvements.

Project Evolution

The project was a multiyear, multiphase initiative that began formally in November 2011. The system was fully rolled out across all Holiday's IL communities in August 2014. We summarize the project's three major phases in the following sections.

Phase 1: Rent Optimization and Proof-of-Concept Analysis

Phase 1 focused on ensuring that Prorize understood Holiday's business, identifying the most effective scientific and disciplined pricing algorithms, and establishing the anticipated benefits. Efforts included business process analysis, data cleansing, data transformation, in-depth data analyses, product segmentation analysis, customer-response modeling, demand-forecasting, optimization, and rent-generation processes. Holiday ruled out including customer segmentation because of the Fair Housing Act, which protects a potential renter from landlord discrimination because of that prospect's background. Although the law technically does not restrict the use of customer segmentation, Holiday wanted to avoid any potential legal issues related to price differentiation by customer segment.

During this eight-month phase, we used data analyses to identify many opportunities for employing RM approaches. For example, we found that Holiday's historical data included a wide range of move-in rents (i.e., initial rents for new customers). This enabled us to measure responses to price changes. We also found that demand is highly seasonal and that we could estimate it. We did not consider unit amenities in this phase, although we knew they would add significant value to the sales process. We achieved the following results in this phase:

(1) Identified key pricing levers and constraints.

(2) Confirmed that available data accurately represented Holiday's business.

(3) Proved that the data include statistically significant patterns, demand is predictable, and customer responses can be estimated within a satisfactory margin of error.

(4) Developed initial RM algorithms for this business.

(5) Showed that RM rent recommendations are aligned with business constraints.

(6) Estimated that significant revenue benefits could be achieved via a demand-arrival process in which each month's data are intentionally withheld from the model at the time of pricing, and estimated revenues are generated one month at a time. The Prorize team estimated the revenue lift to be between 3.2 and 7.2 percent. To ensure that we would not overestimate revenue, we did not allow the simulated optimal rent of a transaction to deviate from its actual rent by more than five percent. We relaxed this assumption when we implemented the solution in the later phases.

Phase 1 was offline. Rents were not deployed. The forecast accuracy and revenue benefits were confirmed by a simulated demand-arrival process. We then needed to confirm that the algorithms would work within Holiday's production business environment and that our rent recommendations would be advantageous to Holiday.

Phase 2: Live Pilot Using an Offline RM System to Confirm Benefits

This phase focused on executing live pilots in which we used a set of pilot properties and created RM system recommendations for each pilot. We compared the results from these pilot tests to those from a set of control properties for which we did not implement RM recommendations. We implemented four pilots in Phase 2, which began in July 2012 and concluded in July 2014. The first two pilots included 10 communities and achieved revenue lifts above 20 percent when compared with the control communities.

Based on the results of the first two pilots, we began Pilot 3 in which Holiday deployed the RM system for its worst-performing, but highly competitive, region. Pilot 3, which included 30 communities, was not a good pricing experiment because it did not include a control group; therefore, it did not initially show positive results when compared with the rest of the company. Although this region differed significantly from the rest of the company, it was the only comparison we used.

Holiday wanted to ensure that the revenue-lift results of the first two pilots were representative of the results it could achieve when it put the RM system into production. Therefore, it requested that we do Pilot 4 using carefully selected pairs of pilot and control communities across the organization. This pilot would help Holiday to determine whether it would roll out the RM system across the organization.

The pair selection for Pilot 4 was done a priori using community-pair attributes, including but not limited to, distance, unit capacity, average rent, current occupancy, average occupancy, demand pattern, demand volatility, demographics, unit mix, neighborhood attributes, turnover, year built, number of Holiday communities within 25 miles, and number of competing communities within 10 miles.

Prorize identified the highest-scoring (i.e., most equivalent or similar) 20 community pairs, and Holiday reviewed them to ensure that none of its business issues would bias the results. From each pair, we randomly selected the pilot community. Holiday ensured that the managers of the control communities would not know that they were being used as a baseline and that the managers of the pilot communities were unaware of the control communities. At the end of each month, we compared the revenue and demand generated in the pilot and control communities and calculated the revenue lift.

After four months, the revenue-lift differential observed from these actual rent deployments averaged 9.3 percent; it ranged from 4.1 to 16.2 percent based on different historical baselines (i.e., up to two years of historical data prior to the pilot start dates). These results gave Holiday confidence that by using data-driven pricing, it could achieve significant revenue increases. Holiday decided to roll out the system across all its communities in August 2014.

Phase 3: Product Development for Full Automation and Integration

Holiday decided to allow Prorize to automate the end-to-end process. This phase began in July 2013, and achieved a milestone when all its communities began using the algorithms in August 2014. Phase 3 concluded in December 2014 when additional automation and user-interface elements (e.g., reports, workflow management) were completed. The scope-of-work requirements included the following:

(1) Automating the data load (one time and incremental) with sophisticated error reporting.

(2) Gathering unit amenities and incorporating differential amenity pricing into the system; Holiday had not previously differentiated unit features (e.g., square footage, unit location, unit floor level, full kitchen, view).

(3) Integrating forecasting and optimization modules.

(4) Building a user interface, and developing reporting and configuration capabilities.

The resulting application developed by the Prorize team is called the Senior-Living Rent Optimizer (SLRO).

Changing the Business Process

Pricing relates to many functional areas, including finance, sales, marketing, and products. Each functional area has competing objectives, which may not align fully with the corporate strategy. For example, the finance department needs a higher average selling price to meet its budgeted targets; however, the sales department wants higher volume because of volume incentives. This conflict often manifests itself in pricing decisions. The performance of a pricing system, as well as all other functional areas, should be aligned around one corporate objective (e.g., increased revenue).

Holiday's CEO and its senior vice president of sales championed the RM system and served as its advocates to the field sales force. This initiative streamlined the pricing processes and ongoing communication between the operations, sales, and pricing teams, and resulted in significant improvements in Holiday's operations and sales processes. Moving from the use of discounting and incentives to a value-based approach required a cultural shift in the mind-set of Holiday's staff, and ultimately resulted in a more focused and informed sales force.

In the new selling process using the RM rent recommendations, the sales representative begins by asking prospects about their needs and the amenities they value most, but keeps pricing out of the initial discussion, if possible. The sales representative then shows the prospect the unit that best matches his (her) preferences. If the price of the unit is less than or equal to the amount the prospect is willing to pay, it likely results in a sale. Otherwise, the sales representative shows a less expensive unit with fewer amenity options and justifies the price differential based on the differences in amenity values.

This added emphasis on value-based selling is a key component and a benefit of the RM system. Ongoing training was critical to ensure teams understood (1) the nuances of the sales process, because value-based selling is focused on specific amenities and locations that are matched to the determination of the specific factors important to that customer; and (2) how to position themselves relative to competitors.

We observed that 60 percent of new residents move in within 30 days of the initial inquiry, 20 percent move in between 30 and 120 days of that inquiry, and the remaining 20 percent move in after 120 days. When pricing was discussed, sales representatives explained that Holiday used a pricing model that was similar to the model hotels use to determine the price of each unit. This model updated the pricing of each unit on a predetermined day of each week. Each prospect was given a quote guarantee of two weeks, which was communicated upfront. Within this two-week period, a prospect could lock in the price for a selected unit by placing a deposit on that unit.

System-recommended rents do not change dramatically from one week to the next unless significant numbers of residents move in or move out. In general, changing rents weekly without upfront communication can be overwhelming for prospects or their family members as they navigate the process. Maintaining a stable pricing policy is key in gaining customer trust. However, Holiday must balance stable pricing against changes in business conditions, which might dictate rent changes. Any changes must be communicated to prospective residents.

Solution

Managerial Problem and Conceptual Overview

The managerial problem involves optimizing single-resident move-in rents so occupancy and rents are balanced to maximize revenue. In this paper, we do not address other fees (e.g., second-resident fees) related to optimizing rents.

Unlike traditional apartments, IL community residents sign month-to-month leases; hence, residents have the flexibility to cancel leases during any month. They pay an upfront community fee (sometimes waived or reduced as an incentive) and then agree on a unit and monthly rent, which is typically locked for one year. For couples, the second resident often pays a nominal fee for meals or other services. Residents choose a community that covers their basic needs, best fits their desire for social activities, and is within their budget. Move-outs tend to be because of death or a required higher level of care for a resident. The average length of stay exceeds 30 months; therefore, Holiday's expected total revenue from each resident ranges from $75,000 to $90,000.

We use one month as our forecast and optimization horizon for several reasons. First, the senior-living industry has a month-to-month leasing environment, because elderly residents and their families do not want to commit to long-term leases in case the residents are unhappy about the environment or they do not survive the committed lease terms. Some states have regulations specifying that seniors can move out any time without incurring further financial obligations. Second, 3–4 percent of existing residents move out each month, making space for new residents. The number of new residents who move in (i.e., move-ins) each month is also around 3–4 percent of existing residents. This creates constant changes in supply and presents a problem with using a one-month horizon. Finally, we observed that forecast errors are higher for both move-ins and move-outs (i.e., the number of residents who move out) for longer horizons, resulting in more volatile rent recommendations from one application run to the next.

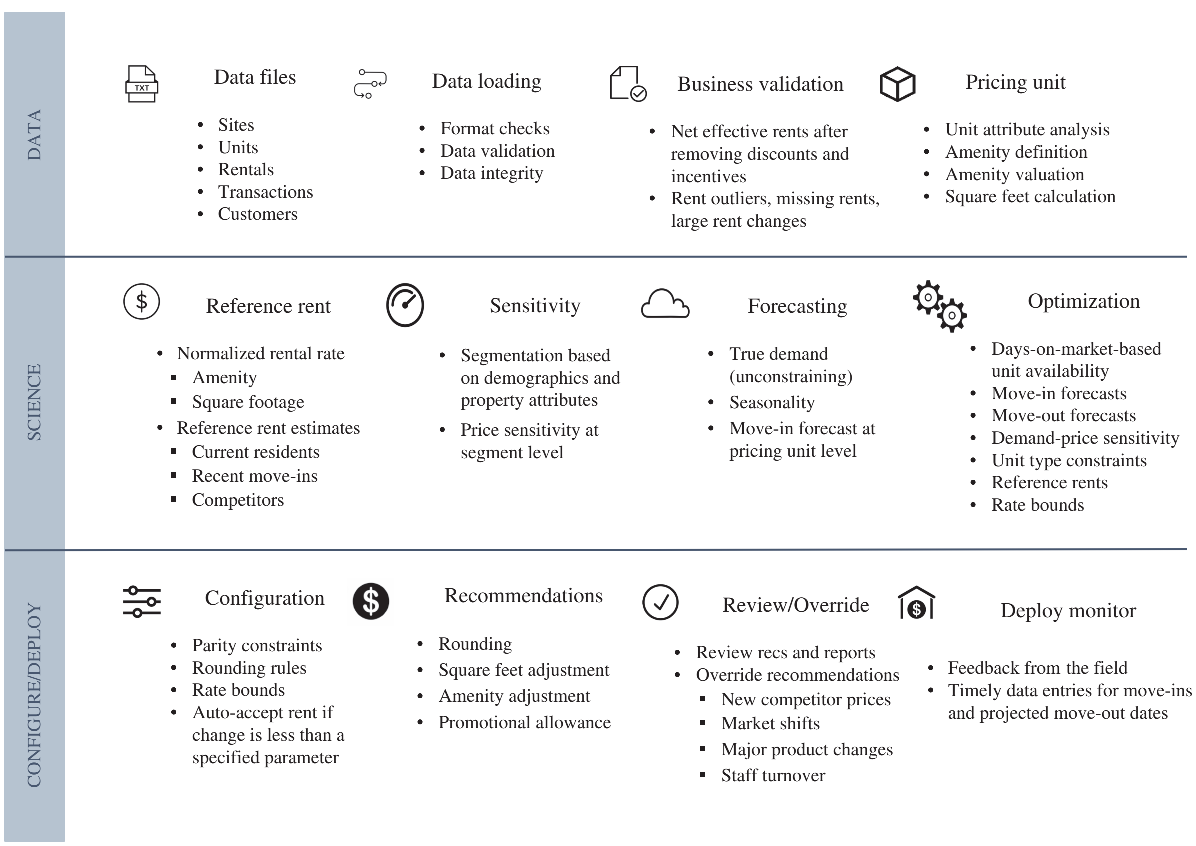
As previously mentioned, pricing and RM in a senior-living community is a special case of matching supply to demand. Available units determine supply, which is uncertain because committed leases may be cancelled or an unanticipated number of residents may move out. Customer requests represent demand, which is uncertain because of multiple factors, including community attributes, demographics, the season, the competitive situation, and lead-generation activities. Therefore, matching demand and supply to maximize long-term revenue is extremely difficult.

The SLRO methodology has three main steps: data, science, and configure/deploy (see Figure 3). The SLRO processes involve repeatedly cycling through these steps and depend on many factors, such as data volume, speed of change in business conditions, and relative importance of decisions. At Holiday, these steps are executed weekly. The entire system is recalibrated annually or when any major change occurs in the business (e.g., an acquisition).

Data and Technology Infrastructure

Developing effective price-optimization models requires collecting all data that reflect historical demand, supply, and market information. We spent considerable time translating lease transactions from Holiday's accounting system. We created a tool that automates the extract, load, and transform (ETL) processes and produces a report that identifies data inconsistencies or errors. Using the application interface, clients can view their original data, see transactions that have been excluded, and determine the reason for the exclusions. The ETL process ensures accurate data by checking for inconsistencies and eliminating the impact of extreme outliers. This process considerably improved

Figure 3. (Color online) The SLRO Process Involves Recurring Cycles of Three Main Steps



Notes. The data step collects, cleanses, validates, transforms, and maintains relevant pricing data. The science step estimates parameters for demand models and generates optimal sets of rents to apply until the next reoptimization. The configure/deploy step involves setting system parameters, processing recommendations, and deploying rents to the client's lease transaction-management system.

client data and helped us to establish a strong data foundation for pricing analytics.

Pricing Unit

A pricing unit defines the level at which pricing and optimization are performed. It is the most discrete and controllable element of an RM system; in Holiday's case, it is a collection of apartments. For example, we do not forecast demand for Apartment 101 in Community A; we forecast demand for studio apartments in Community A. Price differences for apartments within the studio pricing unit are handled by the amenity-pricing process and rent-per-square-foot regression models. After performing data analysis at Holiday, the team decided to use community and unit type as the pricing unit.

The RM system produces forecasts, calculates many statistics, and generates optimum rents at the pricing-unit level. Additional amenity or feature differentiation important for pricing is accomplished by an amenity-pricing process. For example, making an assumption that a renter would pay a $100-per-month premium for being close to the core—the area that houses the dining room and the activity center—is reasonable. Because data are sparse, defining a pricing unit that specifies whether an apartment is close to the core is difficult; however, we could add a predefined close-to-the-core premium in a pricing-rule table. The close-to-the-core premium is usually derived using a separate modeling process, survey, price experimentation, or business judgment.

Unconstrained Demand

Observed demand is inherently censored (constrained) because data are collected based on actual rentals, not on rentals that did not materialize. Details about prospects who decide not to rent after an inquiry or community visit are rarely recorded. Even if they are recorded, the information documented is often imprecise because most reports do not specify the apartment for which the prospect was interested.

We used the projection-detruncation (PD) method for correcting (unconstraining) incomplete demand (Talluri and van Ryzin 2004). All subsequent forecasting and optimization modules used unconstrained demand.

The PD method provides flexible parameter settings to control the aggressiveness of unconstraining demand based on various conditions or seasons. For example, we unconstrain demand less aggressively if demand for a pricing unit is sparse. In addition, we unconstrain more aggressively in summer than in winter because demand is likely to be greater in higher-demand seasons, such as summer; for details, we refer the reader to the *Demand Forecasting* section.

Reference Rent and Decision Variable

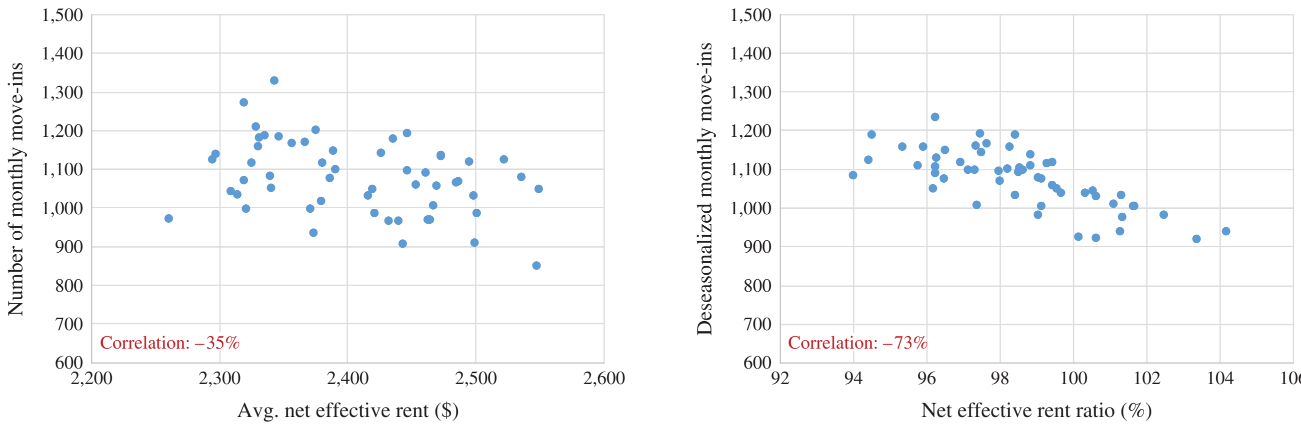
Rent amounts in dollars cannot be used as a pricing variable because absolute dollar amounts are meaningless when aggregated across communities or product segments. For example, $3,000 per month might be an attractive price in Community A, but expensive in Community B. We conduct a series of steps to normalize rents for such differences and use them as part of the forecasting and optimization processes.

Each rental transaction includes rent, and might include incentives (e.g., one month free) and (or) permanent discounts. We calculate "net effective rent" by removing permanent discounts from the transaction rent and adjusting for the impact of incentives based on expected length of stay, which we calculate using historical transactions for the corresponding pricing unit.

We calculate "base reference rent" by pricing unit (community and unit type) and month as follows. First, we use amenities and unit size to adjust the net effective rents of existing customers and net effective rents of recent move-ins. To make these adjustments, we assume that the base reference rent reflects the most common unit size with common amenities value (or sometimes median size and median amenities value) for the pricing unit. We calculate the base reference rent as a weighted average of the adjusted net effective rents of existing customers and adjusted net effective rents of recent move-ins.

We calculate the "reference rent" of an individual unit by taking the base reference rent and adjusting it to incorporate the value of the unit's size and amenities. Reference rent may be viewed as an anchor of a rental rate for a particular unit in a community at a given time. It pertains to the economic value of the unit in the marketplace, and allows us to normalize the pricing variable as a ratio: the net effective rent ratio. The net effective rent ratio is the net effective rent of a unit divided by the reference rent. Accordingly, it indicates, on a percentage basis, how much a rent is above or

Figure 4. (Color online) Left Chart: Company-Wide Relationship Between Average Net Effective Rent and Number of Move-Ins; Right Chart: Stronger Correlation of the Same Data Series After Normalizing Rents Using Net Effective Rent Ratio and Adjusting Move-Ins Using Seasonality



below its reference rent. For example, a net effective rent ratio of 1.15 would indicate a rent that is 15 percent more than its reference rent.

We use the net effective rent ratio for all market-response modeling and as a decision variable in the optimization. The use of net effective rent ratio with deseasonalized move-ins significantly improved the price-sensitivity estimation (see Figure 4). When we considered other possible pricing variables (e.g., splitting rents and incentives into two separate decision variables), the predictions and rent recommendations generated were less stable.

Pricing Segmentation

Company-wide price-sensitivity measurements are not helpful because pricing opportunities are usually hidden within microsegments; thus, pricing segmentation is a foundational component of any RM system.

We explored opportunities for product segmentation, which gave us community-type and apartment-type clusters. We have data for product attributes, including those that are community dependent; examples include average housing price, average income, average multifamily rent, median population age, population over the age of 75, percentage of residents living in a one-bedroom unit, market type (e.g., rural versus metropolitan), state, unit type (e.g., studio, one-bedroom, two-bedroom, cottage), and average length of stay at each community.

To derive pricing segments, the most common methods used are statistical clustering, decision-tree techniques, or business judgments. However, these *alone* are not appropriate. All available clustering techniques tend to generate more segments than are necessary, because to the best of our knowledge, no clustering technique can define clusters based on price sensitivity as a discriminator (Kuyumcu 2007). This is a promising research opportunity.

For example, unit type is a good segmentation dimension if we can establish that the price sensitivity of prospects interested in studio units differs from those interested in one-bedroom units. Similarly, a prospect in an expensive neighborhood might have a different price sensitivity than one living in a less expensive neighborhood.

We combined business knowledge, clustering, and decision-tree algorithms, and defined over 3,000 potential segmentation scenarios. For example, a segmentation scenario may cluster communities as high, medium, or low using an average housing-price variable based on k-means clustering, include rural or metropolitan locations, or contain one-bedroom apartments based on classification and regression tree (C&RT) clusters. We assessed each segmentation scenario using corresponding market-response models.

Market-Response Modeling

The goal of market-response modeling is to relate decision (or pricing) variables, segmentation variables, and customer-response variables via statistical modeling (Hanssens et al. 2001). The output of the market-response model is estimated price sensitivities as a function of the net effective rent ratio.

We used Prorize's proprietary *Science Library and Model Configuration Software* to evaluate thousands of segmentation scenarios, each of which uses multiple forms of market-response functions (e.g., linear and log linear). With monthly demand as the response variable, the segmentation scenario that provided the best regression results included a log-linear functional form with the following segmentation dimensions:

- Unit type.
- Market (e.g., rural versus metropolitan).
- Average housing price within a specific-mile radius (e.g., \$0–\$105,000, \$105,000–\$194,000, \$194,000 and higher).
- Median population age within a specific-mile radius (e.g., 0–33, 33–40, 40 and older).

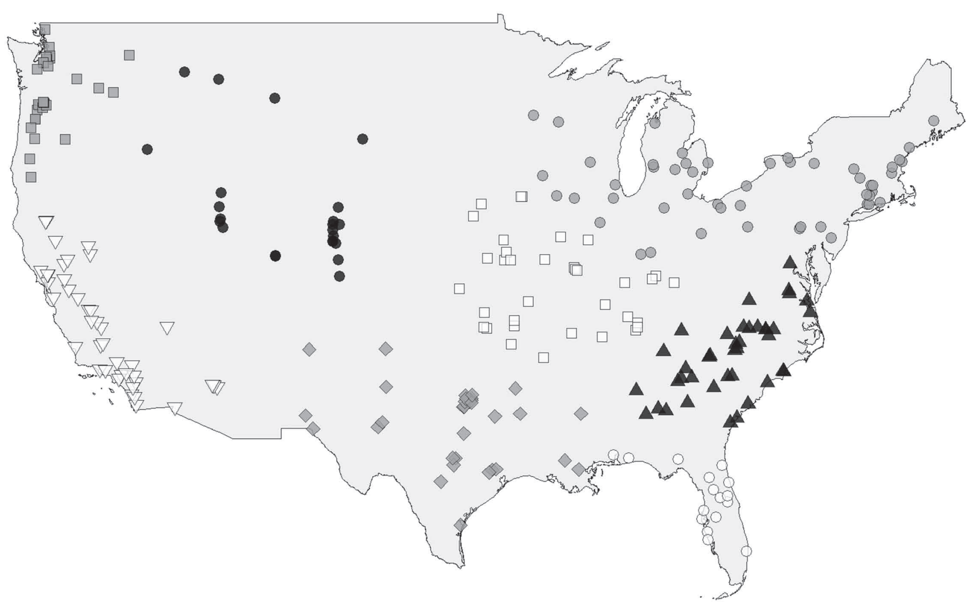
Holiday approved this segmentation scenario based on data availability, maintenance requirements, business judgment, price-sensitivity estimates, and their values relative to each other; for example, we expect residents in less expensive neighborhoods to be more price sensitive than residents in more expensive neighborhoods.

Demand Forecasting

We used seasonally and price-adjusted unconstrained demand to forecast move-in ranges (minimum, expected, and maximum) to reflect the probabilistic nature of the demand. Because weather conditions have a significant impact on move-in demand, we aggregated the zip codes of communities using k-means clustering and further aggregated the groups of communities based on business judgment (see Figure 5). We incorporated the impact of prices and used two-stage Fourier regression models to estimate seasonality and trend parameters.

The forecasts of customers moving in are generated by time-series decomposition after combining seasonality and trend parameters. Our forecasting library has different forecasting methods; these include adaptive rate smoothing, Croston's method, exponential smoothing, double exponential smoothing, moving average of any chosen length, naive forecast, and year-over-year forecasts (Makridakis et al. 1998, Croston 1972). We tested these methods (and a range of PD aggressiveness constants) and configured the system to obtain minimum forecast errors. We used hold-out sampling to evaluate and select the time-series method, its smoothing-parameter values, and PD constants based on information from the forecast evaluation

Figure 5. We Used a K-Means Clustering of Zip Codes and Business Judgment to Aggregate Demand for Each Cluster and Estimate Move-In Seasonality



module described later. Simple exponential smoothing produced the best results. We also estimated variance via exponential smoothing and used this information to create the minimum, expected, and maximum forecast values of move-in demand.

We considered move-out notices from current residents, historical data on residents who moved out, existing customer rents, and move-in rents to forecast the number of customers who would move out. Like the move-in forecasts, move-out forecasts employed time-series decomposition (move-out seasonality and trend) for their base forecasts. Further adjustments were made considering current move-out notices and the number of existing customers, churn rate, existing customer rents, and current move-in rents. Average, minimum, and maximum move-out forecasts were generated.

The SLRO has a forecast evaluation module, which is executed with each run. All forecasts are evaluated based on hold-out sampling techniques (prior to configuration) and reported based on forecast accuracy (i.e., our forecast numbers compared with the sales numbers that Holiday achieved). We monitor 22 forecast-error measurements and report forecasts at multiple levels of aggregation. Examples of these measurements include mean absolute percentage error, actual mean, forecasted mean, mean forecast error, mean error negative (forecast <actual), mean error positive (forecast >actual), standard deviation of forecast error, total number of forecasts, percentage of actual falling within one standard deviation assuming a Poisson distribution, and percentage of actual demand falling within two standard deviations assuming a Poisson distribution.

Supply Availability

The supply constraints in the optimization model are defined by *units available,* which are units that are or will soon be available. This term (also called *units exposed* in the senior-living and apartment industries) refers specifically to (1) units that are unoccupied and for which a new lease has not been signed; or (2) units that are occupied and from which the residents are expected to move out (or have given notice of plans to move) plus the number of residents forecast to move out.

Unit availability is also adjusted for residents who transfer from one unit to another unit within the community; transfer-out residents add to the supply of units available and transfer-in residents reduce the supply. We also include a days-unoccupied parameter, which refers to units that are not included in units available until they are unoccupied for a specific number of days. This gives sales representatives additional days before the system responds with a rent decrease because of higher availability. This parameter was particularly effective for highly occupied unit types because it slowed price decreases resulting from an unanticipated number of residents moving out.

Price Optimization

The optimization model considers move-in forecasts, move-out forecasts, unit availability (i.e., availability based on days unoccupied), minimum rent differences across unit types, rent sensitivities, reference rents, seasonality, net effective rent ratio bounds, and optimized expected revenue. The optimization model employs a modified version of the deterministic pricing models presented in Kuyumcu and Popescu (2006), where move-ins, availability, and price-sensitivity parameters are treated as probabilistic.

The original formulation of the optimization problem was a two-stage stochastic model. We first tried generating all random scenarios and simultaneously solving for them. Each scenario reflected the values of random variables for demand quantities, price sensitivities, and units available. However, solving a two-stage stochastic model for even a single community was time consuming. Because one requirement for the system is to refresh the data weekly and generate rent recommendations in a short amount of time, this solution was unacceptable. Instead, we generated and tested scenarios in which we solved the deterministic version of the model for each scenario many times and then averaged the optimum solutions. We refer to this as a wait-and-see solution. Because we have a low volume of data at this level, it is difficult to fit distributions to it; consequently, we generated the scenarios using the triangle distribution for each random variable (while the implementation allows for other probability distributions to be incorporated as needed in the future). Our analyses show that the average of our wait-and-see solutions is very close to the two-stage stochastic solution, where the difference between the wait-and-see solution and the two-stage stochastic solution is much less than applying the rounding rule to the final rent. See Appendix B for the deterministic version of the optimization model that is run for each scenario.

The solution of the optimization model provides optimum net effective rent ratios, but not actual rents. We still need to convert them to dollars to obtain optimum rents for individual units.

Generation of Rent Recommendations

Rent recommendations are generated for individual apartments using the optimum net effective rent ratio at the pricing-unit level. An apartment's recommended rent is determined by multiplying the net effective rent ratio by the reference rent, and adjusting for rounding rules and promotional allowances.

The SLRO offers users the flexibility to customize their views. It provides users with sorting, searching, and look-up capabilities, thus allowing them to review prices at the community, unit, or amenity levels. They can view, update, accept, reject, override, and deploy price recommendations. Users can also drill down into details of each pricing recommendation and view many reports and related statistics before they decide about each recommendation.

Financial and Business Impacts

Estimated Impact

Prorize and Holiday developed a method for estimating revenue performance by designing and executing four live pricing experiments. In these pilot tests, they compared the results from a set of pilot communities that used recommendations from the RM system with results from a set of control communities that did not use the system. The results from these actual rent deployments showed significant revenue benefits, which were later confirmed by the company's actual revenue growth, as we discuss in the *Realized Impact* section.

Figure 6 shows expected revenue growth for the initial 10-year period using the revenue from August 2013 to July 2014 as a baseline. This estimation disregards any additional revenue growth opportunity because of inflation or other rent adjustments for existing residents. We provide related notation and estimation details in Appendix A.

With $950 million annual revenue, we estimated that Holiday would experience an average revenue growth of $32 million in year 1 and $52 million in year 2 (see Figure 7). Thus, we estimated the total revenue contribution to be $84 million after two years of SLRO deployment. The actual realized revenue contribution for the two years was slightly higher at $88 million, as we describe in the *Realized Impact* section. Similarly, we estimated that the total revenue contribution would reach $302 million after five years of SLRO deployment (see the note of Figure 7). When all existing resident rents are optimized, we expect a continuing annual revenue contribution of $88 million, as the average revenue lift for year 10 shows (see Figure 6).

Realized Impact

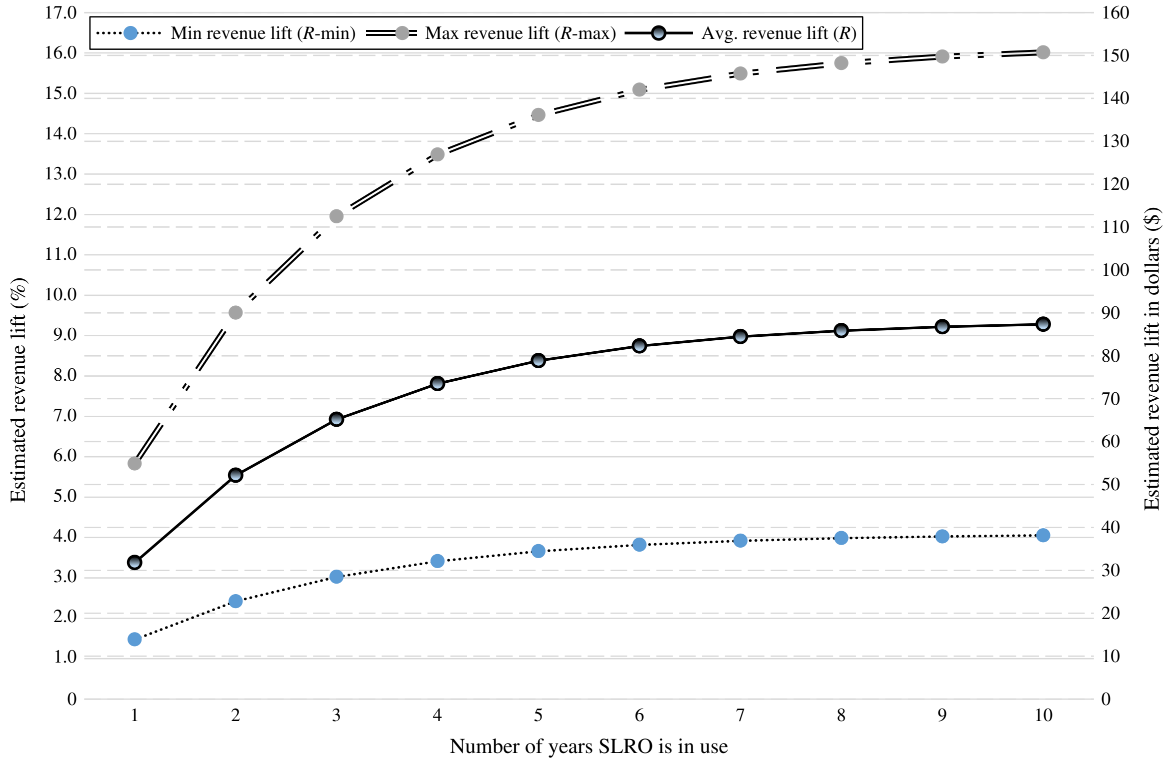
The estimated revenues were confirmed by the company's actual revenue growth after two years of SLRO deployment (see Figure 7). Actual company-wide revenue for single residents increased by 3.8 percent ($34 million) in year 1 and by an additional 2.1 percent ($20 million) in year 2 (summing up to 5.9 percent in year 2 or $88 million in the first two years). This increase is partially due to rent growth, because average existing resident rent was increased by 0.6 percent during the same period. By comparison, during this period, public companies in the senior-housing industry reported levels of revenue that were generally flat.

In addition, the SLRO rents had been deployed to 40 communities before May 2013 and have used system-generated prices for over 3.5 years. By April 2016, over 74 percent of the existing residents used SLRO-generated prices. Holiday experienced a revenue increase of 10.93 percent as of April 2016 (see Figure 8). This is not because of rent growth because average in-place rent for April 2016 is 0.55 percent less than it was in April 2013. Thirty of these communities are from a highly competitive region that includes Holiday's lowest-performing communities at the time. These realized benefits further validate the estimated results.

Reports during this period from public companies in the senior-housing industry indicated that competitors did not experience similar growth in revenue and (or) occupancy.

The revenue lift was primarily because of lower rents (and hence higher occupancy) because unit availability was significantly higher when we rolled out the

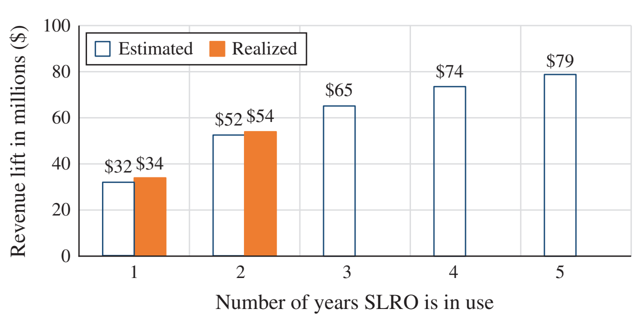
Figure 6. (Color online) Overall Revenue Growth Is Expected to Converge to 9.3 Percent and Range from 4.1 to 16.2 Percent, as More Residents with Optimized Rents Move In in Later Years



Notes. Our estimation of revenue growth is consistent with the revenue growth that Holiday achieved, as we describe our estimation methodology from pilot 4 in *Phase 2: Live Pilot Using an Offline RM System to Confirm Benefits.*

RM system. At the beginning of the deployment, the rents were lower approximately 60 percent of the time, and higher 20 percent of the time. During the latter part of the deployment, occupancy increased and rents also increased more than 55 percent of the time and decreased less than 20 percent of the time. Note that these percentages would change based on unit availability and market conditions.

Figure 7. (Color online) Realized Revenue Growth ($88 Million) Confirms Estimated Revenue Lifts After Two Years of SLRO Deployment

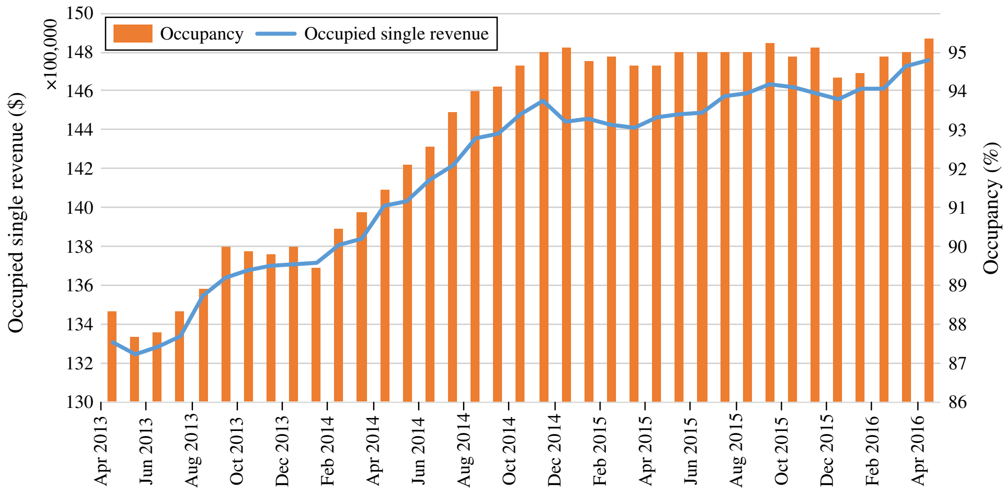


Note. The estimated revenue lift ($302 million) is calculated by totaling the values that the nonshaded boxes show for year 1 through year 5.

Qualitative Impacts

Using an RM system enables a consistent and proactive pricing process across Holiday, while simultaneously providing optimal pricing recommendations for each apartment unit in each Holiday community. The recommended prices give sales representatives confidence that the listed price is the right price, removes the distraction of discounting and price negotiation, and enables the representatives to focus on selling value. The right price gives sales teams the opportunity to shift the conversation with customers from price to value, focusing on how the community's amenities directly satisfy the customer's needs. Thus, Holiday regains control over its corporate pricing process,

Figure 8. (Color online) After Three Years of SLRO Recommendations at 40 Originally Deployed Communities, Revenue and Occupancy Increased Significantly



	April 2013	April 2016	Percent change (%)
Revenue	$13,305,153	$14,759,048	10.93
Occupancy	88.1%	94.4%	7.15
Average existing-resident rent	$2,381	$2,368	−0.55

eliminates inventory devaluation, and maximizes long-term revenue. The SLRO system also provides greater objectivity in the marketplace and reduces the desire to engage in pricing wars. The system also reduces costs for Holiday by enabling one full-time-equivalent employee to effectively manage prices and exceptions for more than 300 communities.

Portability

Brookdale Senior Living also uses the SLRO system for its IL communities. In addition, Prorize employs the algorithms for operators in the self-storage industry. This portability is possible because of similarities in the business environments and in pricing problems across the self-storage and senior-housing industries. Both industries employ month-to-month leases, practice extensive discounting and incentives, and offer products defined by unit type, unit size, unit location, and unit attribute; for example, the companies in the self-storage industry use 10x10 drive-up units with (or without) climate control. We adapted the system to reflect differences between the senior-living and self-storage industries. The self-storage industry has shorter lengths of stay, higher turnover, and greater seasonal changes in move-ins and move-outs. After an extensive pricing experiment involving approximately a quarter of CubeSmart's stores, in which these stores showed notable revenue lift against comparable CubeSmart stores that used legacy RM systems, CubeSmart deployed the Prorize RM system across its enterprise.

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Appendix A. Revenue Growth Model

Pilot results estimated an average revenue lift of 9.3 percent (R) from new leases, ranging from 4.1 percent (R-*min*) to 16.2 percent (R-*max*) based on different baselines using up to two years of prior data.

Because the SLRO optimizes only new leases and Holiday's annual residential turnover rate is 36 percent (τ), we estimated revenue lift as follows:

$$\text{Estimated Revenue Lift}(n) = R(1-(1-\tau)^n), \qquad \text{(A.1)}$$

where n denotes number of years the SLRO is in use. The term $(1-(1-\tau)^n)$ represents the percentage of residents with optimized rents after SLRO has been in use for n years. As the percentage of residents with optimized rents approaches 100 percent in later years, the overall revenue growth approaches 9.3 percent, ranging from 4.1 percent to 16.2 percent (see Figure 6). Note that R-*min* and R-*max* could be used instead of R in Equation (A.1) to derive minimum and maximum revenue-lift values.

Appendix B. Price Optimization Model Formulation

The wait-and-see revenue optimization problem maximizes the revenue for a given community and unit type i by identifying the optimum net effective rent ratio for each individual scenario s for which demand forecast $\alpha_{i,s}$, price sensitivity $\beta_{i,s}$, and the number of units to become available $\xi_{i,s}$ are generated by independently sampling the distribution of three random variables. The formulation of the deterministic optimization model run for each scenario s is as follows.

Sets

- $i \epsilon I$ Set of pricing units (each pricing unit is for a unit type at a community).
- $P(i)$ Set of pricing units for which a parity rule pertaining to pricing unit i is defined; (e.g., a studio unit must be less expensive than a one-bedroom unit with the same size and amenity value).

Probabilistic Parameters

- $\alpha_{i,s}$ Seasonality adjusted and unconstrained demand forecast for pricing unit i and scenario s.
- $\beta_{i,s}$ Price-sensitivity parameter for pricing unit i and scenario s.
- $\xi_{i,s}$ Number of units to become available because of move-outs for pricing unit i and scenario s.

Deterministic Parameters

- R_i Reference rent for pricing unit i.
- C_i Number of units that are currently available to sell for pricing unit i.
- $\Delta_{i,i'}$ Minimum dollar amount that should be maintained between pricing unit i and pricing unit i' (see parity rule above, where $P(i)$ is defined).
- L_i Lower price bound based on historical rent ratio distribution of pricing unit i.
- U_i Upper price bound based on historical rent ratio distribution of pricing unit i.

Decision Variables

- $d_{i,s}$ Accepted demand for pricing unit i and scenario s (accepted demand is the lesser of forecast demand and unit capacity).
- r_i Net effective rent ratio for pricing unit i.

Objective

$$\text{Max} \sum_i R_i r_i d_{i,s}$$

subject to the following constraints:

$$d_{i,s} \le f(\alpha_{i,s}, \beta_{i,s}, r_i) \quad \forall i\epsilon; \qquad \text{(B.1)}$$

$$d_{i,s} \le C_i + \xi_{i,s} \quad \forall i\epsilon I; \qquad \text{(B.2)}$$

$$R_i r_i + \Delta_{i,i'} \le R_{i'} r_{i'} \quad \forall i\epsilon I,\ i'\epsilon P(i); \qquad \text{(B.3)}$$

$$L_i \le r_i \le U_i \quad \forall i\epsilon I; \qquad \text{(B.4)}$$

$$d_{i,s}, r_i \ge 0 \quad \forall i\epsilon I. \qquad \text{(B.5)}$$

Constraint (B.1) limits the accepted demand with a proprietary demand function $f(\alpha_{i,s}, \beta_{i,s}, r_i)$ with parameters of demand forecast ($\alpha_{i,s}$), price sensitivity ($\beta_{i,s}$), and net effective rent ratio (r_i) for the scenario s and pricing unit i. Constraint (B.2) limits accepted demand by availability, which is a function of current availability (C_i) plus the number of units to become available ($\xi_{i,s}$) because of transfers in and out, and move-out activity for the scenario s and pricing unit i. Constraint (B.3) enforces the minimum-dollar-value difference between related pricing units. Constraint (B.4) represents bounds on the net effective rent ratio for each pricing unit i. Finally, Constraint (B.5) establishes the nonnegativity of the decision variables.

References

Croston JD (1972) Forecasting and stock control for intermittent demands. *Oper. Res. Quart. (1970–1977)* 23(3):289–303.

Gottlieb M (2015) Healthcare REITs and their operator partnerships. *Cornell Real Estate Rev.* 13(1):112–125.

Hanssens DM, Parsons LJ, Schultz RL (2001) *Market Response Models: Econometric and Time Series Analysis*, 2nd ed. (Kluwer Academic Publishers, Norwell, MA).

Kochhar R, Oates R (2014) Attitudes about aging: A global perspective. Report, January 30, Pew Research Center, Washington, DC. http://assets.pewresearch.org/wp-content/uploads/sites/2/2014/01/Pew-Research-Center-Global-Aging-Report-FINAL-January-30-20141.pdf.

Kuyumcu A (2007) Emerging trends in scientific pricing. *J. Revenue Pricing Management* 6(4):293–299.

Kuyumcu A, Popescu I (2006) Deterministic price-inventory management for substitutable products. *J. Revenue Pricing Management* 4(4):354–366.

Makridakis S, Wheelwright SC, Hyndman RJ (1998) *Forecasting Methods and Applications*, 3rd ed. (John Wiley & Sons, New York).

Phillips RL (2005) *Pricing and Revenue Optimization* (Stanford University Press, Stanford, CA).

Talluri KT, van Ryzin GJ (2004) *The Theory and Practice of Revenue Management* (Springer Science + Business Media, New York).

U.S. Department of Commerce Economics and Statistics Administration (2010) The next four decades: The older population in the United States: 2010 to 2050. Report, issued May 2010, https://www.census.gov/prod/2010pubs/p25-1138.pdf.

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Kai Hsiao is senior managing director-senior housing properties at HCP. Prior to HCP, Kai was at Holiday Retirement serving in various roles, including president and CEO. Kai was also previously associated with Macerich, where he worked in operations, marketing, and both ground-up developments and redevelopments.

Sheila Donahoe, a former CIO of Holiday Retirement, was responsible for Holiday Retirement's overall technology strategy including the implementation of technology to enable business strategies and accelerate the achievement of business goals. Sheila was named one of the 100 Most Innovative CIOs by *CIO Magazine* in 2001 and was voted South Florida's Best CIO by the *South Florida Business Journal* in 2005 and 2006.

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