RESEARCH

MAY 2022

IPF Research Awards 2021
The Determinants of UK Self-Storage Rents

GRANT AWARDED BY THE IPF RESEARCH PROGRAMME

INTRODUCTION

In 2021, the IPF Research Programme created a grants scheme to provide financial assistance to new or recent entrants to the property industry, including graduate students and junior practitioners, to encourage real estate investment research. While no specific themes were proposed, prospective applicants were encouraged to examine issues that would advance the real estate investment industry's understanding of and implications for asset pricing, risk-adjusted performance and investment strategy.

An evaluation of proposals received by the 30 September 2021 deadline resulted in four submissions being selected as recipients of awards, subject to delivery of final papers by 31 March 2022, with limited supervision of each study provided by a sub-committee of the IPF Research Steering Group during the intervening period.

Three applicants successfully met the requirements of the scheme, covering a diverse range of topics comprising an investigation of foreign real estate investment strategies, an examination of the risks to Indian commercial office portfolios during COVID-19 and the determinants of UK self-storage rents.

Each paper is available to download from the IPF website and we hope you find them interesting reading.

The following paper is that written by Daniel McKegney, *Heitman Investment Research*.

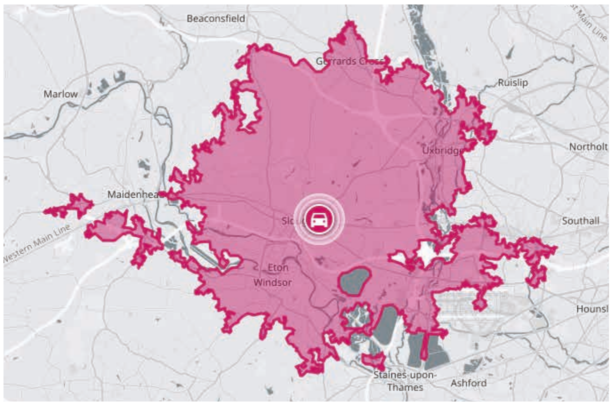
Simon Marx
Chair IPF Research Steering Group
May 2022

CONTENTS

The Determinants of UK Self-Storage Rents

Daniel McKegney, Heitman Investment Research

This paper employs a unique dataset to examine self-storage rental levels in 457 stabilised self-storage facilities in the UK. The dataset integrates information regarding the catchment area, physical characteristics and operator of the self-storage facility. Econometric analysis suggests that self-storage rents behave largely as predicted by theory, and self-storage investors may be rewarded for undertaking thorough market analysis, operator selection, and operational improvements.



IPF Investment Property Forum

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Executive Summary

In this paper, the author models the rents for self-storage units in 457 stabilised self-storage facilities in the UK, drawing on an extensive database constructed using market, store, and operator characteristics specifically for this research. The aim of this paper is to isolate and identify the various factors which determine self-storage rents, including factors that relate to the store itself and the local catchment area.

Using a multiple regression model the author finds that several variables have explanatory power in determining self-storage rents in the UK. This includes the store operator's level of contactability (e.g. toll-free contact number, 24/7 call centre support), their size, and local catchment area house prices – which are all significantly positively related to rent levels. The amount of competing self-storage per capita in the catchment area is significantly negatively related to rents, although a large amount of new development is required to materially impact on rent levels. Store size, local traffic counts, and the number of home sales in the catchment area are not significantly related to rent levels.

1. Introduction

To the best of the author's knowledge, no previously published work has been undertaken in the UK, Europe or US to attempt to analyse the determinants of self-storage rents. Prior research investigating the determinants of property rents has tended to concentrate on the 'traditional' property sectors of office, retail, and industrial/logistics.[1] This last property type most closely resembles self-storage, yet its broader catchment area and greater reliance on unique physical and locational characteristics (e.g. power supply, space for heavy goods vehicles, and access to seaports and motorways) make it unsuitable for direct comparison.

The industry is therefore lacking in an empirical approach to setting self-storage rents and understanding their determinants. This is significant, as assumptions around rents, along with occupancy and the sale of additional services (e.g. insurance) form the key part of total income generated from self-storage assets. In providing an empirical approach to rent setting, this paper seeks to improve the industry's understanding of asset pricing and ability to efficiently underwrite self-storage investments and create value.

The paper is organised as follows: the next section provides a brief overview of the UK self-storage market. In section 3, the author outlines the data employed, and section 4 explains the choice of catchment area. Section 5 describes the empirical methodology. Section 6 provides empirical results and section 7 provides a discussion and some conclusions.

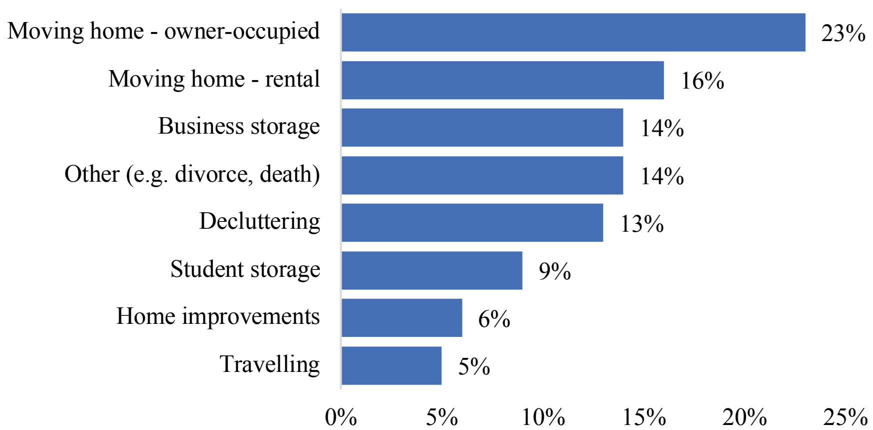
2. The UK Self-Storage Market

Size and growth. The annual industry report by the Self Storage Association (SSA UK) and Cushman & Wakefield is the chief source of information on the UK self-storage market.[2] According to the 2021 edition, there are almost 2,000 stores in the UK, totalling over 50 million square feet of space, as based on the SSA definition. The average store size is accordingly 25,300 square feet. The facilities are operated by almost 1,000 different operators.[3] The SSA's coverage has increased over time, meaning annual store counts are not entirely consistent between years, but for perspective, there were reportedly 1,100 stores in 2016, implying an almost doubling in the past five years. Supply in square feet increased by 34% in that time.

Types of self-storage. There are three major types of self-storage: (1) Conventional stores with units under one roof, (2) Container-based storage, typically using converted shipping containers, and (3) A hybrid of the first two types. According to StorTrack – the self-storage data platform that is the chief information source for this paper – there are 735 stores in the UK that are predominantly of type (1).[4] These conventional stores are the primary focus of this paper, not only to ensure consistency across store types but also because they are the main target of investor capital – which this paper aims in part to inform.

Reasons for using self-storage. Unlike property sectors such as office and retail, where tenant demand is linked to factors like employment and household spending, demand for self-storage is closely tied to life events. In the industry these are sometimes called 'The Four D's': downsizing, dislocation (e.g. moving to a new house following a change in employment), death, and divorce. This provides a first glimpse of those variables that we may expect to influence self-storage demand, and thus the ability of stores to command higher rents. For example, downsizing and dislocation suggest that the size of homes in the catchment area should be important. The significance of both renters and owner-occupiers – as highlighted in Chart 1 below – would suggest that rents are less related to housing tenure in the catchment area. A full discussion of the variables to be used in the model follows shortly.

Chart 1. Reason for using self-storage, as reporters by UK customers in 2021.



Source: Big Yellow Group PLC Annual Report and Accounts 2021; Heitman Research

Comparisons to continental Europe and US. The UK is Europe's most established self-storage market, with self-storage gross leasable area per 1,000 people of 69 in the UK compared to 15 in the rest of Europe.[5] In this sense the UK market may be considered more competitive than in the rest of Europe. In many parts of France and Germany, for example, a self-storage facility may have no competition within a 3-mile or even 5-mile radius. Other factors, like the scarcity of residential space, also vary between countries and could have implications for self-storage demand. The relationship is not clear however, as self-storage space per 1,000 people is 557 in the US (8x that in the UK) despite UK homes only being half the size of those in the US.[6] This suggests other factors, such as cultural attitudes toward accumulation of material possessions, may help explain the demand for self-storage space between countries.

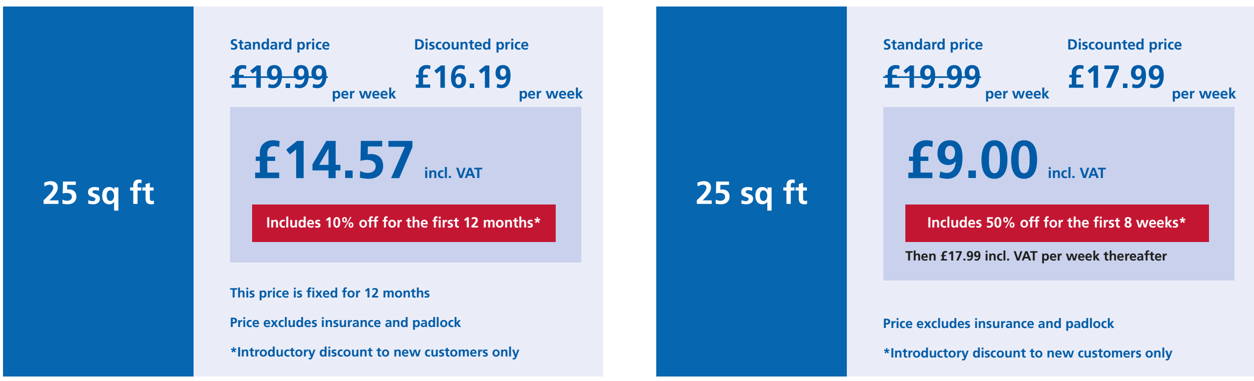
Promotional offers. Similar to rent-free periods in the office sector, 'promotional offers' – typically in the form of initial price discounts – are pervasive in the UK self-storage market. In the sample we have collected, 81% of stores offered these discounts, with virtually all discounts being equivalent to a 50% price reduction for the first 4 or 8 weeks of tenancy. These reductions often apply regardless of the initially requested tenancy duration, in an effort by self-storage operators to induce tenants to 'roll over' their term.

This is highly common in the sector, especially among households. UK households in 2021 reported an average length of stay of approximately 18 months, yet the most commonly selected initial tenancy durations are consistently under 6 months.[7] This suggests households tend to underestimate the duration of their storage needs or seek to avoid the inflexibility created by longer leases. Actual lease lengths typically being different from those initially requested, it is difficult to make a precise conversion of headline rents into effective rents. Effective rents require an assumption about the actual tenancy duration in order to take a weighted average of the rent paid during the promotional and post-promotional period. The model outlined in this paper uses the UK average actual length of stay of 24 months (which combines both household and business customers) in order to incorporate effective rents as the dependent variable. Effective rents better reflect the true economic cost to the customer and economic gain to the operator over the course of the entire tenancy, and therefore should more closely reflect their pricing power and economic environment. The model also uses headline rents not adjusted for promotional offers.

Tenancy duration. Self-storage customers can often select from a range of tenancy options when renting a self-storage unit. In our sample, 60% of stores offered multiple tenancy durations. Some of these stores will offer price discounts for longer tenancies in order to induce customers to select those over shorter durations. The other 40% of stores typically offer a flat weekly rate based on a one-week or one-month tenancy. This paper attempts to control for different tenancy durations and price discounts by using weekly rents charged for a one-week tenancy or, where this is not available, a one-month tenancy or the tenancy duration closest to one month.

An example of both promotional offers and discounts in effect is shown below in Picture 1. We can use the average length of stay in the UK, of 24 months, to estimate the effect of promotional offers on the effective rent over that period.[8] For reference, over an 24-month period the typical ‘50% price reduction for the first 4 weeks’ discount will result in a 2% reduction in the average weekly effective rent, whereas for a 50% discount over 8 weeks there will be a 4% reduction. A small share of stores in our sample (less than 3%) have promotional offers that apply when a customer prepays for a minimum period of tenancy. Because the author is unable to observe how often such prepayment occurs, the author makes the simplifying assumption that no promotional offer exists for those stores and their effective rent is the same as the headline rent.

Picture 1. Advertised rents for a 25 square foot self-storage unit at Safestore Newcastle Central, as of December 2021. The left panel is shown to customers who select the ‘1 year +’ option, whereas the right panel is shown to those who select the ‘4 weeks’ option. This paper uses the ‘discounted price’, which as shown can differ depending on the tenancy duration selected. The author accordingly controls for this discounting factor by selecting a one-week tenancy or, where this is not available, a one-month tenancy or the tenancy duration closest to one month.



Source: Safestore; Heitman Research Website accessed: December 2021

Investment in the sector. Some investment in self-storage properties no doubt goes 'under the radar', but best estimates put annual transaction volume at around £400 million in the UK in 2021.[9] Based on recent deal activity, it is plausible this number will consistently exceed £500 million in the coming years. Investment is rising, yet the sector is likely to remain small relative to the large 'traditional' sectors like office and industrial, where annual volumes averaged £19.5 billion and £10.7 billion during 2017-2021, respectively.[10] Self-storage is characterised by fragmentation among operators and the granularity of assets, which limit year-to-year investment volumes but add to returns potential in the sector.

Reasons for investment in self-storage. Investors have been drawn to the sector due to its resilient cash flows, robust returns profile, and opportunities for value creation. In Q4 2021, JLL reported that prime net initial yields were 4.00-4.50% for self-storage assets in London, compared to 3.00% for logistics assets, indicating a yield spread of at least 100 basis points.[11] This is especially attractive given the era of low interest rates. With large self-storage operators (who manage 10 or more stores) managing only 23% of stores in the UK, market fragmentation has attracted investors seeking to consolidate via platform acquisitions and achieve portfolio premiums for a collection of high-quality assets.[12]

3. The Data

This paper is based on two principal datasets: (1) a self-storage dataset provided by StorTrack, a software company, covering store and operator metrics such as rents, store size, local supply, and scores for operator websites and their contactability, and (2) a catchment area dataset provided by CACI, an information technology company with a focus on location analytics, covering local market data such as population, house prices, and traffic counts.

The rent data was obtained by a proprietary web data extraction algorithm created by StorTrack, which is run daily to collect the latest rents advertised online by hundreds of self-storage facilities around the UK. StorTrack has developed systems to identify and correct for any outliers in the data, and also engages directly with self-storage operators to maintain and fine-tune said systems. The author has verified the accuracy of the rent data used in the sample by using (1) internal rent data for a self-storage company (Space Station Self Storage) owned by the author's company (Heitman), (2) a mystery shopping exercise in which the author contacted 50 randomly-selected stores from the 457-store sample to confirm that rents quoted over the phone matched those recorded by StorTrack, and (3) a visual sense-check of the entire sample.

All the self-storage information collected was for 2021. The store rents represent a 12-month trailing average (to remove seasonality) dated to December 2021. The data collection was targeted on all self-storage facilities in the UK, with filters to ensure consistency. These filters include:

1. A filter for stabilised assets. Due to construction dates not being available for most stores, the author has defined a store as stabilised if it has at least three years of recorded price history. Including stores with less than three years of recorded rent data would create the possibility of including recently-constructed stores that record below-market rents during lease-up (a common industry practice). However, this definition does create the possibility of excluding some stabilised assets that have simply been slow to record their prices online, having only done so within the past three years. The rising share of UK self-storage facilities recording their prices online – from 63% to 73% during 2017-2020 – suggests such stores do exist.[13] While they are excluded from this analysis, they are likely to be few in number, meaning their omission is unlikely to materially affect the sample size nor the conclusions we can draw from it.

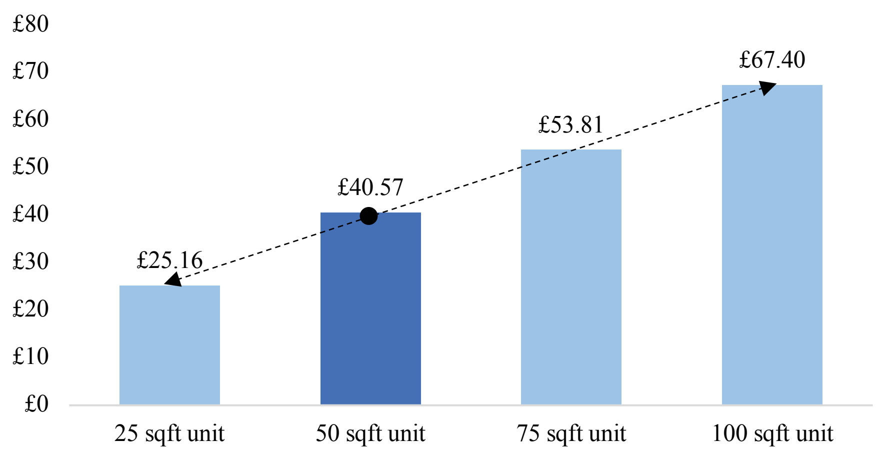
2. Including only traditional self-storage facilities and not variants such as container storage or general warehousing/removals storage. This ensures that the type of facility is consistent across the sample.
3. Including only self-storage units and not variants such as shipping containers or lockers. This ensures that the type of unit is consistent across the sample.
4. Including only non-climate-controlled, economy-class, non-ground floor units. This ensures that the features of the unit are consistent across the sample. Climate-controlled units typically command a rent premium in the market, for example.
5. Including only 50 square foot units. As is to be expected, rents vary according to the size of the unit, meaning it must be controlled for. This does not however mean that the model results cannot be applied to other unit sizes. As shown in Chart 2, there tends to be a relatively consistent, linear relationship in rents between different unit sizes. Using this relationship – where each 25 square foot rise in unit size corresponds to a circa £14 rise in weekly rent – an operator could upscale or downscale to get to the appropriate rent for units within the 25-100 square foot band based on the results of this analysis. For example, if the modelled rent is £32 for a 50 square foot unit, then the implied modelled rent for a 100 square foot unit would be £60 [= £32 + (2 * £14)].

The CACI dataset uses CACI current year statistics – approved by the Joint Industry Committee for Population Standards (JICPOPS) – for catchment areas down to the postcode level. This includes estimates for variables like population up to 2021, based on historical official data from the ONS projected forward at post-code level using ONS projections and a proprietary CACI model. Estimates of household income are based on CACI's 'Paycheck' dataset, which uses a proprietary model to estimate postcode-level household income based on the ONS's Average Weekly Earnings and Living Costs and Food Survey. The house price data was compiled by CACI and comes from Land Registry.

This paper also uses ONS data on residential vacancy rates (as of 2020), average home sizes (2011), and annual home sales (the average during 2016-20) at the local authority level.

The final database includes a total of 457 unique self-storage facilities and stabilised weekly rents.

Chart 2. Average stabilised weekly rent among the 393 UK self-storage facilities on the StorTrack platform that have price data for each of the following unit sizes: 25 sqft, 50 sqft, 75 sqft, and 100 sqft. Note the consistent trend in rents across unit sizes (circa +£14 for each successive 25 sqft increase in unit size).



Source: StorTrack; Heitman Research

Table 1. Breakdown of sample of 457 self-storage facilities by operator.

Operator	*Stores in sample*	*% all stores in sample*
Safestore	100	21.9
Big Yellow	85	18.6
Access Self Storage	54	11.8
Shurgard	26	5.7
Storage Mart	12	2.6
UK Storage Company	10	2.2
'BIG OPERATORS'	287	62.8
OTHER	170	37.2
TOTAL	457	100

Source: StorTrack; Heitman Research

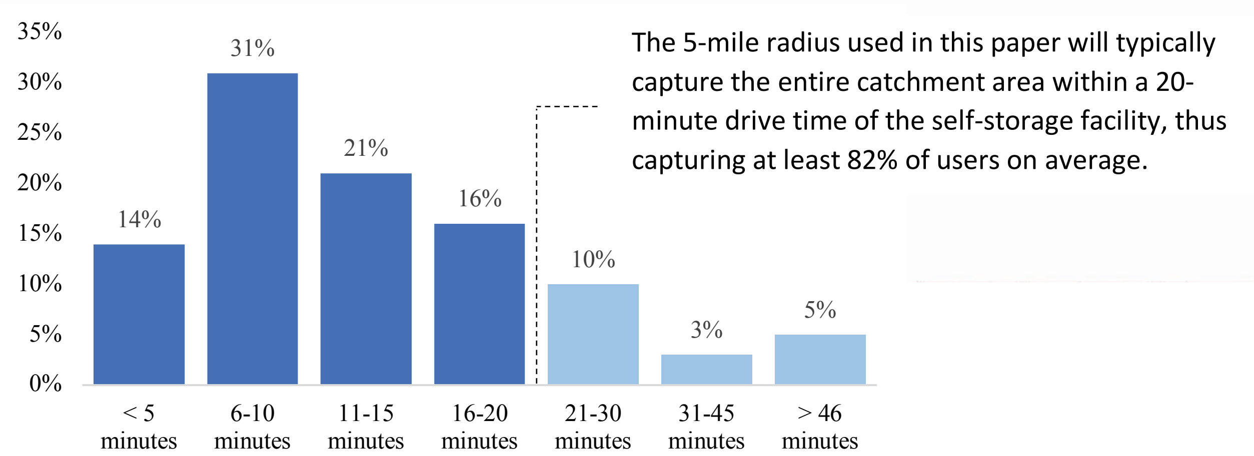
Following application of the five filters, the sample has a reasonable mix of stores managed by 'big operators' (defined as those with 10 or more stores) and smaller 'mom and pop' operators. Geographically, the sample mix is broadly reflective of the dispersion of all self-storage facilities in England, although Scotland and Northern Ireland have no representation in the sample, mainly due to the filter for stabilised rents. Nine stores are situated in Wales, meaning that market is also underrepresented in the sample. Sample stores have a reasonable mix between towns and cities, although tend to be situated in more affluent areas (the average house price in our catchment areas is £426,602, versus the national average of circa £275,000 in December 2021).

4. The Catchment Area

Before selecting which market variables to include in the model, it is necessary to define the size of the market for each self-storage facility. This is likely to vary depending on factors such as local transport infrastructure and the level of local market competition. In areas with good transport links and few self-storage facilities, customers are likely to be able to travel further, and must travel further, to find a store within a convenient period of time. Instead of trying to estimate the individual catchment area for each of the 457 stores in our sample, we have made the simplifying assumption that each store has a catchment area within a 5-mile radius of that store. The justification for this radius now follows.

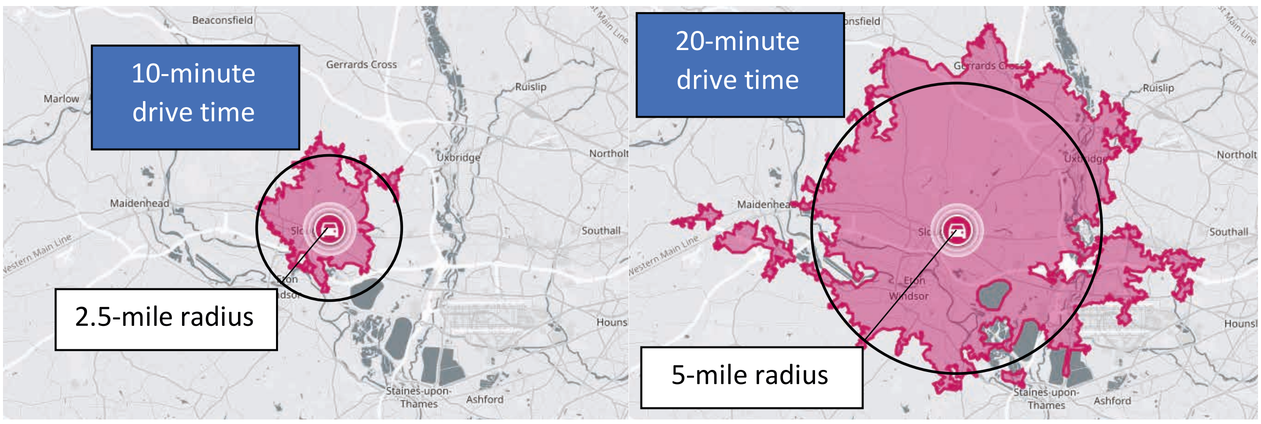
According to the SSA survey, 45% of self-storage tenants are located within a 10-minute drive time from their self-storage facility, and this increases to 82% for a 20-minute drive time.[14] The 20-minute zone typically corresponds to a 5-mile radius around the self-storage facility, based on an analysis undertaken by the author using the platform TravelTime.[15]

Chart 3. Distance to travel to self-storage facility, as reported by UK customers in 2021.



Source: SSA UK Report 2021; Heitman Research

Picture 2. Catchment areas within a 10-minute (left) and 20-minute (right) drive time from Space Station Slough. Note that this store is used as an example but is typical of other stores in the sample.



Source: TravelTime; Heitman Research

5. Methodology

We now employ a multiple regression model to estimate the combined effect of all the independent explanatory variables on self-storage rents. The following independent variables have been selected because we believe economic theory suggests they could play a role in determining rents for self-storage units. Log weekly rent for a 50 square foot self-storage unit is the dependent variable. The initial model is defined as:

$$
\begin{aligned}
\text{Ln}\, Y = \alpha + \beta_1(WESBITE) + \beta_2(CONTACT) + \beta_3(OPERATORSIZE) + \beta_4(STORESIZE) \\
+ \beta_5(INCOME) + \beta_6(SUPPLY) + \beta_7(TRAFFIC) + \beta_8(HOMESIZE) + \beta_9(PRICE) \\
+ \beta_{10}(VACANCY) + \beta_{11}(HOMESALES) + \beta_{12}(RENTING) + \beta_{13}(AGE50) + \varepsilon_i
\end{aligned}
$$

Table 2. Definitions of variables

Variables	*Description*	*Data type*
LnY	Logarithm of rent for 50 square foot self-storage unit, 12-month trailing average	Numerical
WEBSITE	Online website/visibility score (0-25) for operator	Categorical
CONTACT	Contactability score (0-11) for operator	Categorical
OPERATORSIZE	'Big operator' dummy, 1 (10 or more stores), 0 (less than 10 stores)	Dummy
STORESIZE	Square foot size of the self-storage facility	Numerical
INCOME	Median household income per capita within 5-mile radius catchment area	Numerical
SUPPLY	Total square foot self-storage space per capita within 5-mile radius catchment area	Numerical
TRAFFIC	Annual traffic flow within 1-mile radius catchment area, average during five years 2016-20	Numerical
HOMESIZE	Median home size in square meters within respective local authority area	Numerical
PRICE	Average house price within 5-mile radius catchment area	Numerical
VACANCY	Residential vacancy rate within respective local authority area	Numerical
HOMESALES	Annual home sales within respective local authority area, average during five years 2016-20	Numerical
RENTING	Share of households who are renting within 5-mile radius catchment area	Numerical
AGE50	Share of population aged 50+ within 5-mile radius catchment area	Numerical

The author employs log of rent as the dependent variable to control for the dispersion properties of the data.

Several adjustments to the treatment of the variables are also needed.

Firstly, we checked for multicollinearity between independent variables. This was observed between population and total self-storage space within the catchment area, so these were combined to create *SUPPLY* – defined as self-storage space per head of population – and prevent distortion of coefficient standard errors. The website score (*WEBSITE*) was moderately correlated with the contactability score (*CONTACT*) and big operator dummy (*OPERATORSIZE*) so was dropped from the model. Median household income (*INCOME*) was unsurprisingly highly correlated with average house prices (*PRICE*) so was dropped due to it having less explanatory power. This is potentially due to house prices capturing not only the level of affluence within a catchment area – as would household income – but also the relative cost of residential space, which in turn reflects the cost of home storage space – an alternative to self-storage. House prices were also moderately negatively correlated with the share of population aged 50+ (*AGE50*), the residential vacancy rate (*VACANCY*), and the average home size (*HOMESIZE*), so these three latter variables were dropped from the model. Reducing the number of independent variables should also help to limit the risk of over-fitting in the model.

The refined model is then defined as:

$$\text{Ln}\, Y = \alpha + \beta_1(CONTACT) + \beta_2(OPERATORSIZE) + \beta_3(STORESIZE) + \beta_4(SUPPLY) + \beta_5(TRAFFIC) + \beta_6(PRICE) + \beta_7(HOMESALES) + \varepsilon_i$$

We then checked for heteroskedasticity. While the squared residuals of the model visually appear uncorrelated from the dependent variable, using the Breusch-Pagan (1979) test with a 95% confidence level we reject the null hypothesis of homoskedasticity and thus conclude that heteroskedasticity is present in the model.[16] This is a common issue in cross-sectional OLS models. Our second adjustment is therefore White's (1980) adjustment to achieve heteroskedasticity-consistent standard errors.[17]

Next we checked for omitted variable bias by comparing the model residuals with each of the independent variables. This revealed that there were no correlations, indicating that omitted variable bias was not present. Finally, the author tested for non-linear relationships among numerical variables via a variety of transformations including logs, square root and quadratic functions, and various combinations of these.

Based on economic theory and the SSA survey, it is possible at this stage to make some *a priori* predictions regarding the expected impacts of each of the individual explanatory variables on the weekly stabilised rent LnY paid by tenants for a 50 square foot self-storage unit at each of the 457 stores.

We would expect the rental value LnY to be higher for operators with high $WEBSITE$ and $CONTACT$ scores, given that 46% of UK customers find their self-storage facility via an online internet search and 61% of those finding their store offline still search online for more information about the store.[18] A phone call to the store often then follows when customers make a booking. We would expect $OPERATORSIZE$ to be positively related to rent levels, as larger operators have higher enquiry-to-booking conversion rates and stronger brand recognition than smaller operators.[19] Noting that $WEBSITE$ has been dropped from the model in part due to its correlation with $OPERATORSIZE$, size may also be positively related to rents because larger operators have greater capital to invest in their websites and online visibility.

$STORESIZE$ could be expected to be positively or negatively correlated with rent levels. Larger stores offer a greater range of unit sizes, which could draw demand from customers who require flexibility as they suspect their storage needs may change over time. This could enable larger stores to command a rent premium over smaller stores. However, larger stores will also have various economies of scale over smaller stores, enabling them to offer lower rents while maintaining the same EBITDA margins as smaller facilities.

$SUPPLY$ is expected to be negatively correlated with rent levels, on the basis that higher self-storage supply relative to the population within the catchment area should increase price competition among operators. It should be noted that a traditional model of property rents would typically incorporate data on market vacancy instead of the stock per unit of demand (in this instance space per capita). However, vacancy data was not available to the author because it is closely held by self-storage operators and the valuations teams who value their assets. The use of stock per capita therefore benefits from it being a more accessible, visible market metric, while it should still proxy the amount of competing self-storage relatively well.

TRAFFIC would be expected to be positively related to rent levels, as 6% of UK customers find their self-storage facility via billboard signage and advertising along the side of self-storage facilities.[20] *TRAFFIC* is also a potential proxy for road access to the self-storage facility; better access would be expected to command a rent premium as customers are more able to conveniently reach their store.

PRICE should be positively related to rents, as higher house prices signal greater affluence and thus rent-paying capacity, and may also suggest a higher cost of personal storage space at home. It should be noted that postcode-level residential rent data – a potential alternative to house prices – was not available to the author. *HOMESALES* are expected to also have a positive relationship with self-storage rent levels, as the process of owner-occupiers moving between houses is the key reason for which people use self-storage.

6. Results

In the multiple regression results reported in Table 3, most variables are significant and correctly signed according to our *a priori* expectations based on real estate economic theory and the SSA survey.

As expected, self-storage rents are positively and significantly related to the contactability of the operator (*CONTACT*), the size of the operator (*OPERATORSIZE*), and the average house price in the catchment area (*PRICE*). Meanwhile self-storage rents are negatively and significantly correlated with the amount of supply per capita (*SUPPLY*). The size of the self-storage facility (*STORESIZE*), local traffic counts (*TRAFFIC*), and average annual home sales (*HOMESALES*) within the catchment area don't play any significant role.

The size of the store (*STORESIZE*) being insignificant may be explained by the two aforementioned effects – the flexibility effect and economies of scale effect – approximately offsetting one another. Local traffic counts (*TRAFFIC*) not being significant is somewhat surprising, although this may be due to the 1-mile radius (the smallest available in the CACI dataset) still being too large to capture predominantly those traffic flows passing within direct sight of self-storage facilities. With most customers today finding their store via an online search or word of mouth, it is also possible that the physical visibility of the self-storage facility is not as important in the age of the internet. Recent home sales (*HOMESALES*) being insignificant is also surprising, although this may be due to our incorporation of population in *SUPPLY*, which may effectively proxy several forms of self-storage demand including people moving to a new house. The importance of various other demand sources may also weaken the explanatory power of home sales.

The model results are negligibly different when using effective rents instead of headline rents.

Table 3. Model results. Dependent variable LnY: logarithm of rent for 50 square foot unit. $N = 457$

	Headline weekly rents			*Effective weekly rents*		
Variable	*Coefficient*	*T-statistic*	*Probability*	*Coefficient*	*T-statistic*	*Probability*
INTERCEPT	**	61.94	0.00	**	62.39	0.00
CONTACT	**	4.43	0.00	**	4.37	0.00
OPERATORSIZE	**	11.77	0.00	**	10.99	0.00
STORESIZE	-	-0.32	0.75	-	-0.39	0.70
SUPPLY	**	-4.35	0.00	**	-4.39	0.00

TRAFFIC	-	0.97	0.33	-	0.97	0.33
PRICE	**	15.59	0.00	**	15.71	0.00
HOMESALES	-	0.19	0.85	-	0.16	0.87
R^2	0.63			0.62		
Adjusted R^2	0.63			0.62		
F-statistic	111.00			106.45		
Prob(F-stat)	0.0000			0.0000		

- not significant ** significant at 1 per cent level * significant at 5 per cent level

Source: StorTrack; Heitman

7. Discussion and Conclusions

Th results of the regression analysis are highly encouraging. The factors found to influence self-storage rents are largely consistent with our *a priori* expectations derived from microeconomic and real estate theory, and the SSA survey.

The author finds that the strength of the operator – with regard to their contactability and economies of scale – is positively and significantly correlated with self-storage rents, as are house prices in the local catchment area. The coefficient on the contactability variable implies that self-storage operators with the highest score, of 11, can command a rent premium of 25.2% over operators with a score of zero. In practice most operators are somewhere in between, yet small improvements may still have significant benefits for pricing power. For example, a 3-point score increase – equivalent to the operator establishing a toll-free contact number or 24/7 call centre support – would correspond to a 6.3% increase in rent. Online chat support may also be provided. Operators should be highly responsive to customer enquiries and ensure that call-back times are minimised as far as is practical. Ultimately, investors should recognise that the operator is at least as important as the physical and catchment area characteristics of the self-storage facility. This creates the opportunity to drive investment returns through changes at both the operator and asset level.

The big operator premium of 35.7% suggests economies of scale that enable larger operators to command higher rents in the market. This may be due to greater investment in websites and online visibility, stronger brand awareness, and superior management skills. Investors with the capital and expertise to grow self-storage platforms, implement best-in-class operations and identify operating partners may accordingly unlock value. Investors should ensure operators have accessible, up-to-date websites that clearly advertise the range of unit sizes and tenancy durations available. Estimating one's self-storage needs is notoriously difficult until the unit is seen in person, so additional language, graphics and interactive tools on a website can aid customers in selecting the appropriate unit size. It may also help to be upfront about 'hidden costs' such as insurance and put these into perspective for the customer by contrasting them against the value of their belongings.

Investors should be especially conscious when underwriting rents that are in line with those of the large operators that tend to exist across most UK towns and cities and provide the most readily-available comparables data. Analysis by Green Street Advisors suggests that UK self-storage REITs (which are classified as big operators) are able to convert 39% of online enquiries into store bookings, compared to 28% for private operators, which along with the greater brand recognition of the REITs would seemingly justify some rent premium.[21] Investors should accordingly also not assume that slight rent reductions relative to these large operators will be perceived by prospective customers as greater value for money.

Investors also need to consider the amount of competing self-storage space per capita in the catchment area, especially as this can change rapidly over a typical investment horizon in areas of high development. Based on the coefficient for the supply variable, a one standard deviation increase in supply per capita (equivalent to a 51% increase in the supply ratio) corresponds to a -4.5% reduction in rent. One standard deviation is however equivalent to an extra 556,000 square foot of self-storage space within the catchment of the average store in our sample. Based on the average UK store size estimates in the SSA report, this would equate to 22 new stores. This would be considered a very high level of local development that a prudent investor may be able to anticipate and navigate. Less aggressive levels of supply are much more common in the UK and seemingly should not cause a material adverse shock to stabilised self-storage rents, all else equal. In this sense self-storage rents appear to be relatively supply inelastic, which may be due to market frictions (e.g. the inconvenience of moving one's personal belongings) that limit substitution between self-storage facilities. An obvious exception may apply to small towns, for which the sensitivity of rents to new supply may be greater.

Finally, the significance of house prices indicates that self-storage is considered a substitute for home space when people look to store their items. (Houses prices are of course also likely to be an effective proxy for household incomes, another potential driver of self-storage rents.) Areas of increasing housing scarcity and higher house prices may experience the fastest growth in self-storage rents, although our model is not designed to capture such dynamic effects. Conversely, the link to house prices suggests self-storage rents may have some exposure to downturns in the housing market. Based on the coefficient for the house price variable, a -10% decline in house prices corresponds to a -3.2% reduction in rent. This suggests only limited sensitivity and would appear to confirm self-storage as a relatively defensive sector.

Next steps for any future analysis on this topic may include:

- Expanding the analysis to other countries in Europe. Especially in those markets with a much lower number of self-storage facilities per capita (e.g. France and Germany), a researcher could use a dummy variable to test whether single stores within a catchment area display monopolistic pricing due to their local dominance. This extension of the analysis was not possible in the UK due to the preponderance of competing self-storage facilities around sample stores even when using a 1-mile radius. Different cultural attitudes to self-storage and varying levels of access to alternative storage solutions (e.g. attic and basement space) in Europe could also manifest in lower rent sensitivities to variables such as operator visibility and local house sizes. Other European markets are also less institutional and sophisticated than the UK market, meaning rents may be less efficient with respect to market conditions. This could manifest in lower explanatory power of econometric models regardless of their specification and the independent variables used.
- Incorporation of more self-storage data. The SSA and Federation of European Self Storage Associations (FEDESSA) maintain large databases that include variables such as occupancy and EBITDA margins. Should a researcher obtain said data, they may be able to build a more comprehensive model of self-storage performance. For example, it may be possible to assess if the rent premiums commanded by more sophisticated operators come at the cost of increased expenses that erode EBITDA margins. Indeed, valuations evidence reported by the self-storage teams at JLL and Cushman and Wakefield, not included in this paper, suggests EBITDA margins are roughly equal between small and large self-storage operators, despite the presence of rent premiums. A

researcher may also incorporate different independent variables, such as the age of the facility. This data was only available for 132/457 stores in our sample so was not used in the main analysis. That said, for the 132 stores in our sample that do have age of facility recorded, the correlation was only -0.20 (implying insignificance) and the addition of age of facility to the multiple regression model did not add to its explanatory power nor show the variable as significant.

- Assessing explanatory power and correlations over time. As more rent data becomes available over time, it should become possible to test the strength of this model and others in explaining variation in self-storage rents. This approach could offer insights into whether rents are behaving more or less in line with economic theory. Rising explanatory power of the model(s) may suggest rents are more closely converging to efficient, equilibrium levels justified by the strength of the operator, store, and catchment area.

Notes and References

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[7] Source: SSA and Cushman & Wakefield (2021) UK Self-Storage Annual Industry Report, pp. 81-82.

[8] Heitman calculations based on the 2021 weighted average of the length of stay for both household and business customers, as outlined on pages 8 and 80 of the SSA report (2021).

[9] Heitman best estimates based on transaction data compiled by JLL and Green Street Advisors.

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[20] SSA and Cushman & Wakefield (2021) UK Self-Storage Annual Industry Report, pp. 86.

[21] Source: Green Street Advisors Report (2021) Brand Power, p. 2.

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Appendix

Table A1. Descriptive Statistics of Key Variables

Variables	*Mean (S.D.)*	*Data type*
RENT	£38.55 per week for a 50 square foot unit (14.24)	Numerical
POPULATION	681,752 people (659,426)	Numerical
WEBSITE	18 out of 25	Categorical
CONTACT	6 out of 11	Categorical
OPERATORSIZE	Dummy, 1, 0	Dummy

STORESIZE	39,435 square feet of rentable space (25,731)	Numerical
INCOME	£35,115 household income per capita (5,841)	Numerical
SUPPLY	1.5835 square feet per capita (0.81)	Numerical
TRAFFIC	540,721 traffic counts per year in 2016-20 (926,882)	Numerical
HOMESIZE	86.528 square meters (931 square feet) (13.11)	Numerical
PRICE	£436,602 average house price (254,241)	Numerical
VACANCY	2.55% residential vacancy rate (0.84%)	Numerical
HOMESALES	3,569 home sales per year in 2016-20 (2,351)	Numerical
RENTING	33.58% share of households renting (11.29%)	Numerical
AGE50	34.47% share of population aged 50 (6.38%)	Numerical

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