Valuing Sunshine

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Abstract

Sunlight influences people's real estate decisions, but city intensification may reduce sunlight exposure for neighbouring properties, causing a negative externality. There are hitherto no rigorous estimates of the cost of this externality. Using over 5,000 observations on house sales in Wellington, New Zealand, we derive the willingness to pay for an extra daily hour of sun, on average, across the year. After controlling for locational sorting and other considerations in an hedonic regression, we find that each extra daily hour of sunlight exposure is associated with a 2.4% increase in house sale price. This estimate is robust to a variety of alternative specifications. Our results can be used to price negative externalities caused by new development, so replacing inflexible regulations designed to address impacts of development on neighbours' sunshine.

JEL codes

Keywords

Summary haiku

Beams of light and warmth

Make a house desirable,

and we value them.

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Tables and Figures

The history of architectural material . . . has been the endless struggle for light.[1]

1 Introduction

Humans overwhelmingly like to live and work near daylight (Aries et al., 2015). This observation implies that dwellings that are situated with good exposure to sunlight should be preferred, *ceteris paribus*, to dwellings with poor sunlight. Intensification of cities, however, may lead to urban canyons or other forms of overshadowing by neighbouring buildings, reducing sunlight for existing dwellings. Negative externalities are therefore likely to be incurred through intensification where this process reduces sunlight exposure for neighbouring sites. Planning authorities, in practice, either ignore this externality or deal with it through (often inflexible) regulatory rules that specify allowable building parameters. Economists typically prefer to use price-based instruments to deal with externalities but, to date, the urban economics literature has not found a rigorous way to price this negative externality. Indeed, in his survey of hedonic house price indices, Hill (2013) identifies sunlight as a likely omitted variable across hedonic models.[2]

We address this gap in knowledge, employing an hedonic framework to estimate the value that house purchasers place on each daily hour of sunlight received by a residential dwelling. We use Wellington, New Zealand, as our focus, being a city in which nearby houses exhibit considerable variation in received direct sunlight hours due to natural and man-made features. We are able to undertake this analysis by utilising modelled sunlight data for every house in the core metropolitan area of the city, where the modelling takes account of the sun's angle above the horizon, the building envelope and the natural features of the (very hilly) landscape within the city. The modelling enables us to measure the average daily sunlight received by each dwelling separately for each month of the year. We link the sunlight data to data on other characteristics of each house (including elevation and viewspan) and to the market sales price of each house.

The hedonic analysis follows standard procedures and the characteristics vector includes a standard set of variables. It is the estimates enabled by the addition of the sunlight (and also the viewspan) variable that provide the distinctive contribution of our paper. We find, *ceteris paribus*, that each extra hour of sunlight received per day by a house (on average through the year) leads to a 2.4% increase in house price. This estimate remains virtually constant when we test sunlight across seasons and suburb types, and interact its value with elevation and viewspan.

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[1] Statement by Swiss-French architect, Le Corbusier, in 1929; cited by Aries et al (2015), page 21.
[2] Hill's survey appeared initially as OECD Statistics Working Paper, 2011/01.

Our estimates can be used by city authorities to value the externalities caused by a prospective new building within a city that crowds out sunlight to neighbouring sites. This value can be used as part of a price-based mechanism for developers (e.g. through payment of compensation by a developer to neighbours who lose sunlight) which may replace less flexible regulatory approaches to site coverage and building heights. Our estimates may be city-specific; nevertheless, our approach can be used to estimate the value of sunlight in other cities where there is reason to believe that circumstances would yield a different valuation of sunshine than that estimated here.

In the next section we examine findings of related literature, noting that there are no directly comparable studies to ours given the lack of prior hedonic valuation of sunlight hours. Section 3 details our data, including our construction of the sunlight and viewspan variables. Section 4 outlines our estimation approach and presents our results. We present these results both across our full sample, and then with several decompositions, which show the robustness of our estimates after considering several tests, such as the interaction of sunlight with each of viewspan and elevation, and across different suburb types. Section 5 discusses implications of the findings and concludes.

2   Sunlight and real estate

Despite the cited view of Le Corbusier on the importance of sunlight for building design, we could not find any published research in the economics or property literature that rigorously estimates the value accorded to sunshine in the residential property market. There are, nevertheless, four related areas of research that are relevant to the topic, each of which provides insights as to how and why sunshine may be valued by prospective house purchasers.

First, the hedonic literature on the determinants of property values provides evidence that the availability of natural and man-made amenities can have a positive effect on property values. Attributes such as views[3], proximity to open spaces[4], and proximity to street trees[5] are associated with higher property values within cities. In addition, a number of papers investigate variations in prices within high-rise apartment buildings, including the degree to which prices vary by storey and outlook[6]. These studies generally find evidence of a price premium for apartments on upper storeys. It is likely that apartments on upper storeys have greater access to sunshine than those on lower storeys. However, storey and outlook also affect other

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[3] See Bourassa et al. (2004), Filippova (2009), Rohani (2012), Nunns et al. (2015).
[4] See Crompton (2001), Morancho (2003), Bourassa et al. (2005) Brander and Koetse (2011), Nunns et al. (2016).
[5] See Donovan and Butry (2009), Donovan and Butry (2010), Li and Saphores (2012), Anderson and Cordell (1988), Kestens et al. (2004), Willis and Garrod (1993), Pandit et al. (2013), Macdonald and Franco (2016).
[6] Wong et al (2011) summarise a number of prior studies on this topic. In addition, see Chau et al. (2007), Hui et al. (2012), Jim and Chen (2006), Glaeser et al. (2005).

outcomes, such as the quality of views and audibility of traffic noise. As a result these findings cannot be interpreted as a price premium that relates solely, if at all, for access to sunshine.[7]

Second, the urban economics literature investigates determinants of variations in property values and population growth rates between cities. Evidence from the United States indicates that a better climate, often proxied by mean annual sunshine hours or average winter temperatures, tends to be associated with higher property prices and faster population growth rates.[8] Evidence from other jurisdictions tends to show similar patterns in terms of climatic factors having positive effects on growth rates of urban areas, at least within countries.[9]

Third, several studies investigate the impact of built form on energy costs (for example, in relation to home heating and air conditioning). These studies are relevant to the relationship of sunshine and house prices since high energy costs, *ceteris paribus*, should be reflected in a lower house price. The research suggests that shade or access to sunshine may have different effects on energy costs depending upon climate. Strømann-Andersen and Sattrup (2011) model residential energy consumption in Copenhagen. They find that narrow 'urban canyons' raise modelled residential energy consumption by approximately 19% relative to areas with open horizons. By contrast, Donovan and Butry (2009) find that shading from street trees in Sacramento, California tend to *lower* summer cooling costs, while Kolokotroni et al. (2007) observe a "heat island" effect in intensely developed areas such as central London, which raises summer cooling costs while *lowering* winter heating costs. Separately, energy costs may be affected by access to rooftop photovoltaic cells to generate electricity, with the premium paid for such access reflecting sunlight exposure for the house.[10] Thus, to the extent that access to sunshine affects house prices through energy costs, the effect of sunshine hours on house prices may be context dependent.[11]

Fourth, many studies investigate the link between access to sunshine and health outcomes, especially in relation to depression and mood disorders. If a relationship between sunshine and health exists, we can again expect this to be reflected in the price paid for a house. Aries et al (2015) identify 47 studies on the impact of sunshine on a range of human health outcomes, concluding that there is only limited evidence of a link between daylight and health

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[7] One unpublished paper using a small dataset for Auckland, New Zealand (Nunns and Denne, 2016) finds a 17% price premium for north-facing apartments (i.e. those on the sunny side of the building in the southern hemisphere) relative to other apartments, indicative of a sunshine premium.

[8] See Glaeser et al. (2001), Rapaport (2007), Partridge (2010).

[9] See, for instance, Cheshire and Magrini (2006) for Europe, Ferguson et al (2007) for Canada, and Grimes et al. (2016) for New Zealand.

[10] Dastrup et al (2012) show that the price premium is also affected by the socio-economic status and preferences of residents.

[11] In this respect, Wellington (the subject of our study) is more similar to the cited European cities than to Sacramento for summer temperatures but more similar to Sacramento for winter temperatures. The monthly average (of daily high) temperatures range from 12-21 (degrees Celsius) for Wellington, 2-21 for Copenhagen, 6-22 for London, and 12-34 for Sacramento.

outcomes. The Cochrane Database of Systematic Reviews has no reviews on the link between sunshine and health but includes two reviews[12] on the impact of bright light therapy on non-seasonal and seasonal depression. (Artificial light may act as a substitute for sunshine.) While finding some evidence to support modest benefit of light treatment for non-seasonal depression, the reviewers considered that limited data and heterogeneity of studies mean the results need to be interpreted with caution. Furthermore there were too few studies to draw a conclusion on whether light therapy is effective in treating seasonal depression.

Overall, the surveyed literature suggests a number of channels through which the benefits of increased access to sunshine for a residential dwelling may accrue: (i) increased sunshine may be treated as a natural amenity which is valued for its own sake – and this may influence location choices both within and between cities; (ii) increased sunshine may reduce energy costs, at least in some contexts; and (iii) increased sunshine may improve some aspects of health. We note here that the cited studies often measure sunshine indirectly by its converse: e.g. by examining the negative effects on dwellings that are overshadowed by tall buildings. Unlike many of these prior studies, our analysis measures hours of sunshine directly while fully incorporating the effects of the building envelope (and of natural features) on the hours of sunshine that a dwelling receives.

3   Empirical setting and data

We chose the core metropolitan area of the city of Wellington, New Zealand, to focus our study because it presents particular characteristics that makes it a useful case study for our hedonic analysis. First, the city is small, so housing heterogeneity with respect to access to services and amenities is low compared to large cities. Second, its local economy and housing market have been stable, with no important shocks over the study period.

Third, and perhaps the most important attribute of Wellington for our analysis, the geographical topography of the city is marked with several hills and valleys crossing the city, resulting in large variability of sunlight exposure within small neighbourhoods. In addition, man-made features increase the variability of sunlight exposure even for houses located close to each other.[13] Thus, it is not difficult to find houses that, located in the same neighbourhood, have very different exposure to direct sunlight due to the effects of hills, valleys and nearby buildings.

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[12] See http://www.cochrane.org/CD004050/DEPRESSN_light-treatment-for-non-seasonal-depression and http://www.cochrane.org/CD011269/DEPRESSN_light-therapy-prevention-winter-depression.
[13] As an example, the house next to one of the authors receives a daily average of 6.9 hours of sunlight through the year while a house ten houses away on the same street receives a daily average of 9.9 hours of sunlight.

3.1   Housing data and variables

We use data provided directly to us by the Real Estate Institute of New Zealand (REINZ). The dataset included detailed data on characteristics and sale price for houses sold across the city of Wellington for six years –from January 2008 to December 2014. These data include variables capturing properties' sale price, location, number of bedrooms, total floor area, the decade when the house was built, access to off-street parking and the date of sale. To estimate our hedonic models we firstly conducted some adjustments to these data. First, we translated the decade when the house was built to an age value based on the decade mid-point. Thus, for instance, a house built in the decade of the 1970's was coded as a 40 year old house.[14] Off-street parking availability was transformed into a dummy variable (coded as 1 for a house with off-street parking space and 0 for no space) and the date of sale was transformed into 28 quarterly dummy variables. Finally, following standard practice, we transformed the house sale price to natural logarithms. After removing observations with missing information and inconsistencies our final sample consisted of 5,584 observations.[15] Summary statistics of our data can be seen in Table 1.

The average house sale value in our data is $632,000, with a standard deviation of $293,000.[16] The average number of bedrooms is 3.3, while mean total floor area is 148 square metres. The average age of houses is 84 years, with a standard deviation of 31 years. Wellington is a compact city, as the ocean and hills do not allow much space for wide roads, translating into narrow roads and a limited availability of off-street parking across dwellings – in our data 35% of houses do not have access to off-street parking. Given this, we expect to find a positive relationship between off-street parking access and house value.

Using the geographical coordinates of the property sales in the REINZ data, we merged these data to the attributes of houses given by elevation, viewspan and direct sunlight exposure. These attribute measures were constructed using fine-resolution topographical models from the Wellington City Council (WCC). In the following we briefly describe how these measures were estimated and provide more technical details in the appendix.

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[14] Replacing this variable by decade-of-construction dummies does not change the results reported below.
[15] Our sample includes only houses within the core metropolitan area of Wellington as see in figure A1 in the appendix. We did not use data from properties outside this area because detailed fine-resolution digital elevation information, which is necessary for our sunlight estimations, is not available. See appendix for more details.
[16] On average over our sample period, 1 NZD = 0.76 USD.

Table 1: Summary statistics (N = 5,584)

	Mean	Standard deviation	Minimum	Maximum
House sale price (New Zealand Dollars [$NZD], nominal values between Jan 2008 and Dec 2014)	632,103	293,425	81,000	5,650,000
ln (House sale price)	13.289	0.345	11.302	15.547
Number of bedrooms	3.308	0.906	1	10
Total floor area (square metres)	147.699	62.311	20	716
House age (years)	83.782	31.082	5	135
Parking (dummy variable: 1 if off-street parking available, 0 otherwise)	0.651	0.477	0	1
View index 75 (proportion of house views, at roof level, with an horizon angle of at least 75º zenith)	0.521	0.231	0	1
Elevation (elevation of house roof in metres above sea level)	73.592	58.551	4.180	271
Sunlight (hrs/day, year average)	8.698	1.108	3.665	11.270
Sunlight in winter months (average sunlight [hrs/day] across six darkest months - April to September)	6.749	1.561	0.432	9.611
Sunlight in summer months (average sunlight [hrs/day] across six sunniest months - October to March)	10.665	0.898	6.204	13.308
Sale in winter months (dummy variable: 1 if house sold between April and September, 0 otherwise)	0.457	0.498	0	1
Median personal income at suburb level (2006 nominal values, in $NZD)	33,207	7,137	17,643	46,822

Note: *Sunlight*, *Elevation* and *View index 75* are calculated using spatial models based on topographical information available from WCC (2010) –see appendix for more details. All remaining variables are extracted/constructed from data directly supplied by REINZ.

3.2   Views and elevation

Using fine-resolution (1 and 5 metres) digital elevation models provided by the Wellington City Council (WCC, 2011), we built topographic models incorporating building shapes and natural topography across the city. Using these models, we computed the elevation above sea level of the roof of all houses in the REINZ data. We then computed each property's viewspan given by the horizon line seen at roof level, using a zenith angle. The zenith angle of horizon views translates into values ranging from a purely vertical view (=0°) to a full view to the horizon line (=90°). In practical terms this means that houses with a blocked view have as model output an angle close to zero, while an unobstructed view of the horizon translates into an angle of 90°. The zenith angle of a house was computed for all cardinal points every two degrees – i.e., 180 observations. From this computed zenith angle data we created the variable '*View index 75*', which is the proportion of our 180 cardinal points reporting a zenith angle over 75°. In this way, our index captures how much of a view of at least 75° each house has in our dataset.[17]

As seen in Table 1, the average altitude of houses in our sample was 74 metres, with a high standard deviation of 59 metres reflecting the abrupt topography of the city. Our view index has an average of 0.52 (i.e., approximately half of our houses have an average view over 75°) and standard deviation of 0.23.

3.3   Sunlight

We can precisely determine the position of the sun in the sky once we know the location and altitude of an observer on earth and the time of year (Reda and Andreas, 2003). Considering this information plus the topography, man-made features, calculated zenith angles and elevation, we then determined how much sun a given property receives throughout each day of the year, assuming a clear sky. Subsequently, we computed the average daily hours of direct sunlight received during the year by each house in our database. Summary statistics of this variable, as well as variables considering the average per day hours of sunlight in winter and summer months, are reported in table 1.[18] The average house in our sample received 8.7 hours of sunlight per day, on average, across the year. However, as expected, our sunlight data varies considerably across the sample with houses receiving as low as 3.7 hours of sunlight on average across the year, while some houses received more than 11 hours. Also as expected, there is a

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[17] We also computed 'View index' for angles 80° and 85°. For the estimates in this study we use the 75° index as this reported the largest (bell-shaped) variability, compared to the other indexes, which had a sizeable proportion of properties top-coded or bottom-coded. See appendix for more details.

[18] To keep the analysis focused, we defined two seasons: winter (the darkest six months, being April-September) and summer (the lightest six months, being October-March).

difference between summer and winter months, with a higher variation in the latter (standard deviation of 1.6 hrs/day), compared to the former (0.9 hrs/day).[19]

4   Estimation and results

We estimate standard hedonic models for *ln(House sale price)* incorporating *Sunlight*, *Elevation*, views (*View index 75*) and other available house and location variables. We start with a simple specification and then test its robustness by checking whether the sensitivity of sale price to *Sunlight* varies across a number of dimensions such as sunlight in winter versus summer, season of sale, elevation, viewspan and whether the house is in a relatively wealthy of relatively sunny suburb.

We begin with a simple naïve regression of *ln(House sale price)* on our variable *Sunlight* plus a constant. The resulting *Sunlight* coefficient is close to zero (-0.008), with a p-value of 0.051. This naïve regression would imply that variation of *Sunlight* across properties does not affect the market price of houses (or affects them negatively) in our dataset.

However, this simple specification suffers from two important issues: omitted variables and locational sorting. The first is obvious as we are ignoring several factors that could affect the final value of a house in the market. To address this concern, we add the extra house characteristics variables available in our dataset.[20]

The second issue has been widely discussed in the hedonics literature and refers to the ex-ante preferences that buyers have to locate in particular areas (in our case, a preference to locate in areas with more sunlight than others), producing a self-selection bias in our simple estimates.[21] To address this concern, we use a 'within estimator' by including fixed effects at Mesh-block (MB) level in the city.[22] By incorporating MB fixed-effects, we reduce bias due to locational sorting considerably as now our *Sunlight* coefficient is capturing the variation within these neighbourhoods after controlling for location preferences that purchasers might have had when selecting houses. The inclusion of meshblock fixed effects also controls for the price effects of unobserved local characteristics such as accessibility or proximity to local amenities. Our full model incorporating both the full characteristics vector and MB fixed effects is given by

$$\log (Y_i) = \alpha + \beta \, \text{Sunlight}_i + \mathbf{\gamma} \, \mathbf{X}_i + \mathbf{\delta} \, \mathbf{T}_i + e_i , \qquad (1)$$

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[19] To check accuracy of the *Sunlight* variable we conducted random checks across the city using the 'Show sunlight' feature in Google Earth©. This exercise, plus personal observations, confirmed the accuracy of the computed sunlight data.

[20] Omitted variables bias is always possible in hedonic models as many factors influence the market value of a house (Hill, 2013). We reduce the potential bias through the inclusion of *Sunlight*, *Elevation* and *View index 75*.

[21] See Bayer and Timmins (2005), Kuminoff and Jarrah (2010).

[22] MB is the lowest statistical spatial unit in New Zealand corresponding roughly to a city block. For its statistical and geographical representation see www.mashblock.co.nz/meshblock. In our data we have 936 Mesh-blocks.

where Y_i is the sale price of property *i*. $\boldsymbol{X_i}$ is a vector for our available hedonic variables: *Elevation*, *Views*, *Number of bedrooms*, *Total floor area*, *Age of house* (and its squared value), and *Off-street parking access*. $\boldsymbol{T_i}$ is a vector of dummies controlling for the quarter of sale and e_i is an idiosyncratic error term. Using equation (1) we initially used OLS for the hedonic estimation without controlling for MB characteristics and thereafter control for MBs. Results without the MB variables are provided in model (1) in table 2. The inclusion of the house characteristics variables now yields a (positive and significant) coefficient on *Sunlight* of 0.019.

To address locational sorting and additional omitted variables endogeneity from unobserved location-specific time-invariant characteristics, we incorporate the MB fixed-effects in model (2).[23] In this regression, *Sunlight* has a statistically significant semi-elasticity of 2.4% which, at our sample average, translates into approximately $15,000 dollars extra in price for each extra hour of daily sunlight for the property.

Other differences between models (1) and (2) are worth discussing. First, our view index changes from having a statistically significant negative coefficient to having no statistical effect on house values, while elevation changes from barely negative to significantly positive. These changes reflect the correction that the fixed-effect model produces in our estimates: coefficients now capture the variation within a MB (a neighbourhood). This implies that people are willing to pay more to acquire more elevated houses within neighbourhoods, but that a view does not make much of a difference once a location is chosen.[24] With the exception of house age (which is likely to differ on average across mesh-blocks) all remaining hedonic variables keep their sign and significance.

Building from model (2) we test whether sunlight variation across the year has an effect on sale price. Model (3) tests whether there is a differential effect of having more sun in summer versus winter by including the average daily hours of sunlight across the six darkest months (April to September) as a covariate. The resulting coefficient on this variable is not significant. This finding, along with similar tests,[25] indicates that the valuation of sunlight is similar across the year. Model (4) tests whether the valuation of sunlight is related to the season when the house was sold. For this we interacted Sunlight with a dummy variable given by sales reported in the winter (six darkest) months, finding that the interaction term is not significant.

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[23] To address locational sorting we also tried a spatial smoothing estimation, finding no major changes in our results for *Sunlight*.

[24] As MBs are small spatial units within the city, they will capture most of the view variability across our sample and hence the MB fixed effects will capture much of the price effects of views.

[25] We tested averages across different months and always found no difference of sunlight valuation across the year.

Table 2: Hedonic model results. [Dependent variable = *ln (House sale price)*]

	(1)	(2)	(3)	(4)	(5)	(6)
Sunlight (hrs/day, year average)	0.020***	0.024***	0.020*	0.023***	0.024***	0.025***
	(0.004)	(0.005)	(0.012)	(0.006)	(0.005)	(0.005)
View index 75 (prop. of views over 75º zenith)	-0.139***	0.020	0.022	0.019	0.019	0.016
	(0.021)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Elevation (of house roof, in mts./100)	-0.011*	0.078***	0.079***	0.078**	0.079***	0.078***
	(0.006)	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)
Sunlight in winter months (hrs/day, average)			0.003			
			(0.007)			
Sunlight x Sale in winter months (interaction term)				0.004		
				(0.005)		
Sunlight x Elevation (interaction term)					-0.002	
					(0.008)	
Sunlight x View index 75 (interaction term)						0.006
						(0.014)
Number of bedrooms	0.030***	0.045***	0.045***	0.045***	0.045***	0.045***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Total floor area (sq. metres/100)	0.361***	0.234***	0.234***	0.234***	0.234***	0.234***
	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
House age (years/10)	-0.007	0.010*	0.010*	0.010*	0.010*	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
House age ^2 (/1000)	0.021***	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Parking (dummy: 1 if off-street parking available, 0 if not)	0.057***	0.070***	0.070***	0.070***	0.070***	0.070***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	12.412***	12.403***	12.419***	12.419***	12.401***	12.397***
	(0.041)	(0.050)	(0.060)	(0.053)	(0.050)	(0.052)
Mesh-block fixed effects	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.540	0.756	0.756	0.805	0.756	0.756
AIC	-306.7	-3844	-3842	-2439	-3842	-3842
BIC	-68.20	-3606	-3597	-2303	-3597	-3597

Notes: N = 5,584. Time (quarter) dummies are included in all models, but not reported here. All interaction terms are with demeaned variables. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We also test whether the estimated coefficient on *Sunlight* alters when including its interaction with house elevation or viewspan. Columns (5) and (6) report the results of these tests, showing that the effect of price with respect to *Sunlight* remains similar (in extent and significance) when *Sunlight* is interacted with each of elevation and viewspan.[26] Finally, as seen in the statistics of Table 2, the base model (2) reports a lower value for the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) than the other specifications, signalling that not only does the inclusion of interactions provide no further information, but that they also produce poorer models relative to the base fixed-effects estimates.

Even though the value of sunlight remains stable across the model specifications in Table 2, this might change across different suburbs. For instance, it could be the case that people seeking to buy houses in relatively dark suburbs (at the bottom of a hill, for instance) would have a higher willingness to pay for an extra hour of sunlight, or that this is valued differently amongst people seeking houses in high income suburbs. To test these 'suburb specific' cases, we expanded model (2) to include *Sunlight* interactions with suburbs reporting high and low amounts of sunlight, and with suburbs having high and low income on average. Findings of these models are reported in Table 3.

Similar to the results in Table 2, after including interactions of *Sunlight* with high and low income suburbs (model (7)) and with dark and sunny suburbs (model (8)), the coefficient on *Sunlight* remains similar to the base model and the differences in sale price are not statistically significant.[27] Other coefficients also remain stable. These results imply that, regardless of the suburbs where purchasers choose to locate, after controlling for neighbourhood characteristics and house attributes, people are still willing to pay a premium of around 2.4% of the total house value, on average, for an extra daily hour of sunlight across the year.

As described in the appendix, our *Sunlight* measure was computed with topographical digital elevation models built in 2010. There is a possibility, therefore, that we could be missing changes in sunlight for properties that could have occurred because of building intensification across the city between 2011 and 2014. To check any potential biases from this factor we tested model (2) by splitting our observations into two sub-samples: houses sold between 2008 and mid-2011 (N=2,667) and from mid-2011 to 2014 (N=2,917). Results from these two regressions produce significant *Sunlight* coefficients of 0.026 and 0.023 respectively (which are not statistically different from each other), suggesting that any potential changes of direct sunlight received as a consequence of urban intensification did not bias our results.

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[26] Adding a triple interaction of these variables does not change our results. We also tested the *Sunlight* interactions with View Index 80° and 85°, finding also virtually no changes to our estimates.

[27] Standard errors clustered by suburbs are used in these estimations. There are 38 suburbs in our dataset.

Table 3: Variation in value of sunlight by suburb type. [Dependent variable = *ln (House sale price)*]

	(7)	(8)
Sunlight (hrs/day, year average)	0.024***	0.025***
	(0.007)	(0.006)
View index 75 (prop. of views over 75º zenith)	0.019	0.019
	(0.023)	(0.023)
Elevation (of house roof, in mts./100)	0.079	0.078
	(0.055)	(0.054)
Sunlight, x *dummy for high income suburbs* (suburbs in upper quartile of median personal income distribution)	0.001	
	(0.011)	
Sunlight, x *dummy for low income suburbs* (suburbs in lower quartile of median personal income distribution)	0.003	
	(0.007)	
Sunlight x *dummy for sunnier suburbs* (suburbs in upper quartile of *Sunlight* distribution)		-0.001
		(0.003)
Sunlight, x *dummy for darker suburbs* (suburbs in lower quartile of *Sunlight* distribution)		-0.002
		(0.003)
Number of bedrooms	0.045***	0.045***
	(0.008)	(0.008)
Total floor area (sq. metres/100)	0.234***	0.234***
	(0.018)	(0.018)
House age (years/10)	0.010	0.010
	(0.009)	(0.009)
House age ^2 (/1000)	-0.001	-0.001
	(0.007)	(0.007)
Parking (dummy: 1 if off-street parking available, 0 if not)	0.070***	0.070***
	(0.009)	(0.009)
Constant	12.402***	12.402***
	(0.063)	(0.062)
Mesh-block fixed effects	Yes	Yes
R-squared	0.756	0.756
AIC	-3842	-3843
BIC	-3597	-3597

Notes: N = 5,584. Time (quarter) dummies are included in all models, but not reported here. Clustered standard errors (at suburb level) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5   Implications

Direct sunlight exposure is a valued attribute for residential property buyers, perhaps especially in a cool-climate city such as Wellington. However natural and man-made features may block sunlight for some houses, leading to a loss in value for those dwellings. Hitherto, no study in the urban economics literature has estimated the value that house buyers place on sunlight when purchasing a property. We do so, finding that each additional hour of direct sunlight exposure for a house per day (on average across the year) adds 2.4% to a dwelling's market value. This estimate is robust to a variety of specifications that investigate whether the value is conditional on other factors relating to the characteristics of the house or its suburb.

At a policy level, our estimates may be used to facilitate price-based instruments rather than regulatory restrictions to deal with overshadowing caused by new developments. For instance, consider a new multi-storey development that will block three hours of direct sunlight exposure per day (on average across the year) on two houses, each valued at $1,000,000. The resulting loss in value to the house owners is in the order of $144,000. Instead of regulating building heights or the site envelope for the new development, the developer could be required to reimburse each house owner $72,000. In return, the developer would be otherwise unrestricted (for sunlight purposes) in the nature of development. If the development cannot bear the $144,000 then the efficient outcome is that the development does not proceed. Conversely, if the development can bear that sum, then the socially optimal outcome is for the development to occur and, from an equity perspective, the neighbours are compensated for their loss of sunlight exposure.

Developers themselves could also make use of this new information. In deciding how much to bid for land on which to develop, a developer must estimate the sale price of the ultimate property. Knowing whether the dwelling on a site will receive full-day sun or only limited sun exposure will assist the process for the developer of bidding for the underlying land.

Our 2.4% estimate of value (for each hour of sunlight per day on average through the year) is naturally context-specific. Elsewhere, the value may be higher or lower depending on factors such as climate, topography, city size and incomes. Nevertheless, our approach can be replicated in studies for other cities to help price the value of sunlight in those settings.

It is not just our valuation estimates and techniques that may be of use to regulatory authorities and other agents. We show that it is a straightforward task to calculate accurate sunshine exposures for individual dwellings across a city. Information is required only on the building envelope and on natural features. With the ability to calculate sunshine exposures, and the value placed on those exposures, the policy apparatus for dealing with sunlight issues in an urban setting can henceforth be shifted from a regulatory to a price-based approach.

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Supplementary materials - Technical appendix

For this study, we computed daily hours of direct sunlight (our *Sunlight* variable) for multiple locations in the Wellington City Council area from topographical models that consider natural landscapes, building shapes and seasonal sun position in the sky.

The empirical base of our *Sunlight* measure used a digital elevation model (DEM) derived from Lidar observations and distributed by the Wellington City Council (WCC, 2011). Given data and model availability, to cover the core metropolitan area of the city of Wellington we built two fine-resolution topographical models, respectively 1 and 5 metres resolution, i.e. A and B in Figure 1. For these fine-resolution topographical models, building shapes were extruded from the original DEM layer using the Wellington City Building Footprints (WCC, 2010). Specifically, this dataset contains polygonal outline of buildings, types of building and roof elevations. As no specific details are given on roof shapes, our model considers that buildings have flat roofs. We set the elevation of topographical model nodes contained inside building outlines at the corresponding roof elevation.

Determining horizon lines (views)

For every sale location in the REINZ dataset, we computed the horizon line as perceived at roof level of the associated building outline.[28] We discretized the azimuthal orientation (or horizontal angle) in 180 directional bins of 2°, from 0° to 360°. By convention the azimuth is null when facing North and turns clockwise (i.e. equals 90° when facing East). For individual azimuth angles, we searched for the highest point in the topographical models that an observer may see from that location when looking in the corresponding azimuthal direction. By knowing the elevation difference and distance of this point to the observer, we determined the zenith angle (or vertical angle). By convention, the zenith angle is null when looking up to the vertical and equals 90° on the horizon at sea level. Basically, a low zenith angle for a given azimuth means the facing view is obstructed while a high value corresponds to a wider field of view. By repeating this process for every directional bin, we created a 180 elements array of zenith angles to estimate the horizon line perceived by an observer at a given location. The creation of individual horizon lines was then automated for every identified building.

Calculating hours of direct sunlight

The horizon line allows us to determine how much sun a given location is receiving throughout the year, assuming clear sky. By knowing the location and altitude of an observer on earth as well as the time of the year, we can precisely determine the position of the sun in the sky (Reda

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[28] In the case of a sale location that did not match perfectly an outline from the building footprints dataset, we associated the observation to the nearest building by computing the distance between the sale location and the position of polygonal barycentre.

and Andreas, 2003). For an observer's point of view, the position of the sun in the sky can be expressed using just two angles: (1) the azimuth and (2) the zenith. At a given location and for any time of the year, the sun's azimuth and zenith are compared to precomputed horizon lines. For the corresponding azimuth, the observer's horizon zenith angle can be subtracted from the sun's zenith angle. If the result is negative (e.g. horizon line below sun), the observer is likely to receive some sunlight and if the result is negative (e.g. horizon line above sun), the observer is likely to be in the shadow of a building or a natural feature. By following this logic, we computed one minute resolution time series of direct sunlight (sunlight=1, shade=0) for a whole year and for all identified building locations. Yearly-averaged and monthly-averaged hours of direct sunlight received per day were then computed and used in the analysis.

Figure 1: City of Wellington.
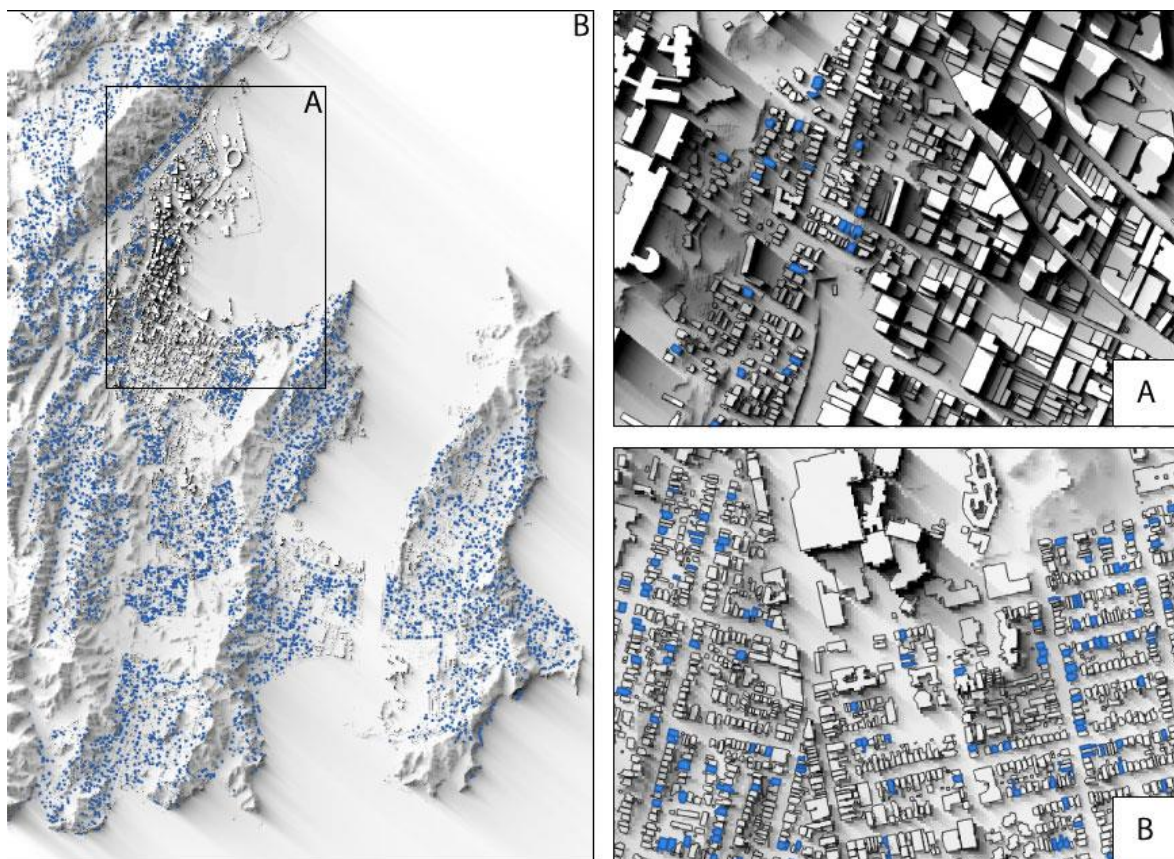
Note: Quadrants A and B show models with resolutions of 1 and 5 metres, respectively, after incorporating natural landscape and building shapes. Locations of properties in REINZ data are shown with dots. Right panel shows close-up views for the two topographical models highlighting spatial resolution differences.

Source. Own calculations with data from REINZ, WCC (2010, 2011).

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