How Big Is the Airbnb Rent Premium? The Case of Sydney

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Abstract:

The rapid expansion of Airbnb has led to concerns that it is crowding-out long-term rentals. We consider how strong is the incentive for landlords to switch properties to Airbnb. The Airbnb rent premium is defined here as the ratio of what a landlord can charge on Airbnb versus in the long-term rental market. Using hedonic regression methods applied to micro-level data on long-term rentals (about a million observations) and Airbnb listings (about 190 000 observations), we calculate the size of the Airbnb rent premium for all the properties in our datasets. On average we find that landlords can earn about 90 percent more per week on Airbnb than in the long-term rental market. The premium is even larger for properties with three or more bedrooms. We find some evidence of a higher Airbnb premium in more expensive postcodes, and those with a higher Airbnb density. We also find that the Airbnb rent premium decreases slightly from 2015 to 2017. (JEL. C13; R31)

Keywords: Sharing economy; Hedonic regression; Double imputation; Airbnb rent premium; Size premium; Airbnb density

PRELIMINARY DRAFT – DO NOT QUOTE

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1 Introduction

Since its inception in 2007, Airbnb has had a large impact on the housing market. According to Forbes magazine its market capitalization in 2018 was at least 38 billion dollars. Airbnb is a rival to hotels in providing short-term accommodation (see for example Zervas, Proserpio, and Byers, 2017, and Coyle and Yeung, 2018). Airbnb may also be crowding out long-term rentals as some landlords switch from long-term contracts to Airbnb. The question of whether Airbnb (or similar sharing sites) reduce the supply of long-term rentals and hence drive up rents (and house prices) has recently been addressed by Horn and Merante (2017) and Barron, Kung and Proserpio (2018).

Our focus here relates to this issue, although our angle is different. We consider the incentive for landlords to switch properties from the long-term rental market to Airbnb. The incentive here is the Airbnb rent premium (i.e., how much more a landlord can earn renting out a property via Airbnb rather than on the long-term rental market). We show how hedonic methods can be used to measure the Airbnb rent premium, and then apply our methods to micro-level data on long-term rentals (about a million observations) and Airbnb listings (about 190 000 observations) for Sydney over the period 2015-2017.

As far as we are aware, this is the first paper to undertake a detailed micro-level analysis of the Airbnb rent premium. First, we build two hedonic pricing models. One model is for long-term rental asking prices using a dataset obtained from Australian Property Monitors (APM). The other is for Airbnb rentals obtained from the Inside Airbnb website. Both hedonic models are estimated using the same set of characteristics for the years 2015, 2016, and 2017.

Second, we use the two hedonic models to predict both long-term and Airbnb rental rates for every property that appears in either the APM or Airbnb datasets. Taking the ratio of the predicted Airbnb rental divided by the predicted long-term rental (both quoted at a weekly frequency) we therefore obtain estimated quality-adjusted Airbnb rent premiums at the level of individual properties. We use a double hedonic imputation approach (i.e., both numerator and denominator in the Airbnb rent opremium ratio are predicted) so as to reduce the impact of omitted variables in the hedonic models.

Having constructed Airbnb rent premiums at the micro level we can then address the following questions:

- How big is the overall Airbnb rent premium in Sydney?
- How does the Airbnb rent premium vary across regions in Sydney?
- How does the Airbnb premium relate to "Airbnb density" (i.e., the number of Airbnb rentals relative to the number of long-term rentals in an area)?
- How does the Airbnb rent premium vary across different market segments (i.e., smaller and larger apartments)?
- Are there seasonal differences in the Airbnb rent premium (e.g., does the Airbnb rent premium rise during the Australian summer)?
- Is there any trend in the Airbnb rent premium from one year to the next?

2 Literature Review

A number of papers have been written in the last 3-4 years exploring the impact of Airbnb on the housing market. Two key debates that have emerged are over the impact of Airbnb on the hotel industry (see for example Zervas, Proserpio, and Byers, 2017) and on the housing market. Notable papers investigating the interaction between Airbnb and the housing market include Sheppard and Udell (2016), Horn and Merante (2017), and Barron, Kung and Proserpio (2018). Coyle and Yeung (2018) address both the impact of Airbnb on hotels and the housing market.

Horn and Merante (2017), for example, argue that Airbnb listings are crowding out long-term rentals. The resulting reduction in the supply of long-term rentals then acts to push up rents. They found that a one standard deviation increase in Airbnb-density in Boston over the period September 2014 to January 2016 reduced the number of long-term rental offers by 5.9

percent and increased rents by about 0.4 percent. In the most popular Airbnb destinations, the effect on price was 3.1 percent. They also note that while only 18 percent of all Airbnb hosts listed more than one property, these hosts listed nearly half (46 percent) of all units for rent. Sheppard and Udell (2016) find that in New York a doubling in the number of Airbnb listings increases property prices by anywhere between 6 and 31 percent, depending on the model specification. Their preferred estimate is 17.7 percent. Barron, Kung and Proserpio (2018) consider the impact of Airbnb on both rents and transaction prices for the entire USA. They find that a 1 percent increase in Airbnb listings leads to a 0.018 percent increase in rents and a 0.26 percent increase in prices at the median owner-occupancy zip-code. They also find that the more owner-occupiers exist in a market, the weaker is the effect of Airbnb on rents.

Our objective here is complementary but different from the existing literature. Our aim is to measure how strong is the incentive for landlords to switch from listing a property for long-term rental to Airbnb. We do this by measuring the Airbnb rent premium. This is calculated by dividing the Airbnb rental price of a property by its corresponding long-term rental price. We use hedonic methods to compute both the numerator and denominator in this ratio at the level of individual properties, using micro-level datasets for Sydney. While hedonic methods have been applied previously to Airbnb data to explain which characteristics contribute most to the listing rental price (see for example by Gibbs et al., 2017), as far as we are aware we are the first to use them to compare Airbnb and long-term rentals at the micro-level.

It should be noted that relative attractiveness for a landlord of renting out a property on Airbnb versus the long-term rental market depends on more than just the Airbnb rent premium. For a start, Airbnb properties are furnished while long-term rentals typically are not. Also, Airbnb apartments need to be cleaned between rentals.

in some cities restrictions are imposed on landlords listing properties on Airbnb. For example, since 2017 landlords in Sydney are only allowed to rent out properties for a maximum of 180 days per year. Such measures should reduce the extent to which Airbnb crowds out long-term rentals. Howeverm the extent of such crowding out also depends on the size of the Airbnb premium. Hence it is important to measure to obtain quality adjusted estimates of this premium, and how it differs across different sectors of the market.

Note: This literature review is still preliminary. It will be expanded in the next version.

3 Predicting the Airbnb Rent Premium using Hedonic Double Imputation

A hedonic model regresses the price of a product on a vector of characteristics, whose prices are not independently observed. The hedonic equation is a reduced form that is determined by the interaction of supply and demand (see Griliches 1961, Rosen 1974, Hill 2013, and Silver 2016).

Here we estimate separate hedonic models for Airbnb and long-term rentals for apartments in Sydney for each of 2015, 2016 and 2017 using a semilog functional form.[1,2] The hedonic model for Airbnb rentals in year t can be written as follows:

$$\ln(R_{A,t}) = X_{A,t}\beta_{A,t} + u_{A,t}, \tag{1}$$

where A indicates that the hedonic model is estimated using Airbnb data. The term $\ln(R_{A,t})$ is an $H_{A,t} \times 1$ vector of natural logarithms of the observed Airbnb rentals (where depending on the context $H_{A,t}$ denotes either the number of apartments listed or the number actually rented in the Airbnb dataset in year t). $X_{A,t}$ is an $H_{A,t} \times C$ matrix of characteristics, $\beta_{A,t}$ is a $C \times 1$ vector of characteristic shadow prices for Airbnb rentals, and $u_{A,t}$ is an $H_{A,t} \times 1$ vector of random errors. The characteristics in our context are dummy variables for the number of bedrooms, number of bathrooms, and postcode. While more characteristics are available in the Inside Airbnb dataset, we only use those characteristics that are also available in the APM dataset.

[1] This section draws on methods developed in Hill and Syed (2016) although applied in a different context.

[2] See Diewert (2003) and Malpezzi (2008) for a discussion of some of the advantages of the semilog functional form in a hedonic context.

Similarly, the hedonic equation for long-term rentals each year t is written as follows:

$$\ln R_{L,t} = X_{L,t}\beta_{L,t} + u_{L,t}, \tag{2}$$

where $y_{L,t}$ is the vector of the logarithms of the long-term rents of apartments in year t, $X_{L,t}$ is the corresponding matrix of rented apartment characteristics, $\beta_{L,t}$ is a $C \times 1$ vector of characteristic shadow prices for long-term rentals, and $u_{L,t}$ a vector of random errors. The characteristics in the long-term rental hedonic model are the same as in the Airbnb model (i.e., dummy variables for the number of bedrooms, number of bathrooms, and postcode).

Our objective is to compute the Airbnb rent premium ratio, defined as Airbnb rent per week divided by long-term rent per week, for each individual apartment in either the Airbnb or long-term rental datasets. We do this using the estimated hedonic models. An Airbnb rent for each apartment h in the Airbnb dataset in year t is predicted using the estimated $\hat{\beta}_A$ parameters from (1) as follows:

$$\hat{R}_{A,t,h}(x_{A,t,h}) = \exp\left(\sum_{c=1}^{C} \hat{\beta}_{A,t,c} x_{A,t,h,c}\right), \tag{3}$$

where $c = 1, \ldots, C$ indexes the list of characteristics over which the price and rent hedonic models are defined. Similarly, a long-term rent for each apartment j rented in year t is predicted using the estimated $\hat{\beta}_L$ parameters from (2) as follows:

$$\hat{R}_{L,t,j}(x_{L,t,j}) = \exp\left(\sum_{c=1}^{C} \hat{\beta}_{L,t,c} x_{L,t,j,c}\right). \tag{4}$$

We can also use the long-term rental hedonic model to predict the long-term rental of an apartment in the Airbnb dataset in year t:

$$\hat{R}_{L,t,j}(x_{A,t,j}) = \exp\left(\sum_{c=1}^{C} \hat{\beta}_{L,t,c} x_{A,t,j,c}\right), \tag{5}$$

and the Airbnb rental hedonic model to predict the Airbnb rental of an apartment in the long-term rental dataset in year t:

$$\hat{R}_{A,t,j}(x_{L,t,h}) = \exp\left(\sum_{c=1}^{C} \hat{\beta}_{A,t,c} x_{L,t,h,c}\right). \tag{6}$$

Strictly speaking, the predictions $\hat{R}$ are biased estimates of R since by exponentiating we are taking a nonlinear transformation of a random variable. Possible corrections have been proposed by Kennedy (1981) and others. From our experience, however, these corrections are small and partially offsetting in our ratio formulas in (7) and (8) below, and hence have virtually no impact on our results.

The Airbnb rent premium (ARP_A) on an apartment in the Airbnb dataset is now calculated as follows:

$$ARP_{A,t,h} = \frac{\hat{R}_{A,t,h}(x_{A,t,h})}{\hat{R}_{L,t,h}(x_{A,t,h})} = \frac{\exp\left(\sum_{c=1}^{C} \hat{\beta}_{A,t,c} x_{A,t,h,c}\right)}{\exp\left(\sum_{c=1}^{C} \hat{\beta}_{L,t,c} x_{A,t,h,c}\right)}. \tag{7}$$

Similarly, the Airbnb rent premium (ARP_L) on an apartment in the long-term rental dataset is calculated as follows:

$$ARP_{L,t,h} = \frac{\hat{R}_{A,t,h}(x_{L,t,h})}{\hat{R}_{L,t,h}(x_{L,t,h})} = \frac{\exp\left(\sum_{c=1}^{C} \hat{\beta}_{A,t,c} x_{L,t,h,c}\right)}{\exp\left(\sum_{c=1}^{C} \hat{\beta}_{L,t,c} x_{L,t,h,c}\right)}. \tag{8}$$

When computing the Airbnb rent premium we use a double imputation approach. This means that we use the estimated hedonic models to predict both the Airbnb and long-term rentals. We could instead have used a single imputation approach, where only the denominator of (7) and the numerator of (8) are predicted. The reason we use double imputation is that it tends to be more robust to omitted variables in the hedonic models. For example, suppose an apartment is located on a very busy road. The predicted rent (both Airbnb and long-term) obtained from the hedonic models will tend to be too high in this case. Using single imputation, the estimated Airbnb rent premium will therefore be too high if this apartment is in the Airbnb dataset, and too low if it is in the long-term rental dataset. By using double imputation, however, the omitted variables biases in the numerator and denominator will at least partially offset each other. For further discussion on the relative merits of single and double imputation in hedonic models see Silver and Heravi (2001), de Haan (2004), and Hill and Melser (2008).

Now let $Med(ARP_{A,t})$ denote the median Airbnb rent premium derived from the distribution of Airbnb apartments in (7), while $Med(ARP_{L,t})$ denotes the corresponding median Airbnb rent premium derived from the distribution of long-term rental apartments in (8). Our reason for focusing on medians rather than means is that the median is more robust to outliers. An overall median is obtained by averaging these two population specific medians as follows:

$$Med(ARP_t) = \sqrt{Med(ARP_{A,t}) \times Med(ARP_{L,t})}. \tag{9}$$

This overall median, as defined in (9) is the main focus in our empirical results, both for the whole of Sydney, and for the various submarkets we consider.

4 An Empirical Application to Sydney

4.1 Airbnb in Sydney

Airbnb opened an office in Sydney in 2012, although Australian households were already listing on the Airbnb website prior to this time. Airbnb's presence has grown rapidly since 2012. Sydney has an enormous influx of visitors each year (around 10 million in 2018 according to Tourism Australia). Indeed according to Airbnb Australia Manager Sam McDonagh, Sydney is the most penetrated market in the world. Hence Sydney is an ideal city for exploring the impact of Airbnb. As a result of government pressure, in 2017 a restriction was imposed that properties in Sydney could not be rented out on Airbnb for more than 180 days per year. An interesting question is whether the imposition of this restriction has had any noticeable impact on the Airbnb rent premium.

4.2 The Airbnb and APM Data Sets

We use Airbnb microdata for Sydney obtained from the Inside Airbnb website created by Murray Cox (see http://insideairbnb.com/). The long-term rental dataset was purchased from Australian Property Monitors (APM). Both datasets provide asking prices quoted on a weekly frequency.

We restrict our analysis to apartments. The number of observations in the Airbnb and APM datasets for each year are shown in Table 1. We restrict our comparison to postcodes with at least 100 Airbnb listings each year. Also, we deleted the top and bottom 1 percent of the Airbnb and long-term rental prices. Such deletions are justified by the high prevalence of data entry errors at the extremes of the price distribution, and the lack of representativity of these extremes for the bulk of the market. Their inclusion could distort the estimated shadow prices of the characteristics in the hedonic models, and hence likewise the predicted rents obtained from the hedonic models. We also excluded any properties with more than five bedrooms or bathrooms. The total number of observations after all deletions are also shown in Table 1.

Table 1: Number of Observations in the Data Sets

	Before deletions		After deletions	
	Airbnb	APM	Airbnb	APM
2015	537 309	44 525	245 788	39 117
2016	642 508	38 778	276 304	33 124
2017	685 605	130 865	503 153	117 277

We are having difficulty on Airbnb distinguishing between one-bedroom apartments and apartments in which one-bedroom is being rented out. To ensure that like is compared with like in our two datasets, we only want to consider whole apartment rentals. Hence in our initial analysis below we restrict attention to apartments that have two or more bedrooms. In the next draft we will bring in one bedroom apartments.

4.3 The Estimated Hedonic Models

Summary of model fit and diagnostics still to be included

4.4 The Airbnb Rent Premium in Sydney

Application of the median formula in (9) to the Sydney data yields the following results for 2015, 2016 and 2017.

$Med(ARP_{2015}) = 2.02$,

$Med(ARP_{2016}) = 1.94$,

$Med(ARP_{2017}) = 1.74$.

These medians are quality-adjusted. Hedonic methods are used to predict the Airbnb rent premium at the level of individual properties. The results given above are medians of the

Airbnb rent premiums (averaged across the properties in the two datasets – i.e., Airbnb and APM). It is interesting also to consider what the corresponding estimates of the Airbnb rent premium are if we do not use hedonics to quality-adjust, but instead simply divide the median Airbnb rent by the median APM rent. These results are shown below:

$Med(Airbnb_{2015})/Med(APM_{2015}) = 2.39$,

$Med(Airbnb_{2016})/Med(APM_{2016}) = 2.38$,

$Med(Airbnb_{2017})/Med(APM_{2017}) = 2.16$.

It can be seen that in each case the quality adjusted Airbnb rent premium is lower than its quality unadjusted counterpart. This finding indicates that the median Airbnb apartment is of lower quality than the median apartment in the APM dataset. Failure to quality-adjust using hedonic methods will cause the Airbnb rent premium to be systematically overestimated.

It is also noticeable that the Airbnb rent premium exhibits a downward trend from 2015 to 2017. This suggests that supply may be rising faster than demand in the Airbnb market in Sydney, or that substitution of apartments from the long-term rental market to Airbnb is acting to gradually reduce the Airbnb rent premium.

The variation in the median APM rent and Airbnb rent by postcode is depicted in Figure 1. The relationship between quality (as measured by APM rental price) and the Airbnb rent premium at the postcode level is explored in Figure 2. It can be seen that in all three years on average the Airbnb rent premium is higher for more expensive postcodes (although the relationship is quite weak). It can also be seen in Figure 2 that the Airbnb premium decreases slightly over time from 2015 to 2017.

In Figure 3 the predicted Airbnb rent is graphed against the predicted APM rent for individual properties. The first graph focuses on the properties in the APM dataset, while the second graph considers properties in the Airbnb dataset. The two graphs look quite similar, which suggests that our double imputation hedonic method is working quite well. This supports the finding in Figure 2. The bold line in Figure 2 is the ordinary least squares (OLS) line of bets fit. The red line is the 45 degree line. From these lines it can be seen that the Airbnb rent premium (here measured by the slope of a ray through each point) is higher for more

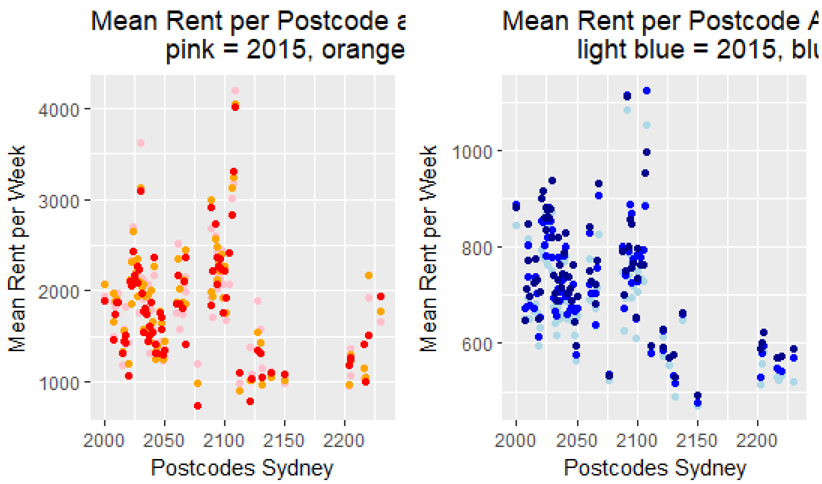

Figure 1: APM and Airbnb Rents by Postcode

expensive properties.

Histograms of the Airbnb densities for each of 2015, 2016 and 2017 by postcode are shown in Figure 4. Here the Airbnb density is defined as the proportion of Airbnb listings to APM listings. These densities are high by international standards.

The relationship between Airbnb density and log-term rents by postcode is shown in Figure 5. There is a clear positive correlation (i.e., higher Airbnb densities are observed in more expensive postcodes).

The relationship between the Airbnb rent premium and Airbnb density at the postcode level is examined in Figure 6. In all three years on average the Airbnb rent premium is higher for postcodes with higher Airbnb density. The downward trend in the Airbnb premium over time can also be seen in Figure 6.

A longitudinal map of postcodes with the Airbnb rent premium colour coded is shown in Figure 7 for apartments with different combinations of bedrooms and bathrooms. It can be seen that as the Airbnb premium systematically rises as the bedrooms and bathrooms rise. Hence bigger apartments tend to attract higher Airbnb rent premiums.

The final set of Figures considered here (Figures 8-11) compare APM and Airbnb predicted rents for different size apartments, as measured by the number of bedrooms. The best fit regression line for the whole dataset is depicted in bold. Perhaps more important is the

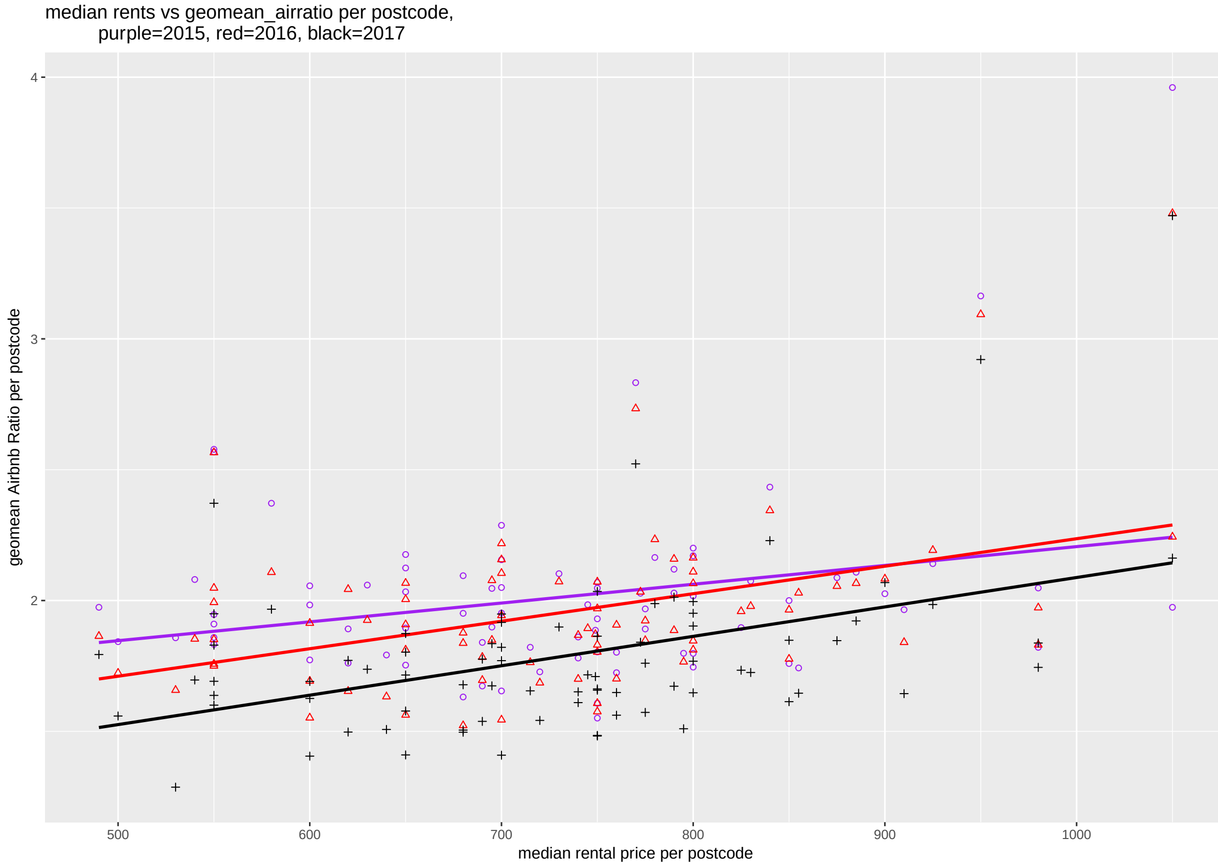

Figure 2: Regression of Airbnb Rent Premiums on Median APM Rents for Postcodes

45-degree line. The more a ray through the origin must be rotated to the left the higher is the Airbnb rent premium of a property. It is noticeable that the Airbnb rent premiums are systematically lowest for 1-bedroom apartments, and highest for 4-bedroom apartments. Again this indicates that, other things equal, better quality properties have higher Airbnb rent premiums.

5 Conclusion

At this stage our conclusions are very preliminary. We find that the overall Airbnb rent premium in Sydney is about 90 percent. Given that rental prices are very high in Sydney, this means that Airbnb is an attractive option for owner-occupiers going on holiday, work related trips, or those who can stay with relatives or friends for limited periods. Long-term

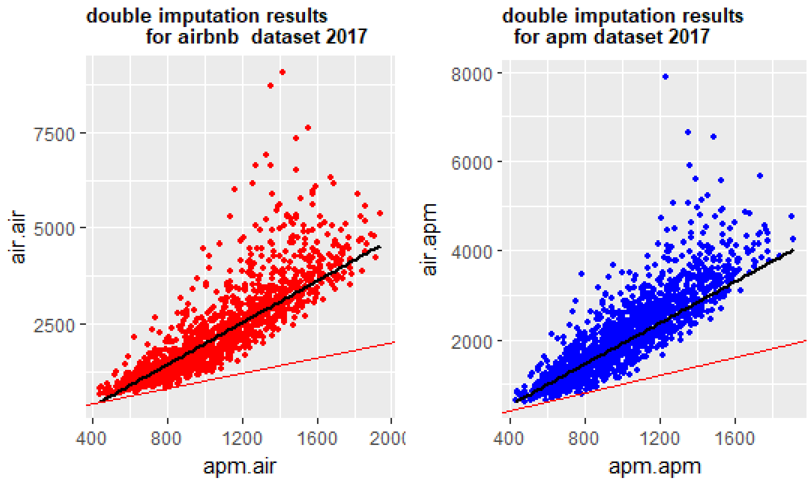

Figure 3: Regression of Airbnb Predicted Rent on APM Predicted Rent

tenants also benefit from Airbnb in this respect, since they often list their rental property on Airbnb when away on trips. The calculation is less clear for a landlord contemplating listing a property on Airbnb rather than the long-term rental market, at least since 2017. This is because of the constraint imposed in Sydney in 2017 that properties can only be rented on Airbnb for a maximum of 180 days per year. This policy was designed presumably precisely to discourage landlords from doing this.

We find a slight downward trend in the Airbnb rent premium from 2015 to 2017. Given we have micro-level estimates of the Airbnb rent premium, this allows us to explore how it varies across our cross-section of properties in each year. In particular we have found evidence that more expensive postcodes tend to have a higher Airbnb rent premium. Postcodes with a higher Airbnb density have a higher Airbnb rent premium. Also, properties with more bedrooms and bathrooms also have a higher Airbnb premium.

The implications of our findings will be explored more in the next draft.

References

Barron, K., E. Kung, and D. Proserpio (2018), The Sharing Economy and Housing Affordability: Evidence from Airbnb, (March 29, 2018). Available at SSRN: https://ssrn.com/abstract=3006832 or http://dx.doi.org/10.2139/ssrn.3006832

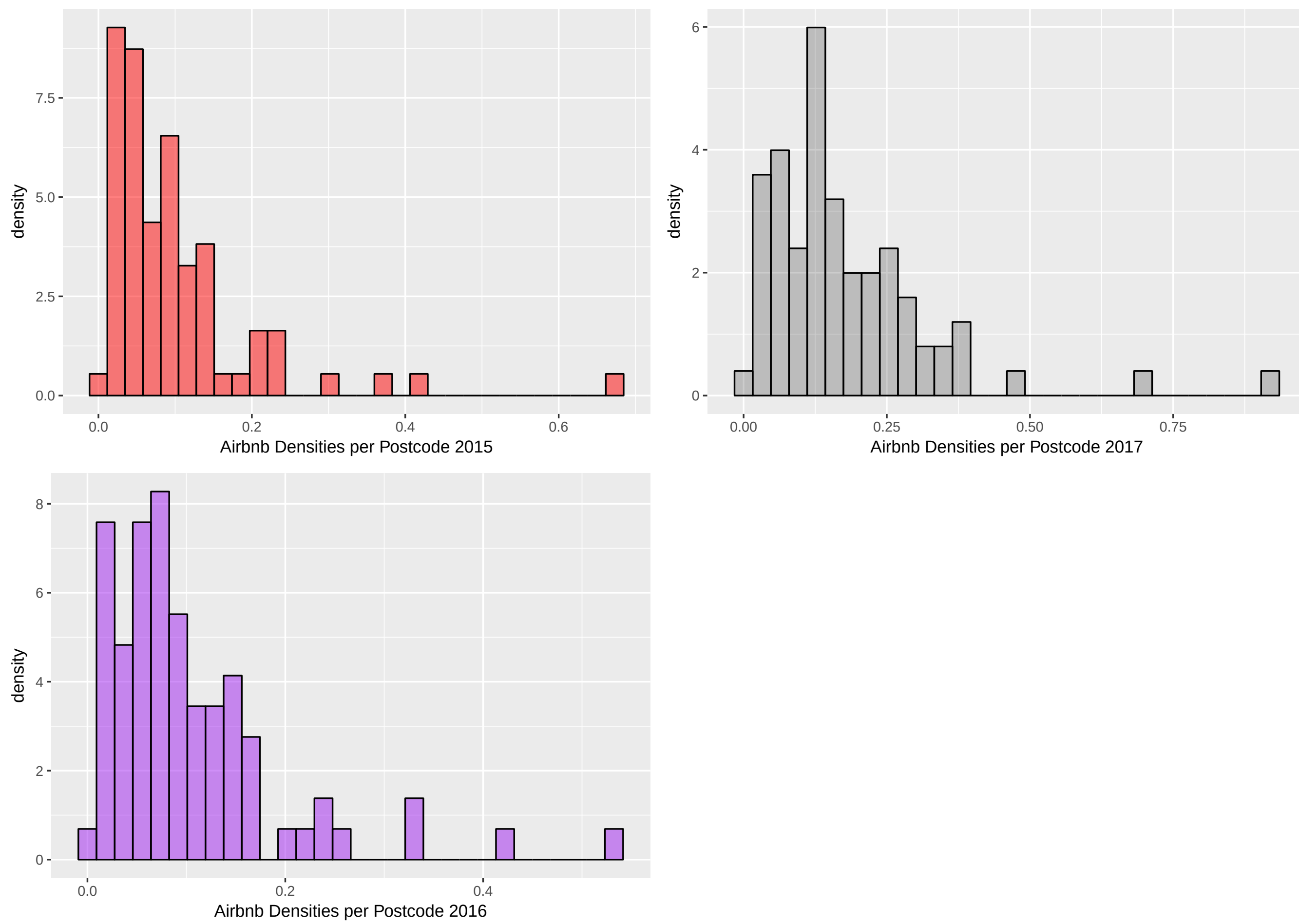

Figure 4: Histograms of Airbnb Densities by Postcodes

Coyle, D. and T. Yu-Cheong Yeung (2018), Understanding AirBnB in Fourteen European Cities, Mimeo.

de Haan, J. (2004), "Direct and indirect time dummy approaches to hedonic price measurement," *Journal of Economic and Social Measurement* 29(4) 427443.

Diewert, W. E. (2003), "Hedonic regressions: A Consumer Theory Approach," in *Scanner Data and Price Indexes, Conference on Research in Income and Wealth*, Volume 64, Robert C. Feenstra and Matthew D. Shapiro (eds.), National Bureau of Economic Research, The University of Chicago Press, 317-348.

Gibbs, C., D. Guttentag, U. Gretzel, J. Morton, and A. Goodwill (2017), "Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings," *Journal of Travel and Tourism Marketing*, forthcoming.

Griliches, Z. (1961), "Hedonic price indexes for automobiles: an econometric analysis of quality change," in G. Stigler (chairman), *The Price Statistics of the Federal Government*.

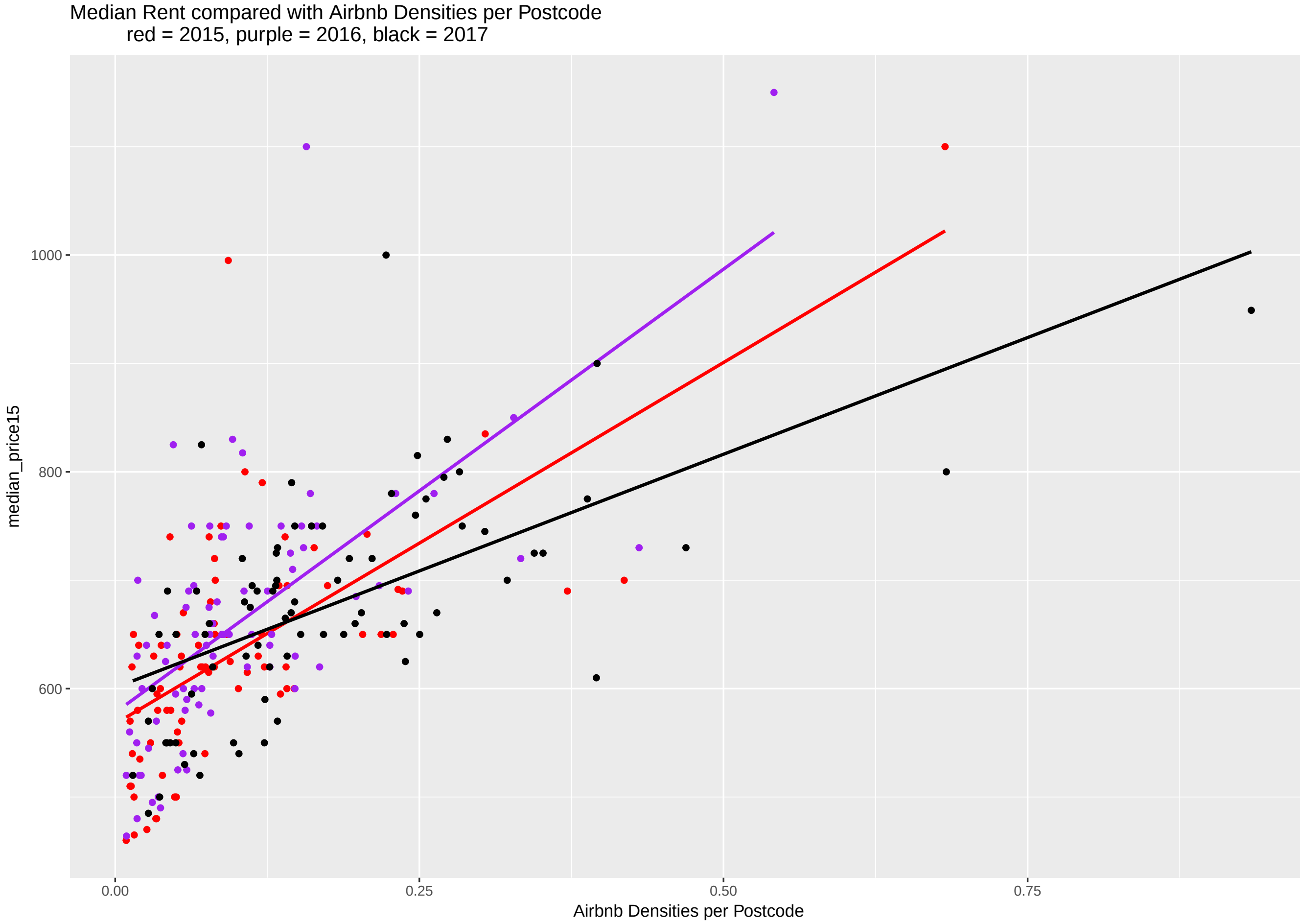

Figure 5: Regression of Long Term Rents on Airbnb Density for Postcodes

Washington D.C.: Government Printing Office.

Hill, R. J. (2013), "Hedonic Price Indexes for Residential Housing: A Survey, Evaluation and Taxonomy," *Journal of Economic Surveys* 27(5), 879-914.

Hill, R. J. and D. Melser (2008), "Hedonic Imputation and the Price Index Problem: An Application to Housing," *Economic Inquiry* 46(4), 593-609.

Hill, R. J. and I. Syed (2016), "Hedonic Price-Rent Ratios, User Cost, and Departures from Equilibrium in the Housing Market," *Regional Science and Urban Economics* 56, 60-72.

Horn, K. and M. Merante (2017), Is home sharing driving up rents? Evidence from Airbnb in Boston, *Journal of Housing Economics* 38(C), 14-24.

Kennedy, P. E. (1981), "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations." *American Economic Review* 71 (4), 801.

Malpezzi, S. (2008), "Hedonic pricing models: a selective and applied review," in T. OSullivan and K. Gibb (eds.), *Housing Economics and Public Policy*, 67-89. Blackwell Science Ltd:

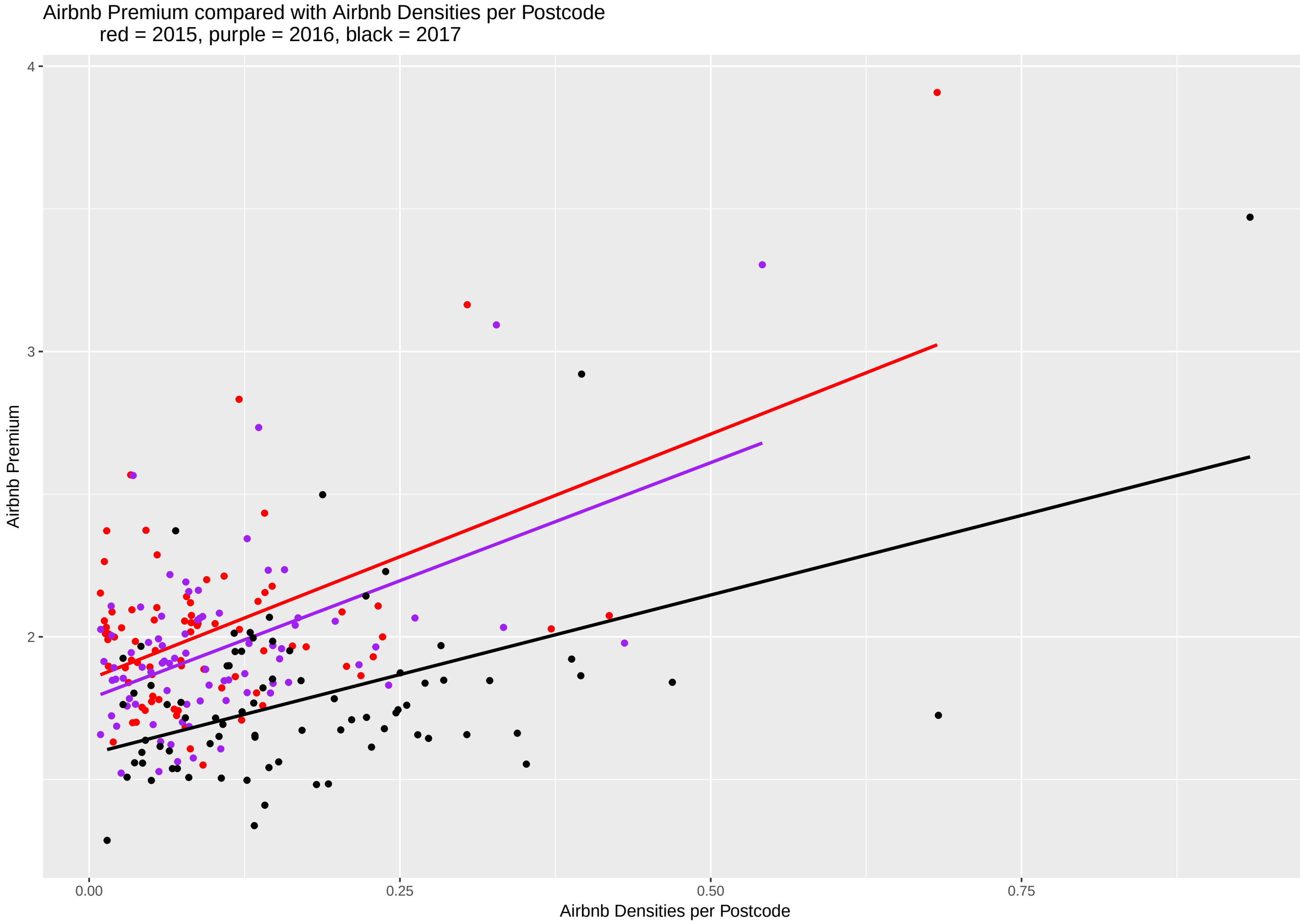

Figure 6: Regression of Airbnb Rent Premiums on Airbnb Density for Postcodes

Oxford, UK.

Rosen, S. (1974), "Hedonic prices and implicit markets: product differentiation in pure competition" *Journal of Political Economy* 82(1), 34-55.

Sheppard, S. and A. Udell (2016), "Do Airbnb properties affect house prices?" Department of Economics Working Papers 2016-03, Department of Economics, Williams College.

Silver, M. (2016), "How to Better Measure Residential Property Price Indexes," IMF Working Paper Series WP/16/213.

Silver, M. and Heravi, S. (2001), "Quality adjustment, sample rotation and CPI practice: an experiment," Presented at the Sixth Meeting of the International Working Group on Price Indices, Canberra, Australia, April 26.

Zervas, G., D. Proserpio, and J. W. Byers (2017), "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry," *Journal of Marketing Research* 54(5), 687-705.

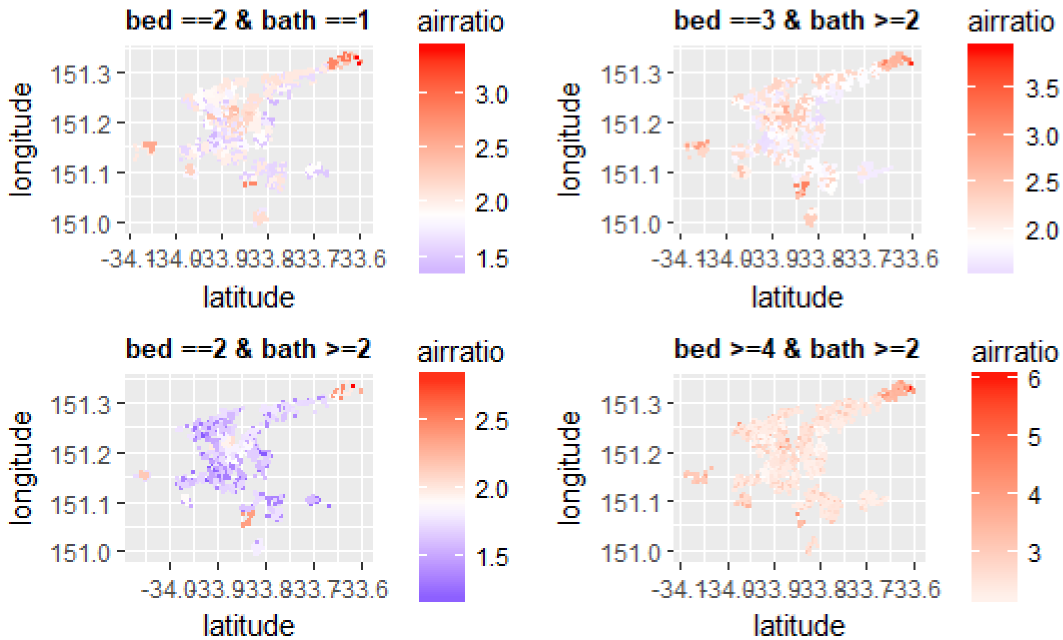

Figure 7: Longitudinal Map Showing Colour Coded Airbnb Rent Premiums

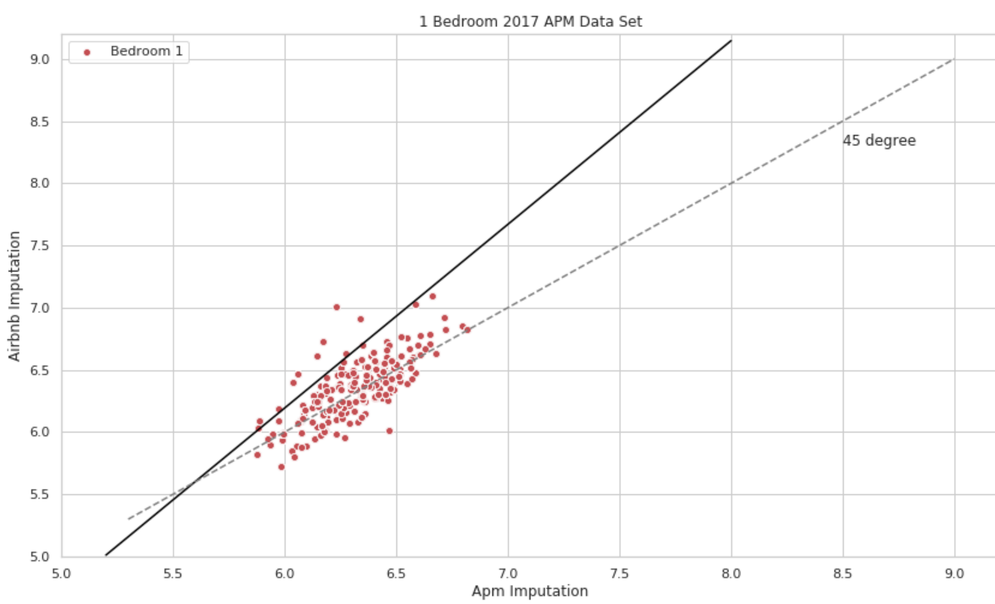

Figure 8: Regression of Airbnb Predicted Rent on APM Predicted Rent for 1 Bedrooms Apartments

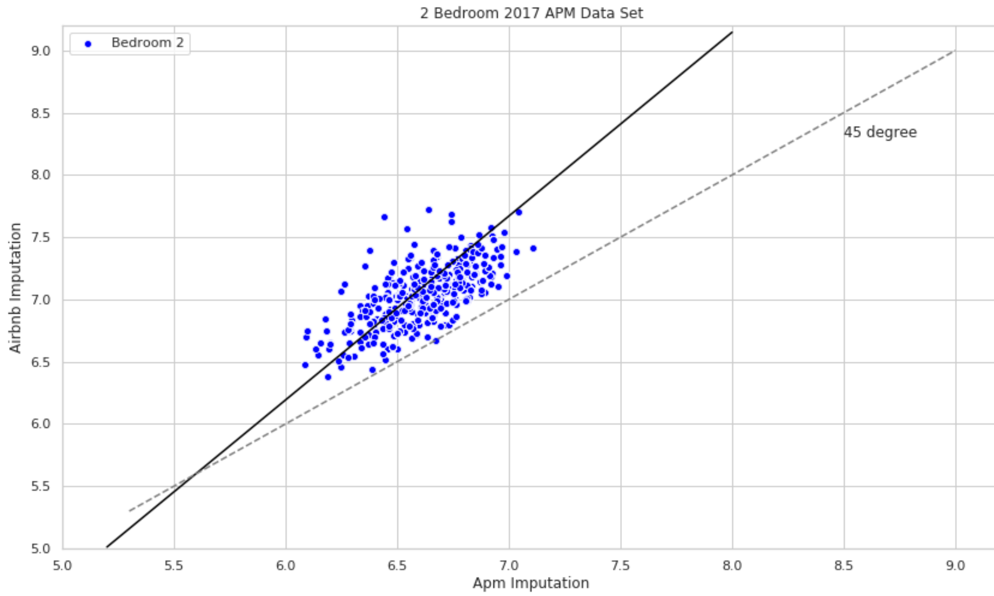

Figure 9: Regression of Airbnb Predicted Rent on APM Predicted Rent for 2 Bedrooms Apartments

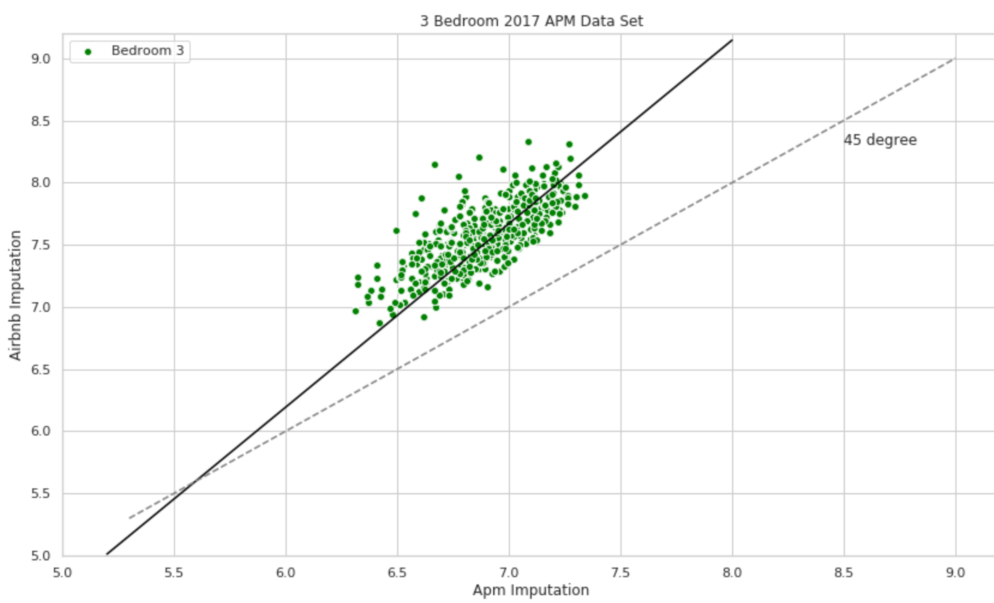

Figure 10: Regression of Airbnb Predicted Rent on APM Predicted Rent for 3 Bedrooms Apartments

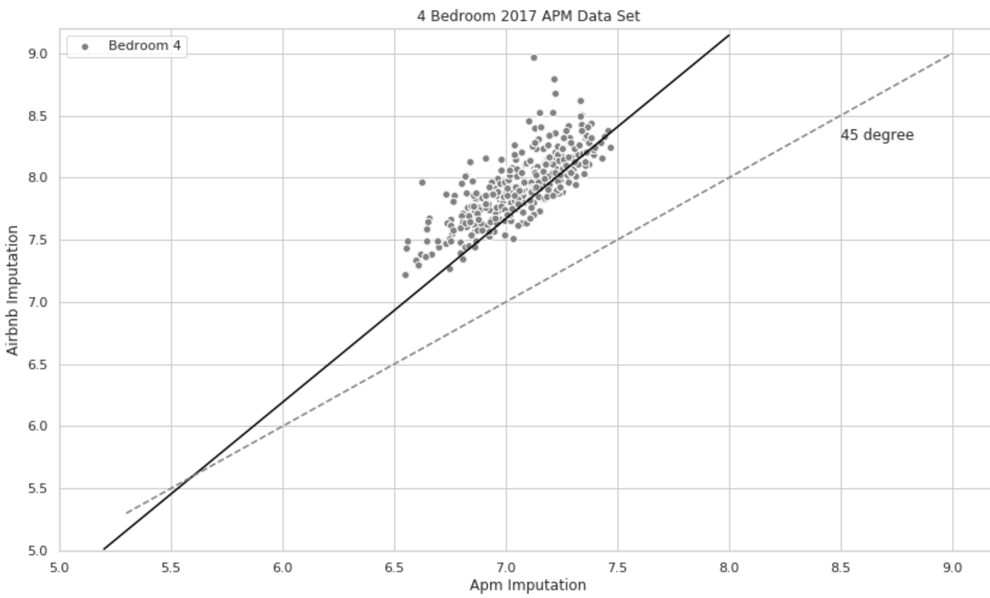

Figure 11: Regression of Airbnb Predicted Rent on APM Predicted Rent for 4 Bedrooms Apartments