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Rent-Imputation for Welfare Measurement: A Review of Methodologies and Empirical Findings

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Abstract

Housing is often the dominant consumption good for households. As such, it should be included in the construction of the consumption aggregate. However, assigning a value to the flow of services from dwellings is problematic. Many households own the dwelling in which they live, making rent an unobserved quantity; others receive subsidies, receiving free housing or facing prices lower than market prices. Over the last decades several estimation techniques have been proposed and implemented by practitioners to deal with this issue. This paper provides a review of commonly used methods to impute rent and discusses identified advantages and disadvantages of using them. We find that there is no consensus on which methods for rent-imputation are the most appropriate for welfare analysis and lack of evidence regarding the distributional impact of including rents in the welfare aggregate, particularly in developing economies.

JEL: C46, D31, I32

Keywords: Welfare Aggregate; Rent-Imputation; Poverty; Inequality

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1. Introduction

Housing is often the dominant consumption good for most households both in developing and developed countries (Stiglitz, Sen and Fitoussi, 2009, OECD, 2013, OECD, 2014). Thus, it is desirable to incorporate housing expenditures in the consumption aggregate to measure people's living standards with precision, and provide policy makers with accurate poverty and inequality estimates. Despite its relevance, practitioners frequently overlook housing in welfare measurement. The problem is that assigning a value to the flow of services from dwellings is not straightforward; many households own the dwelling in which they live, making rent an unobserved quantity; others receive subsidies, obtaining housing from free or at prices lower than those at the market. Although several estimation techniques have been implemented in the past decades to impute these partially observed quantities, there is no broad consensus on which methods are the most appropriate for such endeavor.

One of the reasons behind the absence of consensus on best practices for rent-imputation in welfare measurement is the lack of a thorough review of the advantages and disadvantages of using any of these estimation techniques. In this paper we tackle this problem, providing a review of commonly used methods to impute rent, discussing identified advantages and disadvantages for welfare analysis.

Theoretically, adding rents to the consumption aggregate could change the levels of poverty and inequality. For example, if rent is a growing (decreasing) share of consumption expenditure, then inequality increases (decreases) after including it.[2] Similarly, if rents are incorporated in the consumption aggregate but the poverty line remains unchanged, then poverty falls. However, if we recalculate the poverty line incorporating rents, there would likely be reshuffling: poor (nonpoor) individuals could end-up nonpoor (poor). In contrast, if we use relative poverty lines the effect of including rents in the consumption aggregate on poverty is uncertain: if the level of welfare of those immediately below the original relative poverty line increases more than the increase in the value of the relative poverty line, poverty might decrease; if it is higher than the increase in welfare of those around the initial relative poverty line, poverty might increase.

Empirically, much attention has been given to rent-imputation techniques. Most rent-imputation methodologies follow the *hedonic theory of consumption* (Lancaster, 1966). This theory establishes that utility derives from attributes or characteristics of goods and not from goods *per* se; goods' implicit prices are a function of their associated characteristics. Thus, researchers often use econometric models in which rent is a function of dwelling observable characteristics, and predict the value of rent out of sample. Other approaches are non-hedonic, namely the rent-to-value approach, the user-cost approach and the rental equivalence approach. In the first two implicit rents are understood as the rate of return that would have been obtained by owners if home equity had been invested in an interest bearing account. The third one relies on homeowners' subjective valuations of the market-rent-value of the dwellings in which they live. Thus far, the empirical literature suggests that including rents in the consumption aggregate yields lower levels of poverty and inequality,[3] however only some indicate that they recompute the poverty line after adding rents to the welfare aggregate (e.g., Frick et al., 2010, D'Ambrosio and Gigliarano, 2007, Törmälehto and Sauli, 2010, 2013, Norris and Pendakur, 2013). There is also lack of evidence on the

[2] We cannot infer the distributional impact of imputed rents *a priori* if there is no linear relation between consumption and the share of rent in consumption.
[3] See for example Sounders and Siminski (2005), Crossley and Curtis (2006), Mullan et al. (2007), Norris and Pendakur (2013).

distributional impact of rents on welfare measurement for developing economies, given that most of the empirical literature deals with advanced economies.

We do not find consensus regarding the most appropriate method to impute rents for homeowners and households receiving subsidized housing (i.e., *nonmarket tenants*). Nonetheless, we find that the methods we review here present advantages (or disadvantages) conditional on the type of data available. For welfare measurement in particular, methodologies that are more flexible such as semiparametric and nonparametric seem to be better suited to capture the nonlinearities implicit in the hedonic price function. However, when the share of market tenants (i.e., people renting their dwellings at market values) in the population is small, it is unlikely that implicit rents can be estimated with accuracy. In such cases, non-hedonic models represent appropriate alternatives to estimate the rent-value of dwellings if there is data on capitalization rates, depreciation rates applicable to dwellings, the market value of the dwelling and data on dwelling operating costs for homeowners (and even for nonmarket tenants). In the case where only subjective data on rents is available, mechanisms to correct for subjective bias must be devised.

The rest of the paper is organized as follows. Section 2 describes a number of hedonic and non-hedonic methods for rent-imputation. Section 3 summarizes the advantages and disadvantages of these methods in the context of welfare measurement and discusses the empirical findings of using rents in welfare measurement. Section 4 concludes.

2. Methods for rent-imputation

Housing is the value of the flow of services that the household receives from occupying its dwelling. To measure this flow, the amount of rent paid is the obvious choice. However, many households own the dwelling in which they live. This is by no means a trivial problem. In both developing and developed countries homeownership can range from around 40 percent (e.g., Switzerland or Colombia) to above 80 percent or above (e.g., Nicaragua or Romania).[4] Furthermore, some households receive housing free of charge or at subsidized rates by their employer, friends, relatives or the government. For example, in Austria and Cyprus, social rents can account for more than 20 percent of the total number of households. Therefore, the problem is assigning a value to the flow of the dwelling for these types of households.

2.1. Hedonic methods for rent-imputation

On the basis of the hedonic theory of consumption (Lancaster, 1966), the rent of a household is a function of its dwelling characteristics, including location, structural attributes of the dwelling (e.g., type of construction, number of rooms, age of the building, etc.) and neighborhood characteristics.[5] Nonetheless, there is no consensus about the specific form that the hedonic price function takes (Ekeland et al., 2004, Lisi, 2013). For instance, Kang and Reichert (1987) emphasize the nonexistence of a unique functional form which is superior in every aspect in the context of hedonic models for real market appraisals.

[4] Authors' calculation based on the EU statistics on income and living conditions and the Socio Economic Database for Latin America and the Caribbean.
[5] For a review of the characteristics used in hedonic models in 120 studies, see Sirmans et. al. (2005).

Nevertheless these theoretical limitations, several econometric approaches have been implemented over the last decades to impute rents to owner-occupied dwellings.

2.1.1. Standard linear regression models

Perhaps the simplest approach to impute rent is using a linear model, where rent is a linear function of observable characteristics. In this sense, we could use a linear model on market tenants and use the estimated coefficients to predict rent out of sample. Several researchers, most notably Cropper et al. (1988), have used a linear specification to estimate imputed rents. They concluded that the linear specification performs better when some attributes are unobserved or are replaced by proxies. Nonetheless, the equation defining the hedonic price is nonlinear and it may not be possible to find closed solutions (Rosen, 1974). On this regard, Ekeland et al. (2004) prove that the economic model that produces the linear equations is implausible: it is the closed solution of a linear-quadratic-normal model. Therefore any marginal perturbations to the underlying distributions of preferences and technology can produce large deviations from linearity, rendering full linear models inappropriate for rent-imputation.

In response the previous limitations, researchers have opted for using the log-linear functional form (e.g., Malpezzi, 2002, Diewert, 2003), as it allows the marginal rent-value to be a nonlinear function of size and quality of the dwelling. The problem is that this method may not be flexible enough to capture high-order nonlinearities,[6] or other potential problems such as selection bias or spatial dependency.

2.1.2. Two-stage estimation models

An important limitation of simple linear regression models is that they cannot capture unobservable differences in dwelling quality between homeowners and nonmarket tenants and market tenants. If the choice of tenure type and dwelling characteristics are not independent, then we would obtain inconsistent estimated coefficients (Arevalo and Ruiz-Castillo, 2004). For instance, if owners are more likely to live in higher-end dwellings in comparison to tenants, the rent predicted out-of-sample would underestimate their implicit rent. Consequently, some authors (e.g., Norris and Pendakur, 2013; Arévalo and Javier Ruiz-Castillo, 2004; Deaton and Zaidi, 2002) suggest using a two-stage regression *á la* Heckman (1979).

Other two-stage regression models, such as using instrumental variables (IV), have limited use when we are concerned with measuring poverty or inequality. IV regressions only capture a fraction of the variation in the dependent variable; as a consequence the fitted values will be less variable than the actuals ones, thus imputation will tend to reduce inequality and poverty (Deaton and Zaidi, 2002). The problem is that poverty and inequality depend on dispersion, not conditional means.

2.1.3. Quantile regression

Gasparini and Escudero (2004), Zietz et al. (2007), Cruces et al. (2008) and Ebru and Eban (2011), argue that standard regression models cannot account for marked differences in dwelling characteristics at different house-price levels, as buyers of higher-priced homes could value certain housing characteristics

[6] Higher-order models such as Box-Cox transformations have been also used to enhance flexibility of hedonic econometric models (Malpezzi et al., 1980, Halvorsen and Pollakowsk, 1981, Cropper et al., 1988, Laurice and Bhattacharya, 2005). However, the interest in such models faded away when semiparametric and nonparametric models became available to researchers (Hill, 2013).

differently from buyers of lower-priced homes. In this sense, standard regression models would assign the same value for the intercept to all households, spuriously inflating the value of the low-cost dwellings, and underestimating the value of high-cost dwellings. Quantile regression deals with this problem by allowing the researcher to estimate as many estimated parameters as quantiles have been defined over the distribution of rent.

The problem with this approach is that researchers must assign each nonmarket tenant to a specific quantile. But according to which distribution should homeowners and nonmarket tenants be ordered to? They clearly cannot be order according to the distribution of rents, since it is an unobserved quantity for them. Gasparini and Escudero (2004) use the income distribution, assuming that the monetary value of the demand for unobservable characteristics is related monotonically to the distribution of income, so that the quantiles defined for the distribution of non-observables coincides with the quantiles defined for the distribution of income. However, this might not be the case if, for instance, the quality of rented and owners-occupied dwellings differ (Arevalo and Ruiz-Castillo, 2004, Garner and Kogan, 2007). And although there are semiparametric and nonparametric methodologies that allow addressing selection bias in quantile regression (Buchinsky, 1998, 2001), we are not aware these have been implemented in the rent-imputation literature.

2.1.4. Semiparametric and nonparametric models

The lack of a theoretical *prior* for the functional form of hedonic function of housing prices and the risk of misspecification, have sparked a number of applications using semiparametric and nonparametric models.[7] For example, Gencay and Yang (1996) and Bin (2004) estimate semiparametric models showing that they provide more accurate residential housing price predictions in comparison to standard and higher-order models, both in- and out-of- sample. Similarly, Meese and Wallce (1991) and Pace (1993) find that unrestricted nonparametric models outperform parametric models and improve in-sample predictions. Furthermore, Anglin and Gençay (1996), Fahrländer (2006) and Parmeter et al. (2007) show that nonparametric models are more appropriate than semiparametric ones, and increase the accuracy of predictions in-sample.

In the case of nonparametric models, the literature has favored additive over unrestricted ones (Brunauer et al., 2010, Heckman et al., 2010, Martins-Filho and Bin, 2005, Bin, 2004, Clapp et al., 2002). Multivariate smoothers—required for unrestricted nonparametric modeling—are extremely expensive to compute, and even with the use of sophisticated graphical analysis four or higher dimensional smoothers, results are virtually impossible to represent or interpret. In contrast, additive nonparametric models facilitate interpretation by using univariate smoothing. Since one of the objectives of hedonic price modeling is to easily interpret and isolate the contributions of a given attribute to market price variability,

[7] A common nonparametric approach observed in the rent-imputation literature is stratification. Stratification methods involve creating a number of homogeneous cells defined in terms of various dwelling and household characteristics, or by means of cluster or factor analysis (Olczyk and Lane, 2008). After defining the cells (or strata), homeowners and nonmarket tenants' can be assigned the mean or the median rent in their strata. However, this approach requires a substantial number of market-tenants within strata, which is unlikely to happen in practice (Juntto and Reijo, 2010, Törmälehto and Sauli, 2013). Furthermore, using stratification is at best a shot in the dark because there is no theoretical prior that can tell us which variables should make part of the strata. In this section we focus on applications using semiparametric and nonparametric regression analysis.

holding all other product characteristics fixed, the use of a fully unrestricted nonparametric regression becomes an undesirable alternative. The problem with nonparametric models is that they require increasing amounts of data with the number of variables in order to provide identification, a problem commonly referred to as the curse of dimensionality (Geenens, 2011).

Another advantage of semiparametric and nonparametric regression over standard linear regression models is that both allow correcting for selection bias (Buchinsky, 1998, 2001, Newey et al., 1990, Newey, 2013). Although this clearly enhances the flexibility of the functional form, as we previously pointed out, we are not aware these alternatives have been implemented in the rent-imputation literature.[8]

2.1.5. Spatial models

Although the previous approaches can account explicitly for neighborhood characteristics when information is available, spatial omitted-variable bias might still persist (Hill, 2013). Unlike other statistical approaches, spatial models capture house prices' spatial dependency. In other words, dwellings in the same location are likely to have similar characteristics because they share neighborhood amenities (parks, school, hospitals, etc.), the same afflictions (for instance pollution or crime), or because dwellers could have similar sociodemographic characteristics (Basu and Thinbodeau, 1998).[9] For instance, Kuminoff et al. (2008) find that adding spatial fixed effects to the hedonic price function influences performance in the presence of omitted variable bias. Brunauer et al (2010), in a semiparametric setting, allow the price function to vary among districts in Vienna with spatial scaling factors, finding that the spatial scaling model leads to significant improvement of model quality and predictive power vis-à-vis benchmark models using district-specific intercepts. Lozano-Gracia and Anselin (2012) include explicit spatial (distance) variables obtained from *GIS* data for Bogota, finding that specifications that include local submarkets improve predictive performance, and that the inclusion of these spatial variables is superior to traditional models assuming homogenous zones.

Spatial models are flexible enough to allow for both spatially lagged dependent variables and spatially lagged disturbance terms. There is also a wide range of semiparametric and nonparametric spatial alternatives: kriging (Diggle and Ribeiro 2007, Montero and Larraz, 2010), spatial smoothing (Wood 2006; Wood et al. 2008), approaches based on spatial penalization (Fahrmeir et al. 2013), geographically weighted least squares (Fotheringham et al. 2002), and spatial scaling factor models (Brunauer et al., 2010), that enhance flexibility.[10] The advantage of these models is that, considering that hedonic house price equations attempt to explain variation in house prices using property structural and location characteristics, spatial models allow capturing the fact that the residuals produced by these equations are frequently spatially correlated. The problem is that in spite the growing availability of geospatial coordinates in data sets, most households surveys do not count with such information. Moreover, the literature on selection bias in spatial econometric models is still in development (e.g., McMillen, 1995, Flores-Lagunes and Schnier, 2012).

[8] The superiority of semiparametric and nonparametric models over parametric models has not been uncontested (Laurice and Bhattacharya, 2005, Parmeter et al., 2007, Haput et al., 2010). However, arguments challenging the superiority of semiparametric and nonparametric methods in the rent-imputation literature are absent in the context of selection bias.

[9] In the context of house pricing, spatial dependency is usually verified (Can, 1992, Anselin et al. 1996, Anselin and Bera, 1998, Hill, 2013).

[10] For an elaborate discussion and a review of the literature on spatial dependence, the use of geospatial data and also on spatial semiparametric and nonparametric estimation, see Gao et al. (2006) and Hill (2013).

2.2. Non-hedonic methods

Non-hedonic methods have been widely used when the rental market is not well developed (ILO, 2004, Canberra Group, 2011, Eurostat, 2013); we highlight the rent-to-value, the user-cost approach and the rental equivalence approach.[11] The first two understand the implicit rent as the rate of return that would have been obtained by owners if the home equity had been invested in an interest bearing account; the last one relies on non-market tenants' subjective valuations of the market-rent-value of their dwellings.

2.2.1. Rent-to-value approach

The rent-to-value approach states that, in equilibrium, the asset price of a dwelling should equal the current market rent capitalized at a capitalization rate (Phillips, 1988, Garner and Kogan, 2007, Heston and Nakamura, 2009). The value of the capitalization rate can be calculated as the value of gross imputed owner-occupied rent derived from national accounts divided by an estimate of the gross value of the owner-occupied housing stock that can be obtained from household surveys (Yates, 1994, Sounders and Siminski, 2005).[12] Imputed rents then can be estimated by applying the capitalization rate to the value of the property reported.

There are two problems using this approach. The first consists in using the same capitalization ratio for tenants, nonmarket tenants and homeowners within the same area (Phillips, 1988, Garner and Kogan, 2007). This might be misleading when dwellings' characteristics differ significantly between these population groups. The second problem arises from potential omitted-variable bias embedded in the market-tenant variable, which summarizes underlined differences in the quality of the dwellings between market tenants, nonmarket tenants and homeowners (ILO, 2004, Garner and Kogan, 2007).[13]

2.2.2. User cost approach

While the rent-to-value approach defines endogenously the return rate that transforms a dwelling's value into the flow of services, the user-cost approach needs an exogenous estimate of the capitalization cost. For this two pieces of information are necessary: i) the rate of return for housing and ii) information on operating costs related to homeownership such as maintenance, repairs, rates, insurance, mortgage interests payments, and expected appreciation of the property. Yates (1994) applies this approach to the 1988/89 Australian Household Expenditure Survey (AHES), using subjective assessment of dwelling value and operating cost from the AHES and computing the return rate for housing by comparing the individual estimates with the imputed rent found in the Australian national accounts. He finds that this approach overstates rents if a nominal rate of return is employed and understates them if a real rate of return is applied. However, a more important problem is the inherent inter-temporal volatility of house

[11] We will not cover methods that can be hardly considered imputation methods, such as the payment approach (see Garner and Short, 2001) and using information from external sources (e.g., administrative registers, listings, mortgage transactions, etc.).
[12] The capitalization rate can also be estimated using an hedonic model on household budget survey data, provided the data contains information on both the value of dwellings and the rent paid by tenants (Deaton and Zaidi, 2002).
[13] Regardless of previous caveats, the rent-to-value approach has been used, for instance, in the United States National Accounts imputation for the services of owner-occupied housing (Lebow and Rudd, 2003) as well as in South Africa's 1993 LSMS (Deaton and Zaidi, 2002).

values, especially in case of house price bubbles, which can lead to notable differencese between actual rents and user costs (Verbugge, 2008, Garner and Verbrugge, 2009).[14]

Clearly, a major limitation of the previous two approaches is that of collecting the information on dwelling values and operation costs necessary to estimate rent-values for nonmarket tentants.

2.2.3. Rental equivalence approach

This approach, fairly common for imputing rents (Fessler, 2015), is based on data on homeowners estimates of the market-rent-value of their dwellings. For instance, dwelling residents can be asked in household surveys to estimate how much would they pay if they were renting their home (Frick et.al., 2010). This approach relies on the assumption that owners *can* estimate rental equivalences even when there is no comparable rental dwelling in the area in which they live (Garner and Kogan, 2007). In other words, homeowners should be informed about the value of their dwelling and the amount they would have to pay to rent a home with similar quality and location attributes. The problem is that homeowners may over-estimate the true rental value of their dwelling compared to rented homes with similar characteristics subjectively (Frick et al., 2010).[15] For example, Goodman and Ittner (1992) find for the United States that the median homeowner in the mid-1980s overvalued his/her house by around 6 percent. Similarly, Garner and Rozaklis (2001) find for the US that self-reported housing costs resulted in higher estimates (almost 15 percent) than those based on a hedonic model. Homeowners might have above-market evaluation of their dwellings due to subjective reasons, such as special attachment to specific characteristics of their houses; what Heston and Nakamura (2009) define as owner pride factor.[16]

Using this approach to impute rents could be less problematic in regions where rental market is active and there is a considerable share of the population renting the dwelling in which they live (Lanjouw, 2009). Furthermore, with the help of interviewers, homeowners could be able to give more accurate estimates of market rents (Garner and Kogan, 2007). However, these assumptions have not been tested.

3. A discussion on rent-imputation for welfare measurement

Much attention has been given to rent-imputation techniques, however the literature inquiring about the implications of rent-imputation on welfare measurement is exiguous. Thus far it shows that including rents in the consumption aggregate yields lower levels of poverty and inequality (Table 1), but empirical results must be taken with a grain of salt: On the one hand, some papers do not recompute the poverty line after adding rents to the welfare aggregate—hence lower levels of poverty could be a trivial finding. On the other hand, most papers do not delve into the reasons behind the distributional changes observed. In particular, they do not explore re-ranking effects and thus changes in poverty profiles, providing an incomplete assessment of the distributional impact of rents on welfare measurement.[17]

[14] Some other problems entail making reasonable assumptions on the proper interest rate, depreciation rate, inflation rate, as well as having precise information on value of the dwellings. For a thorough discussion see ILO (2004).
[15] The same problems would exist if we would use the rent equivalence approach to impute rents to nonmarket tenants.
[16] See also Wang (2014) for further discussion.
[17] Some notable exceptions include Yates (1994), Frick and Grabka (2003), D'Ambrosio and Gigliarano (2007), Maestri (2012), Frick et al. (2010) and Törmälehto and Sauli (2010, 2013).

Theoretically, as discussed in the introduction, it is difficult to foresee the impact of imputing rents in the distribution of welfare. Nevertheless, it seems that in practice we usually observe a decrease in dispersion explained by the fact that rents tend to be less unequally distributed across household income (Fessler et al., 2015). Imputed rents for owner occupied housing mainly equalize the upper part of the income distribution, while subsidized housing has an equalizing mainly on the lower part of the income distribution. Regarding the impacts of imputed rents of poverty, there is evidence of re-ranking; that is, households may jump up and down their relative position in the distribution of wealth. Although poverty tends to decrease (Table 1), the effect of adding imputed rents to the welfare aggregate may not the same for all groups in the population; in other words, we can expect considerable re-rankings. The literature has found that for example subsidized housing re-ranks low income households upwards, which at the same time may cause middle income households—not eligible for subsidies—to re-rank downwards (Maestri, 2012). It has also been documented that poverty rates fall in particular for the elderly, married couples and outright homeowners, while poverty rates generally increase for market tenants (Frick and Grabka, 2003, Törmälehto and Sauli, 2010, 2013). Unfortunately, there is still wanting evidence on the distributional impacts of rent on welfare, particularly in developing countries.

[Table 1 about here]

Note as well that there is variation in the type of rent-imputation techniques used across countries; see also Juntto and Reijo (2010) and Törmälehto and Sauli (2013). This is not unexpected given cross-country differences in data availability and data constraints. However, this implies that welfare aggregates are not likely to be highly comparable across countries—even over time if the rent-imputation technique being used changes between survey rounds.

Absent from most papers in the literature is also a discussion about the advantages and limitations of using the different methods of rent-imputation for welfare measurement. Some papers engaging in this discussion use only few of the ones available, and most do not take part in the task of comparing them—identifying strengths and weaknesses. However, on the basis of the discussion made in the previous section, we are able to draw insights on this regard; Table 2 summarizes them.

[Table 2 about here]

All in all, flexible methodologies such as semiparametric and nonparametric seem to be better suited for estimating rents. This is because they capture some of the implicit nonlinearities of the hedonic price function. Nonetheless, these models are subject specification bias stemming from self-selection, spatial dependency and are prone to suffer the curse of dimensionality. Hence, it is always desirable to address these issues whenever possible. The problem with these (hedonic) methods is that making predictions out of the sample of market tenants becomes hard to justify when rental markets are not well developed. It is unlikely that implicit rents can be predicted with some accuracy when the share of market tenants is small. On the other hand, non-hedonic methods, such as the rent-to-value and user-cost approaches, do not solely rely on the scarce information on rents found in household survey data, but may make use of other information sources such as National Accounts. These methods represent appropriates alternative as long as there is data on data on capitalization rates, depreciation rates that can be applied to dwellings, the market value of the dwelling and comprehensive data on dwelling operating costs—with the concomitant of potential biases derived from omitted variables and inter-temporal volatility in the housing market. In

the case where only subjective data on rents is reported, and these are used to impute rents, ways to correct for subjective bias must be devised to avoid biased estimates of welfare. However, thus far, no mechanisms have been created to address this problem.

4. Conclusions

It is essential to include rent in the welfare aggregate to obtain precise estimates of welfare, poverty and inequality. However, the task of assigning a value of rent to homeowners and people enjoying subsidized housing is not an easy task. The literature on housing and welfare has dealt with the problem of rent-imputation through several hedonic and non-hedonic approaches. Nevertheless, there seems to be no consensus on what methods of imputation are preferred for this endeavor, and under what circumstances. The empirical literature has also neglected some aspects of the distributional impact of using imputed rents and different methods of rent-imputation, especially in developing countries. In particular, we find lacking evidence on re-ranking, changes in poverty profiles, and on the distributional effects of using different imputation techniques in a comparative framework.

It seems to be the case that the decision of using a given rent-imputation method becomes conditional on the type and amount of information available—particularly on the size of the rental market. This explains to certain extent why is there so much variation in rent-imputation techniques used across countries, and it calls for a unified framework to collect information on dwelling attributes and addressing rent-imputation that allows for more precise cross-country comparisons of welfare. Furthermore, we need to sharpen our understanding of the distributional implications of using imputed rents and the methods to estimate them. This is crucial to improve welfare measurement globally.

References

Anglin, P., and R. Gençay, "Semiparametric Estimation of a Hedonic Price Function," *Journal of Applied Econometrics*, 11(6), 633—648, 1996.

Anselin, L., A. Bera, R. Florax and M.J. Yoon, "Simple diagnostic tests for spatial dependence," *Regional Science and Urban Economics*, 26(1), 77—104, 1996.

Anselin, L. and A. Bera, "Spatial dependence in linear regression models with an introduction to spatial econometrics," In A. Ullah and D. Giles (eds.), *Handbook of Applied Economic Statistics*, 237—289, Marcel Dekker, New York, 1998.

Arévalo, R. and J. Ruiz-Castillo, "The Rental Equivalence Approach To Nonrental Housing In The Consumer Price Index. Evidence from Spain," Economics Working Papers we041704, Universidad Carlos III, Departamento de Economía, 2004.

Basu, S., and T. G. Thibodeau, "Analysis of spatial autocorrelation in house prices," *The Journal of Real Estate Finance and Economics*, 17(1), 61—85, 1998.

Bin, O., "A Prediction Comparison of Housing Sales Prices by Parametric versus Semiparametric Regressions," *Journal of Housing Economics*, 13(1), 68—84, 2004.

Brunauer, W.A., S. Lang, P. Wechselberger and S. Bienert, "Additive Hedonic Regression Models with Spatial Scaling factors: An Application for Rents in Vienna," *Journal of Real Estate Financial Economics*, 41, 390—411, 2010.

Buchinsky, M., "Recent advances in quantile regression models: a practical guideline for empirical research," *Journal of Human Resources*, 88—126, 1998.

Buchinsky, M., “Quantile regression with sample selection: Estimating women's return to education in the US.,” *Empirical Economics*, 26(1), 87—113, 2001.

Buckley, R.M. and E.N. Gurenko, “Housing and Income Distribution in Russia: Zhivago’s Legacy,” *The World Bank Research Observer*, 12(1), 19—32, 1997.

Canberra Group, “Expert Group on Household Income Statistics: Final Report and Recommendations," Discussion paper, United Nations Economic Commission for Europe, 2011.

Can, A., “Specification and estimation of hedonic housing price models,” *Regional Science and Urban Economics*, 22, 453—474, 1992.

Clapp, J.M., H.J. Kimand and A.E. Gelfand, “Predicting Spatial Patterns of House Prices Using LPR and Bayesian Smoothing,” *Real Estate Economics*, 30 (4), 505–532, 2002.

Cropper, M.L, L.B. Deck and K.E. McConnel, “On the Choice of Functional Form for Hedonic Price Functions,” *Review of Economics and Statistics*, 70(4), 668—675, 1988.

Crossley, T.F. and L.J. Curtis, “Child Poverty in Canada,” *Canadian Journal of Economics*, 52(2), 237—260, 2006.

Crossley, T.F. and K. Pendakur, “The Social Cost-of-Living: Welfare Foundations and Estimation,” Quantitative Studies in Economics and Population Research Reports 407, McMaster University, 2006.

Cruces, G., A. Ham and M. Tetaz, “Quality of Life in Buenos Aires Neighborhoods: Hedonic Price Regressions and the Life Satisfaction Approach,” Inter-American Development Bank, Research Network Working Paper R-559, 2008.

D’Ambrosio, C and C. Gigliarano, “The distributional impact of imputed rent in Italy,” Project no: 028412, AIM-AP, Accurate Income Measurement for the Assessment of Public Policies, Specific Targeted Research or Innovation Project, 2007.

Deaton, A. and S. Zaidi, *Guidelines for Constructing Consumption Aggregates For Welfare Analysis*, The World Bank, 2002.

Diewert, W.E., “Hedonic Regressions: A Review of Some Unresolved Issues,” mimeo, 2003.

Diggle, P. and P.J. Ribeiro, *Model-based Geostatistics*, Springer Series in Statistics, 2007.

Ebru, Ç. and A. Eban, “Determinants of house prices in Istanbul: a quantile regression approach,” *Quality & Quantity*, 45(2), 305—317, 2011.

Ekeland, I., J.J. Heckman, and L. Nesheim, “Identification and Estimation of Hedonic Models,” *Journal of Political Economy*, 112(S1), Papers in Honor of Sherwin Rosen: A Supplement to Volume 112, S60-S109, 2004.

Eurostat, “Impact study of inclusion/exclusion of non-monetary income components and extreme values,” Document LC-ILC/33/09/EN prepared for the Working Group meeting of Statistics on Living Conditions in Luxembourg, 2009.

Eurostat, *Handbook on Residential Property Prices Indices (RPPIs)*, Publications Office of the European Union, 2013.

Fahrländer, S.S., “Semiparametric Construction of Spatial Generalized Hedonic Models for Private Properties,” *Swiss Journal of Economics and Statistics*, Swiss Society of Economics and Statistics, 142(4), 501—528, 2006.

Fahrmeir, L., T. Kneib, S. Lang and B. Marx, *Models, Methods and Applications*, Springer, 2013.

Fessler, P., Rehm, M., and Tockner. L., “The impact of housing non-cash income on the household income distribution in Austria,” Forthcoming at *Urban Studies*, 2015.

Figari, F, A. Paulus, H. Sutherland, P. Tsakloglou and F. Zantomio, “Taxing Home Ownership: Distributional Effects of Including Net Imputed Rent in Taxable Income,” IZA discussion paper series, IZA DP No. 6493, 2012.

Flores-Lagunes, A., and K. E . Schnier, “Estimation of sample selection models with spatial dependence,” *Journal of Applied Econometrics*, 27(2), 173—204, 2012.

Fotheringham, A. S., C. Brunsdon and M. E. Charlton, *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*, Wiley, Chichester, 2002.

Frick, J. and M.M. Grabka, “Imputed rent and income inequality: a decomposition analysis for Great Britain,” *Review of Income and Wealth*, 49(4), 513—537, 2003.

Frick, J., M.M. Grabka, T. M. Smeeding and P.Tsakloglou, "Distributional effects of imputed rents in five European countries," *Journal of Housing Economics*, 19(3), 167—179, 2010.

Gasparini, L. and W.S. Escudero, "Implicit rents from own-housing and income distribution: econometric estimates for Greater Buenos Aires," Documentos de Trabajo del CEDLAS, 2004.

Garner, T. and K. Short, "Owner-Occupied Shelter in Experimental Poverty Measures," Annual Meeting of the Southern Economic Association, Tampa, Florida, 2001.

Garner T. and U. Kogan, "Comparing Approaches to Value Owner-Occupied Housing Using U.S. Consumer Expenditure Survey Data," paper prepared for the Annual Meetings of the Allied Social Sciences Associations Society of Government Economist, Chicago, Illinois, 2007.

Garner, T. and P. Rozaklis, "Owner-Occupied Housing: An Input for Experimental Poverty Thresholds," paper presented at session organized by the Society of Government Economists at the annual meeting of the Allied Social Sciences Associations, 2001.

Garner, T., K.Short, and U. Kogan "What Do We Knows About the Value of Owner-Occupied Housing Services? Rental Equivalence and Other Approaches," Southern Economics Association Annual Meeting, Charleston, South Carolina, 2006.

Garner, T. and R. Verbrugge "The Puzzling Divergence of Rents and User Costs, 1980-2004: Summary and Extensions," In W. Erwin Diewert, Bert M. Balk, Dennis Fixler, Kevin J. Fox and Alice O. Nakamura (eds.), *Price and Productivity Measurement*, Volume 1-Housing, 125—146, 2009.

Gao, J., Z. Lu and D. Tjøstheim, "Estimation in semiparametric spatial regression," *The Annals of Statistics*, 34(3), 1395—1435, 2006.

Gencay, R. and X. Yang "Source Forecast Comparisons of Residential Housing Prices by Parametric and Semiparametric Regression," *The Canadian Journal of Economics*, 29(SI2), pp. S515—S519, 1996.

Geenens, G., "Curse of dimensionality and related issues in nonparametric functional regression," *Statistics Surveys*, 5, 30—43, 2011.

Gibbs, I., and P. Kemp, "Housing Benefit and Income Redistribution," Urban Studies, 30(1), 63—72, 1993.

Goodman, J.L. and J.B. Ittner, "The Accuracy of Home Owners' Estimates of House Value," *Journal of Housing Economics*, 2, 339—357, 1992.

Guenard, C. and S. Mesple-Somps, "Measuring inequalities: do household surveys paint a realistic picture?," *Review of Income and Wealth*, 56(3), 519—538, 2010.

Haput, H., J. Schnurbus and R. Tscherni, "On nonparametric estimation of a hedonic price function," *Journal of Applied Econometrics*, 25(5), 894—901, 2010.

Heckman, J., "Sample Selection Bias as a Specification Error," *Econometrica*, 47(1), 153—161, 1979.

Heckman, J.J., R. L. Matzkin and L. Nesheim, "Nonparametric identification and estimation of nonadditive hedonic models," *Econometrica*, 78(5), 1569—1591, 2010.

Heston, A. and A.O. Nakamura, "Questions about the equivalence of market rents and user costs for owner occupied housing," *Journal of Housing Economics*, 18, 273—279, 2009.

Hill, R. J., "Hedonic price indexes for residential housing: a survey, evaluation and taxonomy," *Journal of Economic Surveys*, 27, 879–914, 2013.

Juntto, A., M. Reijo, "Comparability of imputed rent In EU-SILC 2007 - Differences in variable definitions and methods concerning institutional housing," Methodological Working Paper Series Eurostat, 2010.

ILO, *In Consumer Price Index Manual: Theory and Practice*, Geneva, 2004. http://www.ilo.org/global/publications/ilo-bookstore/order-online/books/WCMS_090721/lang--en/index.htm

Kang, H.B. and A. K. Reichert, "An Evaluation of Alternative Estimation Techniques and Functional Forms in Developing Statistical Appraisal Models," *The Journal of Real Estate Research*, 2(1), 1—27, 1987.

Kuminoff, N.V., C.F. Parmeter, and J.C. Pope, "Hedonic Price Functions: Guidance on Empirical Specification," American Agricultural Economics Association, Annual Meeting, 2008.

Lancaster, K.J., "A new approach to Consumer Theory," *The Journal of Political Economy*, 74(2), 132—157, 1966.

Lanjouw, P. “Constructing a Consumption Aggregate for the Purpose of Welfare Analysis: Principles, Issues and Recommendations Arising from the Case of Brazil,” paper prepared for the OECD/Univeristy of Maryland Conference entitled “Measuring Poverty, Income Inequality and Social Exclusion: Lessons from Europe,” Paris, 2009.

Laurice, J. and R. Bhattacharya, “Prediction Performance of a Hedonic Pricing Model for Housing,” *The Appraisal Journal*, 198-209, 2005.

Lebow, D.E. and J.B. Rudd, “Measurement Error in the Consumer Price Index: Where Do We Stand?” *Journal of Economic Literature*, 41, 159—201, 2003.

Lisi, G., “On the functional form of the hedonic price function: a matching-theoretic model and empirical evidence,” *International Real Estate Review*, 16(2), 189—207, 2013.

Lozano-Garcia, N. and N. L. Anselin, “Is the price right? Assessing estimates of cadastral values for Bogota, Colombia,” Geoda Center for geospatial analysis and computation, Arizona State University, Working Paper n.3, 2012.

Maestri, V., “Imputed rent and income re-ranking. Evidence from EU-SILC data,” Discussion Paper 29, GINI Discussion Papers, 2012.

Malpezzi, S., “Housing,” in M. Grosh and P. Glewwe (Eds.), *Designing household survey questionnaires for developing countries: lessons from the 15 years of the living standards measurement study*, ch.12 , 293—314, Washington, DC: World Bank, 2000.

Malpezzi, S. “Hedonic Pricing Models: A Selective and Applied Review,” in *Housing Economics and Public Policy: Essays in Honour of Duncan Maclennan*, T. O. Sullivan and K. Gibbs (Eds.), Blackwell Science Ltd, 2002.

Martins-Filho, C. and O. Bin, “Estimation of hedonic price functions via additive nonparametric regression,”*Empirical Economics*, 30(1), 94—114, 2005.

McMillen, D. P., “Selection bias in spatial econometric models,” *Journal of Regional Science*, 35(3), 417—436, 1995.

Meese, R. and N. Wallace, “Nonparametric estimation of dynamic hedonic price models and the construction of residential housing price indices,” *Journal of the American Real Estate and Urban Economics Association*, 19, 308—332, 1991.

Montero, J.M. and B. Larraz, “Estimating Housing Prices: A Proposal with Spatially Correlated Data,” *International Advances in Economic Research*, 16(1), 39—51, 2010.

Mullan, K., H. Sutherland, and F. Zantomio, “The Distributional Impact of Imputed Rents in the United Kingdom,” paper prepared for the AIM-AP Project, Institute for Social and Economic Research. University of Essex. United Kingdom, 2007.

Newey, W. K., “Nonparametric instrumental variables estimation,” *The American Economic Review* 103(3), 550—556, 2013.

Newey, W. K., J. L. Powell, and J. R. Walker, “Semiparametric estimation of selection models: some empirical results,” *American Economic Review*, 80(2), 324—328, 1990.

Norris, S. and K. Pendakur, “Imputing rent in consumption measures, with an application to consumption poverty in Canada, 1997–2009,” *Canadian Journal of Economics*, 46(4), 1537–1570, 2013.

OECD, *OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*, OECD Publishing, 2013. http://dx.doi.org/10.1787/9789264194830-en.

OECD, *National Accounts at a Glance*, 2014. DOI: 10.1787/data-00285-en.

Olczyk, A. and S. Lane, “Refining the Stratification for the Established House Price Index,” Australian Bureau of Statistics Research Paper, 2008.

Pace, K., “Nonparametric Methods With Applications to Hedonic Models,” *Journal of Real Estate Finance and Economics*, 7, 185—204, 1993.

Parmeter, C.F., D.J. Henderson and S.C. Kumbhakar, “Nonparametric Estimation of a Hedonic Price Function,” *Journal of Applied Econometrics*, 22(3), 695—699, 2007.

Phillips, R.S. “Residential capitalization rates: Explaining intermetropolitan variation, 1974–1979,” *Journal of Urban Economics*, 23(3), 278—290, 1988.

Sirmans, G., D. Macpherson and E. Zietz, “The composition of hedonic pricing models,” *Journal of Real Estate Literature*, 13(1), 3—43, 2005.

Smeeding, T., P. Sounders, J. Coder, S. Jenkins, J. Fritzell, A.J.M. Haganaars, R. Hauser and M. Wolfson , “Poverty, inequality, and family living standards impacts across seven nations: the effect of noncash subsidies for health, education, and housing,” *The Review of Income and Wealth*, 39(3), 229–25, 1993.

Sounders, P. and P. Siminski, “Home ownership and inequality: imputed rent and income distribution in Australia,” *Economic Papers*, 24(4), 346—367, 2005.

Statistik Austria, “EU-SILC Impact Study on Comparability of National Implementations, Final Report Part 2 - Computation of Imputed Rents,” Discussion paper, Statistik Austria, 2008.

Stiglitz J.E., A. Sen and J. *Fitoussi, Report by the Commission on the Measurement of Economic Performance and Social Progress*, 2009.

Törmälehto, V. and H. Sauli, “The distributional impact of imputed rent in EU-SILC,” EUROSTAT: Methodologies and working papers, 2010.

----------, “The distributional impact of imputed rent in EU-SILC 2007-2010,” EUROSTAT: Methodologies and working papers, 2013.

Verbrugge, R. “The puzzling divergence of rents and user costs 1980-2004,” *Review of Income and Wealth*, 54(4), 671—699, 2008.

Verbist, G., and S. Lefebure, “Country Report Belgium on Imputed Rent,” Accurate Income Measurement for the Assessment of Public Policies Project, 2007.

Wang, C., “Subjective Home Valuations and the Cross-Section of Housing Returns,” Manuscript, Yale University School of Management, 2014.

Wood, S. “Low-Rank scale-invariant tensor product smooths for generalized additive mixed models,” *Biometrics*, 62(4), 1025—1036, 2006.

Wood, S. N., M. V., Bravington and S. L. Hedley, “Soap film smoothing,” *Journal of the Royal Statistical Society* B, 70(5), 931—955, 2008.

Yates, J. “Imputed rent and income distribution,” *Review of Income and Wealth*, 40(1), 43—66, 1994.

Zietz, J., E.N. Zietz and G. S. Sirmans “Determinants of House Prices: A Quantile Regression Approach,” *The Journal of Real Estate Finance and Economics*, 37(4), 317—333, 2007.

Table 1. Distributional effects of including imputed rent in the welfare aggregate

Reference	Country (survey, year)	Welfare Aggregate	Method for rent-imputation	Recomputes poverty line	Effect on Inequality	Effect on Poverty
Buckley and Gurenko (1997)	Russia (Russian Longitudinal Monitoring Household Survey, 1992)	Income	User cost approach	N/a	Reduction	N/a
Crossley and Curtis (2006)	Canada (FAMEX 1986–1996 and SHS 1997–2000)	Consumption	Linear regression	Yes	Reduction	Reduction
D'Ambrosio and Gigliarano (2007)	Italy (EUSILC and SHIW, 2004)	Income	User cost	Yes	Reduction	Reduction
Figari et al. (2012)	Belgium (EUSILC, 2004), Germany (SOEP, 2002), Greece (HBS, 2004/05), Italy (EUSILC, 2004), and the UK (FRS 2003/04)	Taxable income	Heckman error correction selection for Belgium, Germany and Greece; rental equivalence for Italy; user cost for UK.	N/a	Ambiguous	N/a
Fessler et al. (2015)	Austria (HFCS, 2010)	Income	Linear regression	N/a	Reduction	N/a
Frick and Grabka (2003)	Great Britain (BHPS 1993-1998), Germany (SOEP 1993-1998) and USA (PSID 1994-1999)	Income	User cost	No	Reduction in Germany and USA. Increase in Great Britain	Reduction
Frick et al. (2010)	Belgium (EUSILC, 2004), Germany (SOEP, 2002), Greece (HBS, 2004/05), Italy (EUSILC, 2004), and the UK (FRS 2003/04)	Income	Heckman error correction selection for Belgium, Germany and Greece; rental equivalence for Italy; user cost for UK.	Yes	Reduction	Reduction
Garner and Short (2009)	USA (AHS 2005, CE 2005-2006)	Income and consumption	Heckman error correction, rental equivalence and user cost	N/a	Increase	N/a
Garner and Verbrugge (2009)	USA (CE 2004-2007)	Consumption	Rental equivalence and user cost		Reduction	
Gasparini and Escudero (2004)	Argentina, Greater Buenos Aires (National Household Expenditures Survey, 1996-1997)	Income	Quantile regression	N/a	Reduction	N/a
Guenardand and Mesple-Somps (2010)	Madagascar (EPM, 1993) and Cote D'Ivoire (ENV, 1998)	Income and consumption	N/a	N/a	Reduction	Reduction
Maestri (2012)	European Countries (EU-SILC, 2007-2009)	Income	N/a	N/a	Considerable re-ranking of households	N/a
Mullan et al. (2007)	United Kingdom (FRS, 2003-2004; FES, 2000-2001)	Income	Log-linear parametric model and stratification	N/a	Reduction	Reduction
Norris and Pendakur (2013)	Canada (SHS, 1997–1999)	Consumption	Heckman error correction	Yes	N/a	Reduction
Smeeding et al. (1993)	Australia, Canada, Netherlands, Sweden , U.K., U. S., Germany (LIS, 1960, 1975, 1981)	Income	Rent-to-value	No	Reduction	Reduction
Sounders and Siminski (2005)	Australia (HES, 1993-1994, 1998-1999)	Income	Rent-to-value	N/a	Reduction	N/a
Törmälehto and Sauli (2010, 2013)	European Countries (EU-SILC, 2007-2010)	Income	Heckman error correction	Yes	Reduction	Reduction for elderly poverty
Yates (1994)	Australia (HES, 1988-1989)	Income	Rent-to-value approach	N/a	Increase	N/a

Source: Authors' compilations.

Table 2. Advantages and disadvantages of different rent-imputation methods

Method	Advantages	Disadvantages
	Hedonic methods	
Simple linear regression	Allows rent-values to be a linear function of dwelling attributes.	The theoretical equation defining the hedonic price is nonlinear; it is also subject to selection bias and spatial dependency.
Log-linear regression	Allows the marginal rent-value to be a nonlinear function of dwelling attributes. It outperforms standard linear regression.	Does not capture high order nonlinearities; it is subject to selection bias and spatial dependency.
Heckman error correction	Corrects for selection bias in the decision of being a market tenant.	Not flexible enough to capture high order nonlinearities; it is subject to spatial dependency.
Instrumental variables	Corrects omitted variable bias in the decision of being homeowner, nonmarket tenant or market tenant.	Not flexible enough to capture high order nonlinearities; it captures a fraction of the variation in the dependent variable, underestimating the implicit value of rents.
Quantile regression	It captures the possibility that buyers of higher-priced homes could value housing characteristics differently from buyers of lower-priced homes.	Not flexible enough to capture high order nonlinearities; it is subject to spatial dependency and also to selection bias in its parametric form.
Semiparametric regression	Allows capturing high order nonlinearities and selection bias. It outperforms parametric models on average.	It can be subject to the curse of dimensionality; it can also be subject to spatial dependency.
Nonparametric regression	Allows capturing high order nonlinearities and selection bias. It outperforms parametric models on average and can outperform semiparametric models.	Less parsimonious than semi-parametric regression; subject to the curse of dimensionality; it can also be subject to spatial dependency.
Spatial regression	It models spatial dependency and it can capture high order nonlinearities.	Lack of data: most household surveys do not count with spatial data; it can be subject to selection bias.
	Non-hedonic methods	
Rent-to-value	It can be used when the share of market tenants is small. It exploits information from other sources, such as national accounts.	Using the same capitalization ratio for tenants, nonmarket tenants and homeowners may lead to selection bias and omitted variable bias. It may be impossible to impute the value of rent to nonmarket tenants.
User cost	It can be used when the share of market tenants is small. It exploits information from other sources, such as national accounts.	It demands a great deal of information on operating costs. It is subject to inter-temporal volatility that can lead to notable differences between actual rents and user costs. It may be impossible to impute the value of rent to nonmarket tenants.
Rent equivalence	It uses data on self-reported estimates of the market-rent-value of the dwelling.	Homeowners and nonmarket tenants might not provide a good market evaluation of their dwellings due to subjective biases.

Note: It is important to keep in mind that hedonic models need a fairly large share of market tenants in order to provide accurate predictions of implicit rents.
Source: Authors' compilations.