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RENT-IMPUTATION FOR WELFARE MEASUREMENT: A REVIEW OF METHODOLOGIES AND EMPIRICAL FINDINGS

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Housing should always be included in the construction of the welfare aggregate for welfare analysis. However, assigning a value to the flow of services from dwellings is problematic. Many households own the dwelling in which they live, making this value unobserved; others receive free housing or face prices lower than those at the market. Over the last decades, several estimation techniques have been proposed and implemented by practitioners to overcome this issue. This paper provides a review of methods commonly used to impute rent and discusses the relative advantages and disadvantages of each. We find no consensus on which imputation method is the most appropriate for welfare analysis, as well as a lack of evidence regarding the distributional impact of including rents in the welfare aggregate, particularly in developing countries. Moreover, practices for imputing rents vary across countries, calling for the future development of a unified framework.

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1. INTRODUCTION

For most households in both developing and developed countries, housing is usually the dominant consumption good (Stiglitz *et al.*, 2009; OECD, 2013; OECD, 2016).[1] Thus, it is important to incorporate housing in the welfare aggregate, in order to precisely measure living standards and provide policy makers with accurate poverty and inequality estimates. Despite its relevance, practitioners frequently overlook housing in welfare measurement. For instance, it is excluded in the official welfare aggregate used to measure poverty across member states in the European Union (Törmälehto and Sauli, 2013); moreover, in a sample of 69 observations of recent official available poverty estimates, the World Bank has recently estimated that in only 28 instances was housing clearly included in the welfare aggregate (The World Bank, 2016).

For the purpose of welfare analysis, housing refers to the value of the flow of services that a household receives from residing somewhere; it does not refer to the expenditure of purchasing a house, which should not be included in the welfare aggregate since it is a large and non-recurring expenditure. However, assigning a value to the flow of services from housing is complex. Though the value of

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[1]Housing represents between 14 and 23 percent of total adjusted disposable household income in OECD countries in 2014 (OECD, 2016).

the flow of services for renters is easily approximated by the value of the rent they pay, many households own the dwelling in which they live, making rent an unobserved quantity. Others receive subsidies, obtaining housing for free or at prices lower than those at the market. As the proportion of these different types of households (e.g. tenants, owners, subsidized tenants) varies both across countries and within countries over time, ignoring housing not only leads to imprecise welfare estimates for a particular country and period, but also compromises the international and inter-temporal comparability of poverty and inequality estimates.

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 an endeavor. The aim of this paper is to provide a thorough review of methods commonly used to impute rent, which will serve to inform researchers, development practitioners and policy makers about the relative advantages and disadvantages of using any of these estimation techniques; it also provides a discussion of the potential distributional effects of adding housing to the welfare aggregate.

Theoretically, adding rent into the computation of the welfare aggregate could change the levels of poverty and inequality. For example, if rent is an increasing (or decreasing) share of welfare, then inequality increases (or decreases) after including it (for further theoretical discussion see Balcazar *et al.*, 2015). Similarly, when using absolute poverty lines, if rents are incorporated in the welfare aggregate and the poverty line remains unchanged, then poverty does not increase. On the other hand, if we recalculate the absolute poverty line incorporating rents, the effect on the poverty level becomes unclear. Moreover, even if the share of poor individuals does not change, there would likely be a reshuffling: poor (or non-poor) individuals could end-up non-poor (or poor).

If we use relative poverty lines, the effect of including rents in the welfare 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. On the contrary, if the increase in the value of the relative poverty line 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 is derived 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 a dwelling's observable characteristics, predicting the value of rent out of sample. Other approaches, namely the rent-to-value approach, the user-cost approach and the rental equivalence approach, are non-hedonic. 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 their residences. Thus far, the empirical literature suggests that including rents in the welfare aggregate yields lower levels of poverty and inequality (for examples on this see Saunders and Siminski, 2005; Crossley and Curtis, 2006; Mullan *et al.*, 2011; Norris and Pendakur, 2013). Note however, that results on poverty mainly rely on analyses where poverty lines are not recomputed after adding rents to the welfare aggregate, which as mentioned above, could lead to imprecise results (exceptions are Frick *et al.*, 2010; D'Ambrosio and Gigliarano, 2007; Törmälehto and Sauli, 2010, 2013; Norris and Pendakur, 2013; Verbist and Grabka, 2016). There is also a lack of evidence on the distributional impact of rents on welfare measurement in developing economies, given that most of the available empirical literature deals with advanced economies.

We do not find consensus regarding the single most appropriate method of imputing rents for homeowners and households receiving subsidized housing (whom we label throughout the text, *nonmarket* tenants). Nonetheless, we find that the methods reviewed here present relative advantages and disadvantages, depending on the type of data available. For welfare measurement in particular, methodologies that are more flexible, such as semi-parametric and nonparametric models, 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 an appropriate alternative for estimating the rent-value of dwellings when there is available data on capitalization rates, depreciation rates applicable to housing, the market value of the dwelling and data on operating costs for homeowners (and for nonmarket tenants). In the case where only subjective data on rents is available, mechanisms to correct for subjective bias must be devised.

We also uncover a largely underdeveloped stream of research. On the one hand, we find that there is absence of a systematic analysis exploring the distributional impacts of including rent in the welfare aggregate in developing economies. On the other hand, we observe that there are no analyses that seek to identify the most appropriate method(s) for rent-imputation in welfare measurement, nor analyses dealing with the implications for cross-country and over time comparisons of different rent-imputation techniques.[2] Thus, this topic provides a potentially rich research agenda for academics dealing with welfare measurement and poverty and inequality analysis.

The rest of the paper is organized as follows. Section 2 describes the most relevant methods for rent-imputation found in the literature. 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

The housing component of the welfare aggregate refers to the value of the flow of services that the household receives from a residence. The amount of rent

[2]Some papers, such as Frick *et al.* (2010, 2012) and Törmälehto and Sauli (2010, 2013) deal with the distributional implications of rent imputation in European countries, but heterogeneous imputation methods are applied in different countries, which diminishes the value of the comparative exercise. Verbist and Grabka (2016) apply a harmonized method to imputing rents in a selection of European countries, but their analysis is limited to the effect of subsidized rent.

paid would be the most obvious value to measure this flow. However, many households own the dwelling in which they live. This is by no means a trivial consideration in the calculation of the welfare aggregate. In both developing and developed countries homeownership can range from around 40 percent of the country population (e.g. Switzerland or Colombia) to more than 80 percent (e.g. Nicaragua or Romania).[3] Furthermore, some households receive housing free of charge or at rates subsidized by their employers, friends, relatives or the government. For example, in Austria and Cyprus, subsidized renters can account for more than 20 percent of the total number of households. Therefore, the problem is assigning a value to the flow of services from housing for these types of households.

2.1. *Hedonic Methods for Rent-Imputation*

On the basis of the hedonic theory of consumption (Lancaster, 1966), a household's rent is a function of the characteristics of its dwelling, including location, structural attributes (e.g. type of construction, number of rooms, age of the building, etc.) and neighborhood characteristics.[4] 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. Regardless of these theoretical limitations, several econometric approaches have been implemented over the last decades to impute rents to owner-occupied dwellings (see Hill, 2013, for an extensive review of hedonic methods applied to housing).

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). Ekeland *et al.* (2004) prove that an economic model that produces linear equations for rents 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 to the previous limitations, researchers have opted for using the log-linear functional form (e.g. Malpezzi, 2002; Diewert, 2003), as it allows the

[3]Authors' calculation based on the EU statistics on income and living conditions and the Socio Economic Database for Latin America and the Caribbean.

[4]For a review of the characteristics used in hedonic models in 120 studies, see Sirmans *et al.* (2005).

marginal rent-value to be a nonlinear function of size and quality of the dwelling. However, this method may not be flexible enough to capture high-order nonlinearities,[5] or other potential problems such as selection bias or spatial dependency.

Two-Stage Estimation Models

An important limitation of simple linear regression models is that they cannot capture unobservable differences in dwelling quality between homeowners, 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. Deaton and Zaidi, 2002; Arévalo and Javier Ruiz-Castillo, 2004; Norris and Pendakur, 2013) suggest using a two-stage regression *á la* Heckman (1979).

Other two-stage regression models, such as instrumental variables (IV), which can correct for omitted variables bias, have limited use in measuring poverty or inequality. IV regressions only capture a fraction of the variation in the dependent variable, thus fitted values are less variable than observed ones, meaning that 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.

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 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 an equal number of estimated parameters as the number of quantiles that 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. However, the question remains, to which distribution should homeowners and nonmarket tenants be assigned? They clearly cannot be ordered according to rent distribution, as rent is an unobserved quantity for those groups. Gasparini and Escudero (2004) use income distribution, assuming that the monetary value of the demand for unobservable characteristics

[5]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 semi-parametric and nonparametric models became available to researchers (Hill, 2013).

is related monotonically to the distribution of income, such that the quantiles defined for the distribution of non-observables coincide with the quantiles defined for the distribution of income. However, this might not be the case if, for instance, the quality of rented and owner-occupied dwellings differs (Arevalo and Ruiz-Castillo, 2004; Garner and Kogan, 2007). Although there are semi-parametric and nonparametric methods that allow addressing selection bias in quantile regression (Buchinsky, 1998, 2001), we are not aware that these methods have been implemented in the rent-imputation literature.[6]

Semi-Parametric 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 semi-parametric and nonparametric models.[7] For example, Gencay and Yang (1996) and Bin (2004) show that semi-parametric models provide more accurate residential housing price predictions in comparison to standard and higher-order models, both in- and out-of- sample. Similarly, Meese and Wallace (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 semi-parametric ones, and increase the accuracy of in-sample predictions.

In the case of nonparametric models, the literature has favored additive over unrestricted specifications (Clapp *et al.*, 2002; Bin, 2004; Martins-Filho and Bin, 2005; Brunauer *et al.*, 2010; Heckman *et al.*, 2010). Multivariate smoothers-required for unrestricted nonparametric modeling-are extremely expensive to compute, and even with the use of sophisticated graphical analysis, with 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, 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 as the number of variables increases,

[6]These alternatives have been implemented mostly in the labor economics literature to analyze wages, allowing researchers to correct for self-selection bias in the context of quantile regression. Nonetheless, the added flexibility of these models due to their semi-parametric and nonparametric nature, could lead to incurring the risk overfitting. Therefore, these alternatives should be considered carefully.

[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 which variables should make up the strata. In this section we focus on applications using semi-parametric and nonparametric regression analysis.

the model requires increasing amounts of data in order to provide identification, a problem commonly referred to as the curse of dimensionality (Geenens, 2011).

Another advantage of semi-parametric 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 noted, we are not aware these alternatives have been implemented in the rent-imputation literature.[8]

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 home prices' spatial dependency. In other words, dwellings in the same location are likely to have similar characteristics because they have access to neighborhood amenities (parks, school, hospitals, etc.), because they share the same afflictions (for instance pollution or crime), or because dwellers may have similar socio-demographic 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 semi-parametric 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, which assume 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 semi-parametric 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 (for a review on spatial dependence, the use of geospatial data and also on spatial semi-parametric and nonparametric estimation, see Gao *et al.*, 2006 and Hill, 2013). The advantage of these models is that, considering that hedonic house price equations attempt to explain variation in housing 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

[8]The superiority of semi-parametric 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 semi-parametric 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).

in spite of the growing availability of geospatial coordinates in data sets, most households' surveys do not include such information. Moreover, the literature on selection bias in spatial econometric models is developing (e.g. McMillen, 1995; Flores-Lagunes and Schnier, 2012).

2.2. *Non-hedonic Methods*

Non-hedonic methods have been widely used when the rental market is under-developed (ILO, 2004; Canberra Group, 2011; Eurostat, 2013); we highlight the rent-to-value, the user-cost approach and the rental equivalence approach.[10] 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.

Rent-to-Value Approach

The rent-to-value approach states that, in equilibrium, the rental price of housing should equal the current asset price 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, which can be obtained from household surveys (Yates, 1994; Saunders and Siminski, 2005).[11] Imputed rents can then be estimated by applying the capitalization rate to the reported value of the property.

As the available literature highlights (see Phillips, 1988; ILO, 2004; Garner and Kogan, 2007), the main issue with this approach is that it assigns the same capitalization rate to all households within the same area (which can be as large as the country as a whole, according to the available data), despite the fact that dwellings' characteristics and quality may differ significantly for homeowners, tenants and subsidized tenants. 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).

User Cost Approach

While the rent-to-value approach endogenously defines the return rate that transforms the value of housing 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

[10]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.).

[11]The capitalization rate can also be estimated using a hedonic model on household budget survey data, provided that the data contains information on both the value of dwellings and the rent paid by tenants (Deaton and Zaidi, 2002).

operating costs related to homeownership such as maintenance, repairs, property tax 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 values, especially in case of house price bubbles, which can lead to notable differences between actual rents and user-costs (Verbrugge, 2008; Garner and Verbrugge, 2009). 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).

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 tenants.

Self-Assessment Approach

The self-assessment approach, which is fairly common for imputing rents (Fessler *et al*., 2016), 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 they would 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 are assumed to 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 (Frick *et al*., 2010). The same problems would exist if we would use the rent equivalence approach to impute rents to nonmarket tenants. For example, Goodman and Ittner (1992) find that in the U.S. in the mid-1980s the median homeowner overvalued his/her house by around 6 percent. Similarly, Garner and Rozaklis (2001) find that in the U.S., self-reported housing costs resulted in higher estimates (almost 15 percent) than those based on a hedonic model. Homeowners might have above-market valuations of their housing, based on subjective reasons, such as special attachment to specific characteristics of their houses, or what Heston and Nakamura (2009) define as owner pride factor (see also Wang, 2014 for further discussion). The level of precision of homeowners' estimates might also be correlated with tenure, as suggested by Gonzalez-Navarro and Quintana-Domeque (2009).

Using this approach to impute rents could be less problematic in regions where rental markets are active and thick (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, to our knowledge, these assumptions have not yet been tested.

3. A Discussion on Rent-Imputation for Welfare Measurement

Much attention has been given to rent-imputation techniques, though there is little literature inquiring about the implications of rent-imputation on welfare measurement. Thus far, the literature has only shown that including rents in the welfare aggregate yields lower levels of poverty and inequality (Table 1); however, empirical results must be taken with a grain of salt. On the one hand, some papers do not re-compute the poverty line after adding rents to the welfare aggregate, meaning that 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.[12]

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.*, 2016). Imputed rents for owner-occupied housing mainly equalize the upper part of the income distribution, while subsidized housing has an equalizing effect focused on the lower part of the income distribution. Regarding the impacts of imputed rents on poverty, there is evidence of re-ranking: households' relative position may move up or down in the distribution of wealth. Although poverty tends to decrease (Table 1), the effect of adding imputed rents to the welfare aggregate may not be the same for all groups in the population; in other words, we can expect considerable re-rankings. For example, the literature has found that subsidized housing tends to re-rank low-income households upwards, while simultaneously re-ranking middle-income households-not eligible for subsidies-downwards (Maestri, 2012). It has also been documented that, in particular, poverty rates tend to fall 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; Verbist and Grabka, 2016). Unfortunately, there is still need for further evidence regarding the distributional impacts of rent on welfare, particularly in developing countries.

Note as well that there is variation in the type of rent-imputation techniques used across countries, and also in the measure used for the welfare aggregate, which can be consumption- or income- based (see also Juntto and Reijo, 2010 and Törmälehto and Sauli, 2013). This is not unexpected, given cross-country differences in data availability, data constraints and measurement standards. However, this implies that welfare aggregates are not likely to be comparable across

[12]Some notable exceptions include Yates (1994), Frick and Grabka (2003), D'Ambrosio and Gigliarano (2007), Frick *et al.* (2010), Törmälehto and Sauli (2010, 2013), Maestri (2012) and Verbist and Grabka (2016).

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.* (2017)	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.* (2016)	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.* (2011)	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

Table 1 *Continued*

Reference	Country (survey, year)	Welfare Aggregate	Method for rent-imputation	Recomputes poverty line	Effect on Inequality	Effect on Poverty
Smeeding *et al*. (1993)	Australia, Canada, Netherlands, Sweden, U.K., U. S., Germany (LIS, 1960, 1975, 1981)	Income	Rent-to-value	No	Reduction	Reduction
Saunders 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
Verbist and Grabka (2016)a	17 European Countries (EU-SILC, 2011)	Income	Heckman error correction	Yes	Reduction, except in Belgium, France, Ireland, the UK	Reduction
Yates (1994)	Australia (HES, 1988–1989)	Income	Rent-to-value approach	N/a	Increase	N/a

Source: Authors' compilations.
[a] The analysis in this case includes only the impact of including imputed rent for social housing.

countries-or indeed, over time if the rent-imputation technique used changes between survey rounds. More research on this issue is evidently needed.

A discussion about the advantages and limitations of using the different methods of rent-imputation for welfare measurement is also absent from most papers in the literature. Some of the papers engaged in this discussion use only a few of the methods available, and the large majority do not compare them, identifying their relative strengths and weaknesses. However, based on the discussion in the previous section, we are able to draw insights in this regard; Table 2 summarizes them.

All in all, flexible methodologies such as semi-parametric and nonparametric seem to be better suited for estimating rents, given that they capture some of the implicit nonlinearities of the hedonic price function. Nonetheless, these models are subject to specification bias stemming from self-selection and spatial dependency, and are further prone to suffer from the curse of dimensionality. Hence, it is always desirable to seek solutions to these issues whenever possible. The problem with these (hedonic) methods is that making predictions out of the sample of market tenants is hard to justify when rental markets are thin and underdeveloped, as is the case of many developing countries. It is unlikely that implicit rents can be predicted with any great 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 rather may make use of other information sources such as National Accounts. These methods represent appropriate alternative, so long as there is data on capitalization rates, depreciation rates that can be applied to housing, information on housing market value and comprehensive data on housing operating costs-with the concomitance 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, it is essential to derive means to correct for subjective bias in order to avoid biased estimates of welfare. However, thus far, no mechanism has been created to address this problem.

4. Conclusions

In order to obtain precise estimates of welfare, poverty and inequality and to allow for meaningful international and inter-temporal comparisons, it is essential to include rent in the welfare aggregate. Nonetheless, the task of assigning a rental value to homeowners and recipients of subsidized housing is not an easy one. 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. Therefore, our review first illustrates the relative advantages and disadvantages of the most common rent-imputation approaches; secondly, it reveals that the empirical literature has 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 a

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 semiparametric 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.
Self-Assessment	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.

Source: Authors' compilations.

lack of evidence on re-ranking, changes in poverty profiles, and on the distributional effects of using different imputation techniques in a comparative framework. It also seems that the decision to use a given rent-imputation method is conditional on the type and quality of information available-particularly on the size of the rental market. This explains to a certain extent why there is so much variation in rent-imputation techniques across countries. Nonetheless, it calls for further investigation and analysis of the implications of different rent-imputation techniques for cross-country and over time comparisons of welfare.

With this in mind, future research on this topic should investigate the distributional implications of using imputed rents and of using different imputation methods for such endeavor, looking for consensus about the most appropriate method(s) for rent imputation. There is a need for the creation of a unified framework, which will homogenize aspects of questionnaire design and data collection on housing and guidelines for imputing rents, in order to maximize the comparability of welfare aggregates across countries and over time. Given the data constraints on non-market tenants and the cross-country heterogeneity on the size of the housing market, this framework should aim to identify a method that allows researchers to maximize the precision of their estimates, while minimizing data requirements. Furthermore, it should be adaptable to the variable conditions of housing markets, without sacrificing comparability of estimates over time. Given that housing is one of the most important components of the household welfare aggregate, such advances will be crucial to improving the measurement of welfare globally.

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