

# Quality of life in French cities

Measuring the *je ne sais quoi*

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## Abstract

This paper aims at estimating the quality of life in French cities from a revealed-preference approach. Using official city-level data on wages and amenities, as well as web-scraped information on housing prices, we perform a two-step analysis. First, we study how rents and wages co-vary to estimate quality of life. We then use those results to find out how households value amenities. We prove that using a direct measure of available income to model households' location choices or trying to replicate expected wage produces very similar results in terms of quality of life estimation. Overall we find that cities in Southern France and in the Alps offer the highest quality of life, while areas in rural regions of central France fare worst. Households appear to highly value proximity to the shore and mild-winters. Easy access to cultural amenities and health services is also found to significantly impact quality of life.

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## Introduction

Households deciding on their city of residence need to strike a balance between highly-paid jobs, good quality of life and low housing costs. Those three elements are often difficult to obtain together, since desirable areas in terms of amenities are generally expensive. This paper seeks to exploit this threefold relationship, and uses information on rents and revenues to develop a quality of life index of French cities, based on households' willingness to pay to live in a city.

Because households are heterogeneous and imperfectly mobile, and because quality of life is a complex concept containing many subjective components, this index can only provide a limited perspective on an intricate question. Nevertheless, it provides an economic intuition and results that are in line with popular expectations on quality of life, with urban areas in Southern France or in the Alps being ranked highest, and cities located in decaying regions of central France being ranked lowest.

The literature on quality of life is large, and generally relies on the assumption that quality of life can be measured as a weighted average of amenities. The obvious question is then how to determine the weights of each amenities.

An empirical answer to that question builds on the theory by Tiebout (1956) that households "vote by their feet" and will move to the area that fits best their preferences for publicly-provided goods. By assuming that households are fully mobile and perfectly informed, it then becomes possible to evaluate the valuation of such publicly provided goods, or amenities, from the workers' location choice. If people can vote with their feet and move freely to the place that maximises their utility, it follows that in equilibrium, no one could be made better-off by moving to a new city.

Rosen (1979) was the first to use this type of model to implicitly estimate the valuation of amenities through the analysis of wage variation across areas. The intuition behind his method is that in spatial equilibrium households are only willing to accept lower wages in exchange for better amenities. Studying how wages co-vary with amenities hence allows to estimate how much households are willing to pay to access an amenity. Rosen then used the computed valuation to weight amenities and construct a quality of life index that was directly determined from the workers' observed behaviour. Roback (1982) later extended this model to include variation in rents, arguing that the worker could pay for access to amenities both through lower wages and through higher rents. She hence used co-variance in wages, rents and amenities to directly estimate household's valuation of amenities, and then compute a quality of life index.

Since then a large number of quality of life indexes have been developed based on the co-variation of wages, rents and amenities, mainly on US data (Berger, Blomquist, and Waldner, 1987, Blomquist et al., 1988, Chen et al., 2008...).

Albouy (2008) builds on the Rosen-Roback model of compensating differentials, and improves it with three adjustments. First, he tries to account for differences in cost of living that do not stem from rents. Second, he incorporates into the model sources of income other than wages, that do not depend on location. Finally, he introduces taxes into his quality of life equation. With those three amendments, he obtains a quality of life ranking that is more believable and more in line with the non-academic literature on areas' livability than the previous estimates. He then regresses quality of life on some amenities, to deduce their valuation by households. This two-steps estimation

is the reverse of the approach by Roback (1982) who estimated valuation of amenities and used those results to estimate quality of life. The method we use in this paper, following Albouy, has the advantage that it does not require any assumptions on which amenities are most valued by households and should be included in the computation of a quality of life index. Therefore, it does not rely either on the availability of data on a large range of amenities.

Most of the literature on quality of life focuses on US data. Some studies have previously been done in Russia (Berger, Blomquist, and Peter, 2008), Germany (Buettner et al., 2009), or Italy (Colombo et al., 2014), but to the best of our knowledge no hedonic quality of life rankings has ever been computed on French data. This might be simply be due to a lack of available data on housing prices, a core element of the revealed-preferences approach. Another specificity of the European case, is the relative immobility of European workers. Cheshire et al. (2006) argue that European households are less mobile than their American counterparts, which would weaken the theoretical foundation of the revealed-preference. However, the authors also find that population movement *within* European countries does respond to quality of life differences, and in particular to climate. There is hence some space to try and estimate a compensating differentials model within countries.

In this paper, we will try to use Albouy's (2008) model on French data, with a few amendments to the model. First, differences in wages are replaced by difference in available income, which is what Albouy tries to recreate when he incorporates taxes and non-wage revenues. We will also compute differences in *expected* wages, which include city-dependent taxes and unemployment rate, to obtain an alternative quality of life measure. Those amendments are presented in the first section of this paper. Section 2 presents the data we used. Section 3 explains the limitations of our analysis, and details the endogeneity issues we face in our estimations. Section 4 is used to compute comparable housing prices and incomes, which are net of education effects. We also test in this section whether net wages in French cities exhibit the bell shaped curve predicted by theory. Section 5 presents our quality of life indexes, while section 6 regress those estimates on various amenities to try to determine their valuation by households.

## 1 A model of households residential choice

We use the model developed by Albouy (2008) and slightly adapt it, to replace wages first with available income and then with *expected* wages.

### 1.1 Using available income

#### Households characteristics and preferences

Households are homogeneous, fully mobile, and have full information about the conditions of life in different cities, indexed  $c$ . For each city they observe: the price of housing  $p_c^H$ ; the price of other consumption goods  $p^x$ , assumed to be a numeraire;  $k$  amenities  $A_c^k$ , regrouped into an index  $Q_c = \tilde{Q}(A_c^k)$ , referred to as "quality of life"; and the final income they would earn in that city,  $y_c$ . Households supply one unit of labour in their city of residence, in exchange for this final income which includes wages  $w_c$ , taxes  $\tau_c$ , and the external income that does not come from wages  $I$ . External income is assumed to be independent of the household's place of residence.

From those observations, the households choose their city of residence  $c$  and their consumption of housing  $H$  and other consumption goods  $x$ . Households have utility  $U(x, H; Q_c)$  which is increasing and quasi concave in  $x$ ,  $H$ , and  $Q$ .

Hence the budget constraint of a household is

$$p_c^H H + p^x x \leq y_c$$

with  $y_c = (1 - \tau_c)(w_c + I)$

The expenditure function can be defined as:

$$E(p_c^H, p^x, y_c, u; Q_c) = \min_{H, x} \{p_c^H H + p^x x - y_c \mid U(x, H; Q_c) \geq u\}$$

It represents the minimum net expenditure that a household needs to make in order to reach utility level  $u$  in city  $c$ .

### Equilibrium

Households are homogeneous and fully mobile by assumption, so in equilibrium the utility must be equalised in all cities at level  $\bar{u}$ . This means that no household needs to make extra expenditure in order to reach utility  $\bar{u}$ . This equilibrium condition can be characterised using the expenditure function:

$$\forall c \quad E(p_c^H, p^x, y_c, \bar{u}; Q_c) = 0 \quad (1)$$

Differentiating equation (1) around national averages  $\bar{p}_c^H$ ,  $\bar{y}_c$  and  $\bar{Q}_c$  yields the following condition.

$$\forall c \quad \frac{\partial E}{\partial p_c^H}(p_c^H, p^x, y_c, \bar{u}; Q_c) \cdot dp_c^H + \frac{\partial E}{\partial y_c}(p_c^H, p^x, y_c, \bar{u}; Q_c) \cdot dy_c + \frac{\partial E}{\partial Q_c}(p_c^H, p^x, y_c, \bar{u}; Q_c) \cdot dQ_c = 0 \quad (2)$$

with  $dp_c^H$ ,  $dy_c$ , and  $dQ_c$  representing deviation from the national average in city  $c$ .

Applying Shephard's lemma we obtain :

$$\forall c \quad p_c^Q dQ_c = H^*(p_c^H, p^x, \bar{u}) \cdot dp_c^H - dy_c \quad (3)$$

where  $p_c^Q = -\frac{\partial E}{\partial Q_c}(p_c^H, p^x, y_c, \bar{u}; Q_c)$  represents the marginal valuation of amenities by households ; and  $H^*(p_c^H, p^x, \bar{u})$  is the Hicksian demand for housing. Evaluating this at the national average we get:

$$p_c^Q dQ_c = \bar{H} \cdot dp_c^H - dy_c \quad (4)$$

where  $\bar{H}$  is the national average of housing expenditures.

This equation illustrates how a higher available income compensates workers for higher living costs or lower amenities. Conversely, higher living costs are paid by households in order to access better amenities, or a higher income.



## Operationalisation

We can use equation (4) as a basic index of quality of life. In order to render it operational, we divide the equation by  $\bar{y}$  the average available income, and we define the log-differentials  $\widehat{p}_c^H = \frac{dp_c^H}{\bar{p}_c^H}$ ;  $\widehat{y}_c = \frac{dy_c}{\bar{y}}$ . We also define  $\widehat{Q}_c = \frac{p_c^Q}{\bar{y}} dQ_c$ , the fraction of average income that households are willing to pay for a marginal increase in their quality of life. Evaluating this at the national average allows us to create a unified index. Inserting this into equation (4) yields the final equation

$$\begin{aligned}\widehat{Q}_c &= \frac{\bar{H} \bar{p}_c^H}{\bar{y}} \cdot \widehat{p}_c^H - \widehat{y}_c \\ &= \bar{s}_H \widehat{p}_c^H - \widehat{y}_c\end{aligned}\tag{5}$$

where  $\bar{s}_H$  is the average share of income that is spent on housing goods.

In his article, Albouy (2008) uses variation in wage instead of available income, that he then weights down to account for taxation and the relative importance of other sources of income. The advantage of the model above is that it considers variation in available income, which already includes all those elements and does not require any assumptions on average tax rate or on the share of income that stems from labour. Nevertheless, in a later part of the analysis we also compute a wage-based quality of life index founded on the following model.

## 1.2 Expected Wages

The model using wage is very similar to the one introduced above. Households are again homogeneous, fully mobile and fully informed. Following the intuition of Harris et al. (1970), we further assume that households make their location choice based on *expected* income, taking into account unemployment levels. Albouy chose to ignore the city employment rate in his model, but we suspect that it might be a relevant factor in households migration in France, where unemployment is higher than in the United States. Households provide one unit of labour in their city of residence, in exchange of which they receive a wage  $w_c$ . In addition, they observe the unemployment rate  $u_c$  and tax rate  $\tau_c$  in all cities, and deduce from this their expected wage  $\tilde{w}_c = (1 - \tau_c)(1 - u_c)w_c$ . We assume now that tax only applies to labour income. The households' total income in city  $c$  is then  $\tilde{w}_c + I$ . The assumptions on prices and the shape of the utility functions are the same as before.

With those amendments, the expenditure function becomes:

$$E(p_c^H, p^x, \tilde{w}_c, u; Q_c) = \min_{H,x} \{ p_c^H H + p^x x - (\tilde{w}_c + I) \mid U(x, H; Q_c) \geq u \}$$

From the assumption that households are fully mobile, we know that the utility must be equalised at level  $\bar{u}$ , and  $E(p_c^H, p^x, \tilde{w}_c, \bar{u}; Q_c) = 0$ . Differentiating this condition around the national averages  $\bar{p}_c^H$ ,  $\bar{\tilde{w}}_c$  and  $\bar{Q}_c$ , and applying Shephard's Lemma, we obtain the following condition:

$$p_c^Q dQ_c = \bar{H} \cdot dp_c^H - d\tilde{w}_c\tag{6}$$

Defining as previously  $\widehat{p}_c^H = \frac{dp_c^H}{p_c^H}$ ;  $\widehat{w}_c = \frac{d\tilde{w}_c}{\tilde{w}_c}$  and  $\widehat{Q}_c = \frac{p_c^Q}{\bar{y}}dQ_c$ , and dividing the equation by average income  $\bar{y}$  we reach our quality of life equation:

$$\begin{aligned}\widehat{Q}_c &= \frac{\bar{H}p_c^H}{\bar{y}}.\widehat{p}_c^H - \frac{\bar{w}_c}{\bar{y}}.\widehat{w}_c \\ &= s_H\widehat{p}_c^H - s_w\widehat{w}_c\end{aligned}\tag{7}$$

where  $s_H$  is the housing expenditure share out of total income, and  $s_w$  is the share of income that comes from labour.

### 1.3 Empirical strategy

To estimate equations (5) and (7), we need to select the correct parameters  $\bar{s}_H$  and  $\bar{s}_w$ , and to compute the log differentials for housing prices, available income, and expected wages.

For the share of housing in expenditure  $\bar{s}_H$  we use the result of Combes, Duranton, et al. (2012) who find a share of 32.5% for a city of average size in France. Their results are also used to compute in parallel another index in which the share of housing in expenditure varies with cities' population. We use their preferred coefficient of 0.048 on city population to compute the share of a city as  $s_H = 0.325 + 0.048\ln(\frac{N_c}{\bar{N}})$ , with  $N_c$  the population in city  $c$  and  $\bar{N}$  the average of city size in the subsample. This is only done on the 200 largest cities in our sample cities because it broadly corresponds to the sample used by the authors in their regressions. Using the smallest cities in our sample leads to a logarithm too negative, and a negative share of housing in expenditure in those cities.

While we did not find a satisfying way to incorporate a share of housing that varies with city into the theoretical model, the intuition behind this empirical specification is that if households spend a larger share of their income on housing in larger cities it will increase the urban costs for those cities. Fully informed households should know that they will spend relatively more on housing in some cities, and should take that into account when making a residence choice. We find however that the results on quality of life are not significantly changed when including a variable share of housing in expenditure.

To estimate equation (7), we use an average share of wages in available income of 0.53 in 2014, computed from national level data provided by the French Statistical Institute\*.

In order to partially control for the sorting of people into different cities according to skills, which Combes, Duranton, et al. (2008) have demonstrated to be a strong determinant of spatial wage disparities in France, we compute the differentials of income and expected wage net of the effect of education. To do this, we first regress income, wage and unemployment in an urban area on characteristics of the area: population, education and land area. The results of those first-step regressions are reported in section 4. The obtained coefficients are used to render the variables net of education. We then compute the log differentials as the deviation from the national average. The same strategy is used to compute housing prices net of education effect.

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\* *Tableaux de l'économie française, revenus des ménages*, found at this address: <https://www.insee.fr/fr/statistiques/3303428?sommaire=3353488>

## 2 Data

### 2.1 Sampling

The main geographical level of the analysis is urban areas in mainland France. In its 2010 version, the definition of French geographical units provided by the National Institute of Statistics and Economic Studies (INSEE) defines 760 urban areas. Out of those, only 609 have available housing costs data. The urban areas we lose all have less than 50,000 inhabitants.

Because the data on housing prices is only available at the urban unit level we also perform all our analysis for urban units, to check that this geographical discrepancy does not affect the results. All the graphs and tables at the Urban Unit level can be found in Appendix E.

According to the 2010 definition by the National Institute of Statistics there are 2217 urban units in mainland France. We only have housing cost data for 1397 of those. All the urban units we leave out due to this lack of data have population below 27,000.

Urban units are defined as a set of municipalities which contains a built area of at least 2,000 inhabitants, with no housing being more than 200 meters away from its closest neighbour. Urban areas are defined around a central urban unit of at least 1500 jobs, and include all the surrounding municipalities of which at least 40% of the population works in the urban unit or associated municipalities. We use these definitions to find the set of urban units that are at the centre of an Urban Area on which we later perform the urban unit analysis.

### 2.2 Income and wages

We use two different specification of income in our analysis: available income, and average net hourly wage. Both are available from the French National Institute of Statistics and Economic Studies.

The data on average net hourly wage in 2014 is obtained from the Annual Declaration of Social Data (*Déclaration annuelle de données sociale*, DADS). This is an administrative database that is collected from a yearly declaration compulsory for all French employers, containing information on their employees and their establishment. The hourly wage data is available directly at both the urban unit and urban area levels. Hourly wage is calculated as the quotient of the yearly wage on the total of hours paid including overtime, as well as paid holidays, sick days... The net hourly wage is attached to the worker's place of residence.

For available income, we use data from the Localised Social and Fiscal File (*Fichier localisé social et fiscal*, FiLoSoFi). This data set is managed by the National Institute of Statistics and Economic Studies. It gathers administrative data on fiscal matters from the French General Directorate of Public Finances (*Direction Générale des Finances Publiques*), as well as information on social allowance from several benefit funds (National Family Allowance Fund (Cnaf), National Old-age Insurance Fund (Cnav), and Central Agricultural Social Mutual Fund (CCMSA)).

For each urban unit and for each urban area, the FiLoSoFi data set provides characteristics of the distribution of available income per consumption unit in 2014 (in particular the median). A household's available income includes all of its revenues (work-related or not), net of social contributions on wages and of taxes. This available income is divided by the number of consumption units in the household, in order to be able to compare households that are composed differently.

Both available income and mean wage are available for all urban units and all urban areas save one.

Information from the FiLoSoFi data set was also used to compute a tax rate per urban area and urban unit.

## 2.3 Housing prices

There is no official publicly available data on housing prices at the municipality, urban unit or urban area level in France. Notaries record information on housing price and characteristics for all transactions they make, but this data is not easily accessible. However the High Council of French Notaries (*Conseil Supérieur du Notariat*), the official organisation representing all notaries, allows users of their website<sup>†</sup> to explore the map of France and get information on housing prices in different areas and for different types of goods. The different categories available are type of building (house, apartment, apartment block, bare land...), age (new or already existing building), number of rooms, surface, and availability of a parking slot. We took advantage of this opportunity and performed web scrapping operations on their website.

The notary website provides access to this data at different geographical levels: neighbourhood, municipality, urban unit, department... but not at the urban area level. It is important to note that the notaries only publish data for a type of good in an area if more than 20 such transactions occurred in the area during the time period. For this reason, the more we narrowed the criteria, the less observations we could collect.

As a result, we decided to only focus on the broadest geographical scale that is still relevant to the study of cities: urban units. We also decided to only exploit the possibility of filtering goods by their age. All other criteria were too narrow and would have allowed us to collect data on very few urban units.

We built an algorithm using R that allowed us to retrieve all the html code of a web page, as well as all the information processed by javascript but hidden in the html code. We then extracted from the obtained code the median price per square meter in the area. When an area for which no data is available is selected, the website automatically enlarges the criteria, both for the geography (going from municipality to department for instance) and for the housing characteristics (going to 5-rooms houses to all houses). We had to ensure that such results were not recorded in the data set created. We applied this algorithm to all French urban units, for five different type of transactions: new houses, new apartments, existing houses, existing apartments, and existing houses and apartments together. After the data collection we observed that only this last group (old houses and apartments grouped together) yielded data for more than half of the urban units. It might have been better to supplement this variable with one on the price of new housing, but only 6% of urban units had data on new apartments, and for new houses this proportion fell to less than 2%.

The data obtained from the website concerns the last trimester of 2017 (from the 1st of October, to the 31st of December). It is corrected for seasonal variations by the notaries before they publish it. It is also cleaned to exclude unusual goods such as castles or extremely small attic rooms.

To obtain a measure of price in an urban area, we averaged prices in all urban units comprised

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<sup>†</sup><https://www.immobilier.notaires.fr/>

in the urban area, weighted by population.

## 2.4 Amenities

*Artificial amenities:* For artificial amenities, we use data on the year 2016 from the French Permanent Census of Equipements (*Banque Permanente des Equipements, BPE*). The data is available at the municipality scale, and we aggregate it at the urban area and urban unit levels. The data is maintained by the National Institute of Statistics and Economic Studies. The primary data sources are the National Registry of Establishments (siren) for retail establishments such as restaurants and cinemas; the French Ministry for Education for primary, middle, high schools, and universities; the French Ministry of Culture for museums; and the Ministry of health for doctors, hospitals and medical services.

*Climate:* Climate data originally comes from the ATEAM European project. We only obtained it aggregated at the *département* level. The value of climate variables for an urban area (resp urban unit) is computed by associating each municipality to the value of its *département*, and calculating the average of municipalities within the urban area (resp urban unit) weighted by land area.

## 2.5 Other data

*Unemployment:* The unemployment rate per city was computed using information from the 2014 census on the number of unemployed persons per municipalities, and the size of the labour force.

*Land Area:* In order to compute the land area of cities, we use the the GEOFLA data set provided by the French National Geographical Institute. It contains land area information for all French municipalities, and we aggregated this data to obtain the land area of urban area and urban units.

# 3 Limitations

We acknowledge a number of limitation to our analysis, both in the theoretical model and in the empirical approach we adopt.

## 3.1 Limitations of the model

The standard concept of equilibrium we use in which utility is equalised across geographical units and among homogeneous households has strong weaknesses. First, it requires the assumption that households are perfectly mobile, which is not verified in real life: moving to a new city incurs a various costs, in terms of money, time and even social networks. Consequently, households will only take advantage of a difference in utility between two cities if their expected utility gain is greater than the cost of moving. This is confirmed empirically in the US by Berger and Blomquist (1992) who find that moving costs matter in households' decision to move or not. Furthermore, the assumption that households have full information about their location options is also unlikely to be true, furthering the chance that some potential utility discrepancy between cities could remain even in equilibrium.

The imperfect mobility of households is also reinforced by idiosyncratic preferences. While we assumed that households were homogeneous, individuals might actually have a special link to their city of birth, or a preference for a certain local culture or a type of climate, which means that they would differ in their valuation of certain amenities. This weakens the analysis performed in section 6, in which the valuation of some amenities is estimated for typical households. Life cycle effects could also be a source of heterogeneity among households. As exemplified by Chen et al. (2008), households at different point in their life cycle do not choose their location residence based on the same criteria. A family with young children would probably put more weight on wages in their decision, while retired people should be concerned solely with housing costs and amenities. We do not control for this life cycle effect in our analysis.

Our model also relies on the assumption that consumption goods other than housing have constant prices across cities. This simplification can be defended using empirical work by Handbury et al. (2014) who demonstrated that once variety is taken into account the price of groceries in the US does not vary significantly with city size.

### **3.2 Limitations of the empirical strategy: identification problems**

A major issue faced in the analysis is that of endogeneity, which arises at several levels.

A first concern in our wages and rents regression is the possibility that some variables which are correlated with both wages (or rents) and city size are not included in the equation.

While we do control for the sorting of households according to education, our variable for education consists in the share of the population with a higher education degree, which is quite imprecise and does not capture very precisely the skills of workers in a city. It is hence very likely that there is some sorting due to unobserved skills that we do not control for.

Furthermore, households might sort into cities according to other variables than education, such as the industry they work in. A large city such as Paris concentrates more highly paid industries like finance. One could consider this to be a direct effect of agglomeration, with larger cities offering some advantages that make them more attractive to highly-rewarding industries, in which case industry composition should not be controlled for in our regressions. Yet, if we consider that this concentration is due to historical or political reasons, then it means that the higher wages we observe in larger cities are not due to agglomeration economies. In that case, it would be better to control for the industrial composition of the city, to compare identical workers in identical industries. We chose not to control for industry composition due to the lack of appropriate data, but fully recognise that this might not necessarily be the "correct" way estimate the elasticity of wages with respect to city size.

Another concern in our analysis is the question of reverse causality. The implicit assumption in our wage regressions is that the higher level of wages empirically observed in larger city is due to agglomeration economies. But it could be argued that the correlation is due to the reverse mechanism: there are innate productivity advantages in some places that lead to higher wages. Those higher wages attract more workers into the city, and make it even larger. In reality, both mechanisms are probably at play and wages and city size are simultaneously determined. A similar issue is at play for rents, since cities where rents are higher would be less attractive to households which should lead them to be smaller. This is accentuated by the fact that city size itself could be

perceived by households as an amenity, which introduces another source of endogeneity.

We try to control for those issues by using control variables in our regression. We include the share of high-skilled workers in both our rent and wages regression. In the rent equation, we also include income, which should affect the demand for housing, and geographic information which could either make building more difficult (slope, maximum altitude), traduce a specific housing market effect (dummies for sharing a border with another country), or make cities more attractive, increasing both housing price and population (proximity to a body of water).

There are other potential ways to circumvent those issues that have been used in the literature. For instance one could using panel data and run regressions that include city fixed effects as well as characteristics of the housing (size, distance to the centre, type...) in the rent equation(Albouy, 2008, Combes, Duranton, et al., 2012). For the wage equation, one could add individual fixed effects or characteristics (age, race, gender, education...), and possibly industry fixed effects (Albouy, 2008, Albouy and Lue, 2015, Combes, Duranton, et al., 2008). The city fixed effects would then measure an index of wage and housing in each city, net of all other controlled characteristics. It would also be possible to instrument city size with historical variables (Combes, Duranton, et al., 2008), or geology (Rosenthal et al., 2008). But all those methods require data that was not available to us.

Another empirical challenge was the potential presence of spatial auto-correlation due to omitted variable like market potential. This might be a problem particularly at the urban unit level: by definition, workers in two urban units within the same area share very similar employment and housing markets. This is the reason why, in our analysis at the urban unit level, we only consider urban units that are at the centre of an urban area. All other urban units are likely to share too many characteristics with their neighbour, which would induce auto-correlation.

Finally, the quality of our housing price data is not perfect. First, because there is almost no information on housing characteristics we cannot control for housing quality at all. This could bias the estimates of quality of life if some cities offer housing of lesser quality on average. The lower prices due to lower quality would then be interpreted for a lower quality of life.

Furthermore, the data is not corrected for distance to the city centre of each housing unit. Because housing prices decrease with distance to the centre, as demonstrated for the case of France by Combes, Duranton, et al. (2012), and because the land area of a city like Paris is much larger than for instance Grenoble, using the median of housing price underestimates the housing costs differences across cities. This also complicates the interpretation of the land area variable we use in some of our regressions. Because of the incompleteness of our data, land area will capture both the extensive margin effect of extending urban sprawl, and the fact that average distance from the centre is generally larger in more populated cities.

Keeping in mind all those limitations will be important in the interpretation of our results in later stages.

## 4 First-step regressions: Wages and rent gradients

### 4.1 Rent estimates

A first necessary step towards computing quality of life estimates, is to obtain comparable estimates of housing prices across cities. To obtain this price index for a comparable household, we compute

housing prices net of the effect of education. To that end, we estimate the equation

$$\ln p_c^H = \alpha^P + X_c^P \beta^P + \mu_c^P \quad (8)$$

where  $p_c^H$  is the median price of old housing per square meter in city  $c$ ,  $\mu_c^P$  is the error term, and  $X_c$  is a set of controls for the city's characteristics which include at least the natural logarithm of the city's population, and some extra controls which are used to try to alleviate the endogeneity issues presented above.

Table 1 reports the results of several OLS regressions with various set of controls. Column 1 corresponds to a simple regression of housing prices on population, controlling for geography with maximum altitude and slope, dummies for being on the border with a neighbouring country, being on the coast of one of the main seas (British Channel, Mediterranean Sea, Atlantic Ocean) being on one of the 5 main rivers (Rhône, Garonne, Rhin, Seine, Loire). Column 2 controls for the log of median available income. Column 3 adds a control for the share of population with a higher education degree. Introducing those controls for the socio-economic composition of the city lowers the estimated coefficient on population, to the point that it becomes non-significant in column 3. This suggests that when the city is allowed to expand geographically, an increase in population keeping the same type socio-economic composition of the city does not affect housing prices.

Table 1: Housing price and city size, across Urban Area

<i>Dependent variable:</i>						
	log median price of old housing per square meter			Land area controlled		
	Fringe adjustment					
	(1)	(2)	(3)	(4)	(5)	(6)
ln Population	0.071*** (0.010)	0.037*** (0.009)	-0.002 (0.010)	0.168*** (0.021)	0.150*** (0.019)	0.112*** (0.018)
ln Income		2.171*** (0.182)	1.252*** (0.209)		2.269*** (0.176)	1.348*** (0.201)
Education			3.453*** (0.439)			3.467*** (0.421)
ln Land area				-0.109*** (0.021)	-0.129*** (0.019)	-0.130*** (0.018)
Geography	Y	Y	Y	Y	Y	Y
Observations	608	608	608	608	608	608
R <sup>2</sup>	0.427	0.589	0.602	0.464	0.630	0.647
Adjusted R <sup>2</sup>	0.413	0.578	0.591	0.451	0.620	0.636

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Housing price of an Urban Area corresponds to the mean of the housing prices of the Urban Units within the area, weighted by population. Controlling for geography as slope and max altitude, as well as dummies for France's neighbouring countries, seas, oceans and main rivers.

However in the case of France, where land use policies try to limit the spatial spread of cities, it is most relevant to think about the case where the boundaries of the city are fixed. This is what we do in columns 4 to 6, which repeat the previous pattern now controlling for the log land area of the city. The strong negative effect of land area on housing prices can be explained by the fact



that it captures both the average distance of housing units to the city centre, and the extensive margin effect: by allowing land area to increase for a given population, the supply of land increases and the prices decrease.

The same extensive margin reasoning explains why the estimated population elasticity of housing prices is much higher when we do not allow for land area to adjust. In columns 1 to 3, an increase in population had two opposite effects. First, density could increase leading to a higher demand for housing and an increase in prices. But in the medium to long-run the supply of land could increase through an expansion of the city, leading to a relative decrease in prices, and attenuating the first effect. In the second part of the table however, an increase in population can only mean an increase in housing density which means a rise in price.

Our preferred specification is that of column 6 which controls for both the composition of the city and its land area. It yields an estimate of 0.112 for the population elasticity. This is significantly smaller than the elasticity of 0.208 found by Combes, Duranton, et al. (2012), but can be explained by the fact that their measure of prices at the centre of cities captures higher differences in prices across cities than the median of the urban area we use. We will later use this column 6 to render the housing prices net of the education effect.

## 4.2 Wages and income

To compare the situation of similar workers in different cities, we also need to estimate the relationship of wages with city size and education.

We regress first wages on density, with the following equation:

$$\ln w_c = \alpha^w + X_c^w \beta^w + \mu_c^w \quad (9)$$

where  $W_c$  is the mean hourly wage in city  $c$ ,  $\mu_c^w$  is the error term, and  $X_c$  corresponds to a set of city characteristics, including at least the natural logarithm of density or population.

In a first regression, we use density of population as the main explanatory variable of equation 9, and add controls for education, land area, or both. Results are reported in Table 2.

The advantage of controlling for both density and land area is that it allows us to really distinguish the extensive and intensive margin of city size. The coefficient on density is much larger than that on land area, by a factor of two in column 3 to four in column 4, when controlling for education. This result implies that an increase in population which goes through a higher density (keeping land area constant) would have a much higher effect on wages than an increase where the city expands but density doesn't change.

The density elasticity of wage is relatively stable across the specifications, around 3.5%. This result is in line with the previous estimate of 3.7% obtained by Combes, Duranton, et al. (2008).

In table 3 we report the results of a series of OLS regressions with the natural logarithm of population as an explanatory variable, instead of density.

The elasticity of wages with respect to population is this time very sensitive to whether or not we include land area. Figure 4 in Appendix A represents graphically the results of this table on a scatterplot of wages on population.

The coefficient on the logarithm of land area, which is now negative, can be explained by

Table 2: Wage and density across Urban Areas

	<i>Dependent variable:</i>			
	ln Mean hourly wage			
	(1)	(2)	(3)	(4)
ln Density	0.036*** (0.004)	0.030*** (0.003)	0.044*** (0.004)	0.034*** (0.003)
Education		1.002*** (0.051)		0.860*** (0.061)
ln Land Area			0.023*** (0.002)	0.008*** (0.002)
Observations	759	759	759	759
R <sup>2</sup>	0.104	0.409	0.269	0.423
Adjusted R <sup>2</sup>	0.103	0.408	0.267	0.420

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

the fact that when the city expands, keeping population constant, the density will mechanically decrease. As seen in table 2, such a decrease in density would lead to a decrease in wage, probably through lesser agglomeration gains.

Table 3: Wage and city size (across Urban Area)

	<i>Dependent variable:</i>			
	Fringe adjustment		Land area controlled	
	(1)	(2)	(3)	(4)
ln Population	0.026*** (0.002)	0.013*** (0.002)	0.044*** (0.004)	0.034*** (0.003)
Education		0.806*** (0.063)		0.860*** (0.061)
ln Land area			-0.021*** (0.004)	-0.026*** (0.003)
Observations	759	759	759	759
R <sup>2</sup>	0.239	0.375	0.269	0.423
Adjusted R <sup>2</sup>	0.238	0.373	0.267	0.420

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Whether we use density or population as an explanatory variable, education keeps a strong explanatory power. Out of our independent variables, it is the one that has the strongest effect on wages. This result seems intuitive, since we should expect skills to be a primary determinant of wages, and it confirms the importance of computing wages net of education in our quality of life index. This will be done using the results of column 4 since, as argued before, keeping land area constant is the most relevant way to model French urban policies.

But our model is one of *household* location choice. While wage should provide interesting

insights into the determinants of a *individual worker's* choice of a place of work, it could be expected that households as a whole take more than wage levels into account when deciding where to live. A family making a decision on their residence would probably consider the total income they would earn, including some city-dependent elements other than wages (the unemployment rate or local taxation for instance).

For this reason, we now estimate again equation (9) with available income per consumption unit as the dependent variable. The measure of available income we use includes all income (work and non-work related) and already deduces all direct taxes. It should hence be a good measure of what people consider in their location decision. The results are reported in table 4.

Table 4: Available income and city size (across Urban Area)

	<i>Dependent variable:</i>			
	ln Median available income			
	Fringe adjustment		Land area controlled	
	(1)	(2)	(3)	(4)
log Population	0.016*** (0.002)	-0.006*** (0.002)	0.007 (0.004)	-0.008** (0.003)
Education		1.302*** (0.061)		1.296*** (0.061)
log Land area			0.011** (0.004)	0.003 (0.003)
Observations	760	760	760	760
R <sup>2</sup>	0.083	0.428	0.090	0.429
Adjusted R <sup>2</sup>	0.082	0.427	0.088	0.427

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

The effect of population on revenue is not so clear anymore when considering income instead of wages. This could come from several channels.

First, our measure of income is available income *per unit of consumption*. This means that the composition of households could be a missing variable whose absence biases the estimate. Indeed, city size and household composition are likely to be correlated, but their relationship is not an obvious one. On the first hand, larger cities are more expensive (as seen in table 1 for the price of housing). As a result, families with similar socio-economic characteristics (income, education, age) should tend to have less children. This would imply that available income *per unit of consumption* should be larger in large cities, since there would be less units per households. On the other hand, larger cities are also more productive and offer higher wages. This means that a couple with similar education would actually earn more, and hence would tend to have more children. This would bias our estimate in the opposite direction. It is therefore difficult to predict whether our estimates are biased upward or downward before further work is done on the relationship between city size and household composition.

But there are other variables that are missing and could be correlated with both population and available income. The composition of the city could be very important. For instance, one could argue that small cities are more likely to have a high share of retirees, who do not earn much

money, or a higher unemployment rate, which would also decrease available income. Given our very limited set of controls, there are a number of reasons that could explain why our estimates of the population elasticity of available income are so sensitive to the specification chosen.

However, the share of population with a higher education degree is remarkably stable, and is in both columns 2 and 4 strongly positive and significant. The effect is even stronger than in our previous wage regressions. Hence, despite the complex relation of available income and population, we still use the results of column 4 to compute a measure of median income net of education in further sections.

### 4.3 On the way to expected wages: unemployment and tax rate

Equation (7) requires the computation of inter-urban expected wage differentials. In order to compare similar workers in every cities we want to control for the effect of skills, measured by education, on the expected wage. We have already done the necessary regression for wages, but we still need to measure the two other elements of expected wage (unemployment and tax rates) net of education as well.

Thus, we regress the unemployment rate, computed as the number of unemployed people over the number of persons in the labour force, on education, land area and quadratic and cubic terms for the log of population, according to the equation:

$$u_c = \alpha^u + \gamma_c^u \ln N_c + \delta_c^u (\ln N_c)^2 + \eta_c^u (\ln N_c)^3 + X_c^u \beta^u + \mu_c^u \quad (10)$$

where  $N_c$  is the population of city  $c$ ,  $X_c^u$  is a set of controls including land area and education, and  $\mu_c^u$  is the error term. Results are reported in table 5. Quadratic and cubic terms are introduced progressively, in columns 2 and 3, then 5 and 6.

The table suggests that the relationship between unemployment and log population is concave over our range of population, and decreasing at least after a threshold. The coefficient on education is remarkably stable, whether we include land area or not, and whatever the degree of the population polynomial. This is reassuring for the next step of the analysis where we use this estimate to compute an unemployment rate net of education. To do this, we use the results of column 6, which seems to be the specification that best fits the case where land area is controlled.

We perform the same analysis on tax rate, estimating an equation of the form:

$$\tau_c = \alpha^\tau + X_c^\tau \beta^\tau + \mu_c^\tau \quad (11)$$

where  $\tau_c$  is the tax rate in city  $c$ , and  $X_c^\tau$  corresponds to city characteristics, including the natural logarithm of population, education and the natural logarithm of declared income per unit of consumption (before tax deduction).  $\mu_c^\tau$  is the error term.

We chose not to include land area as a control, since it did not seem obvious that the tax rate in a city would depend on its spread, especially once income is controlled for. We include population to control for the possibility that larger cities provide more publicly funded amenities (cultural or transport ones for instance), which could be reflected in the local tax rate for a given income. This possibility is not confirmed in our results, since population loses significance as soon as controls for

Table 5: Unemployment and city size across Urban Areas

	<i>Dependent variable:</i>					
	Fringe adjustment		Unemployment rate		Land area controlled	
	(1)	(2)	(3)	(4)	(5)	(6)
log Population	0.009*** (0.001)	0.031*** (0.010)	0.178*** (0.065)	0.011*** (0.001)	0.016 (0.014)	0.408*** (0.081)
square log Population		-0.001** (0.0005)	-0.015** (0.006)		-0.0003 (0.001)	-0.039*** (0.008)
cube log Population			0.0004** (0.0002)			0.001*** (0.0003)
Land Area				-0.0000*** (0.0000)	-0.0000 (0.0000)	-0.0000*** (0.0000)
Education	-0.521*** (0.038)	-0.520*** (0.038)	-0.523*** (0.038)	-0.515*** (0.038)	-0.516*** (0.038)	-0.511*** (0.037)
Observations	760	760	760	760	760	760
R <sup>2</sup>	0.201	0.206	0.212	0.209	0.209	0.233
Adjusted R <sup>2</sup>	0.199	0.203	0.208	0.205	0.205	0.228

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

skills and income are added in the regression in columns 2 and 3. However, it is still possible that the tax rate is larger in some cities due to a higher density of public amenities, even if those cities are not necessarily the largest ones. Since we want to find out the tax rate faced by a worker with a given education in computing our net tax rate, we need to estimate the effect of skills on taxes. When including only education in our equation, in column 2, we find that cities with a higher share of high-skilled workers have a significantly higher tax rate. However, this is likely to be due to educated workers earning higher wages. For this reason, we include in column 3 of the regression the median declared income in the city (before taxes). Even when controlling for income, we find that more educated cities have higher tax rates, which might be due to educated households highly valuing some sort of publicly provided amenity a lot and hence sorting themselves into cities that have higher tax rates but also higher amenities. We use the result of column 3 to compute the tax rate net of education.

Table 6: Tax rate and city size across urban areas

	<i>Dependent variable:</i>		
	Tax rate		
	(1)	(2)	(3)
log Population	0.004*** (0.0004)	0.0002 (0.0004)	0.0005 (0.0004)
Education		0.250*** (0.012)	0.167*** (0.015)
log income			0.050*** (0.006)
Observations	759	759	759
R <sup>2</sup>	0.152	0.449	0.499
Adjusted R <sup>2</sup>	0.151	0.448	0.497
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01	

#### 4.4 Is there a bell curve?

From all the regressions above, we compute log wages, income and rents, as well as unemployment rate and tax rate net of education.

Those estimates are then used to test whether French urban areas exhibit the inverted U-shape relationship of net wage to city size first theorised by Henderson (1974). As seen in table 3, wages increase with city size as a result of agglomeration economies. On the other hand, urban costs increase also with city size, as is represented in table 1 for the specific case of housing costs. This increase in cost of living should be the factor that limits the expansion of cities. The assumption behind the idea of inverted U-shape curve is that wages increase faster than cost of living at first, until a population threshold is reached after which the relationship is inverted. Initially, as cities are small, agglomeration brings benefits through higher wages. Once the threshold is reached, the higher costs of living take the upper hand and further agglomeration results in net wage loss (net wage being here the wage received by households once living costs are deduced).

This inverted U-shaped curve can only exist if either wages or rents have a non-linear relationship with population. Results of the regression of log housing costs and log wages on quadratic and cubic terms for population are presented in Appendix B. They suggest that while the housing costs are linearly increasing with population (in log terms), mean hourly wages are increasing and slightly convex on the range of population of French cities. Obtaining a bell shaped curve is therefore theoretically possible.

In order to evaluate the U-shape relationship, we need to weight down housing costs by their expenditure share. This is done to avoid overestimating the variation of urban costs with city size, since rents only represent a fraction of total cost of living, and we assumed earlier that the prices of non-housing goods did not vary across cities.

In table 7 are the results of a regression of log wages minus log housing costs on the square and cube of log population. We perform this regression with a share of housing that is constant across cities, and with the city size dependent share we computed earlier. We also do it controlling or not for land area, to distinguish the effect of density and of population increase on the net wage. Figure 6 in Appendix B plots the net wage on the log of population. Both the plot and the table

seem to suggest a relationship that is at most log-linear and decreasing, but not concave. The log of population squared or cubed are never significant.

The findings when using a variable share of housing in expenditure, even if interesting, are to a large extent due to the way computed this share of housing in expenditure in the first place. Because we did not use actual data, but simply computed a share that linearly increased with the log of population, we eliminated all variations not due to city size that might have been present in the raw data. The strong relationship between share of housing in expenditure and city size was forced by the way the share was computed. Hence, when we multiply housing prices by this share of housing in expenditure, we remove a large part of the variation in living costs, and further increase the difference in urban costs between small and large cities. This explains the strongly significant coefficient obtained in columns 3 and 7, the very high  $R^2$  in columns 3-4 and 7-8, and the much better fit in figures 6b and 6d of Appendix B. The analysis performed with this variable share is still interesting as an illustration of how the allocation of household's expenditures would affect net wages and later quality of life estimates. But it is important to keep in mind this limitation whenever we use it, and to realise that our results might be a mechanical result of the relationship we impose.

Nevertheless, our results could be the sign that cities in France are located on the decreasing half of the bell shaped curve, and are hence oversized.

Table 7: Bell curve: net wage and city size (Urban Areas)

	<i>Dependent variable:</i>							
	ln(mean wage) - $s_w$ *ln(median housing price)							
	Cst share (0.325)		Variable share		Cst share (0.325)		Variable share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Population	0.031 (0.042)	0.092 (0.301)	-0.299*** (0.061)	-0.383 (0.640)	0.008 (0.043)	0.097 (0.300)	-0.307*** (0.062)	-0.424 (0.643)
Square ln Population	-0.002 (0.002)	-0.007 (0.027)	-0.002 (0.003)	0.005 (0.050)	-0.001 (0.002)	-0.009 (0.027)	-0.001 (0.003)	0.008 (0.051)
Cube ln Population		0.0002 (0.001)		-0.0002 (0.001)		0.0002 (0.001)		-0.0002 (0.001)
Land Area controlled	<i>N</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
Observations	608	608	198	198	608	608	198	198
R <sup>2</sup>	0.002	0.002	0.973	0.973	0.010	0.010	0.973	0.973
Adjusted R <sup>2</sup>	-0.001	-0.003	0.973	0.973	0.005	0.004	0.973	0.972

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Housing price of an Urban Area corresponds to the mean of the housing prices of the Urban Units within the area, weighted by population.

We computed the same regression on expected log wage, including unemployment and tax rate. Results are reported in table 19 of Appendix B. Again, the coefficients on log population are never significant when we use a constant share of housing in expenditure. With a variable share, we find a decreasing and slightly concave relationship between net expected log wage and the log city size.

## 5 Indexes of Quality of Life

### 5.1 Testing the parameters in the quality of life equation

The empirical estimation of equations (5) and (7) is extremely sensitive to the choice of parameters on rents and wages. Since it is impossible to perfectly recreate the relative importance that households put on wages and rents, it is up to the researcher to decide whether or not to include a variable, or how exactly to measure another. Albouy, 2008 for instance does not include unemployment in his index, but it might not be a negligible parameter in the French case. Endless discussions could be had on how to best parametrise the compensating differentials equations. We tried to justify our choice of parameters, but we will also check from our data whether or not they are plausible.

By rearranging equations (5) and (7), we can express housing prices as a function of income or expected wages and quality of life:

$$\begin{aligned}\bar{s}_H p_c^H &= \hat{y}_c + \hat{Q}_c \\ \bar{s}_H p_c^H &= \bar{s}_w \hat{w}_c + \hat{Q}_c\end{aligned}$$

Under the perfect mobility assumption, these equation should hold for all cities. Therefore, if we could directly measure quality of life, a regression of housing costs on income should yield the correct parameter on  $\hat{y}_c$  and  $\hat{w}_c$ .

To test the validity of our parametrisation, we regress  $s_H p_c^H$  on our measure of available income. From the theory, we expect to obtain a value of 1. Column 1 of table 8 reports the result of this simple OLS regression.

Table 8: Housing price and available income by Urban Areas

	<i>Dependent variable:</i>					
	0.325 * differential housing price			share housing *differential housing price		
	(1)	(2)	(3)	(4)	(5)	(6)
differential available income	0.401*** (0.080)	0.610*** (0.067)	0.605*** (0.066)	0.123* (0.065)	0.267*** (0.059)	0.280*** (0.060)
Natural amenities	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>N</i>	<i>Y</i>	<i>Y</i>
Artificial amenities	<i>N</i>	<i>N</i>	<i>Y</i>	<i>N</i>	<i>N</i>	<i>Y</i>
Observations	608	606	606	198	198	198
R <sup>2</sup>	0.040	0.472	0.497	0.018	0.435	0.461
Adjusted R <sup>2</sup>	0.039	0.461	0.484	0.013	0.398	0.417

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Rents and housing costs are net of education effects

Artificial amenities include the number of universities, cinemas, and doctors per capita.

Natural amenities include dummies for proximity to the sea or an ocean, as well as climate variables

The estimated coefficient of 0.4 does not correspond to our expectations. But this basic uncontrolled regression suffers from an obvious endogeneity issue: the correct coefficient should only be obtained if we control for quality of life. In column 1, we completely ignore that variable. But since by assumption quality of life is correlated with both income and housing costs, not including it in the equation could be a major cause of bias. In particular, if quality of life is negatively correlated with income, which is a result of our model, then the estimated coefficient in column 1 will be biased downward. It is not possible to directly measure quality of life to include it as an



explanatory variable in the equation and eliminate this bias. Our best option is hence to control for amenities that we expect to be strong determinants of quality of life, in order to try to capture the effect of quality of life on housing cost.

This is what we do in columns 2 and 3 of table 8, introducing first natural amenities (dummies for location on sea or ocean front, climate variables, maximum altitude and slope) and then artificial ones (number of cinemas rooms, universities, and doctors per thousand). As expected, the introduction of amenities as explanatory variables significantly increases the estimate by 50% from 0.4 to 0.6. The  $R^2$  is also multiplied by 10, suggesting that quality of life does affect housing prices through amenities. It is interesting to note that artificial amenities have a much smaller explanatory power than natural ones, and do not significantly affect the estimated coefficient. This might be due to the fact that we use a very limited number of artificial amenities, which, on their own, might not have a very strong explanatory power on quality of life.

Several reasons could explain why the estimate is significantly different from 1, even when introducing all controls. First, it is likely that our selection of amenities is incomplete, and does not measure the whole effect of quality of life on rents. Some quality of life elements are not observable, and we do not have data on others that could have been measured and might be relevant (number of restaurants or pollution levels for instance). Furthermore, the artificial amenities we include are highly endogenous: larger cities for instance might have more cinemas per capita, and also exhibit both higher rents and higher wages; people with higher income might sort into cities with more cultural offer...(explain). Finally, the coefficient on differential income should only be one if we assume that there is indeed perfect mobility, which might simply not be the case for reasons explained in section 3.

Repeating the same regressions with a variable share of housing in expenditures, we obtain results that are even further from our expectations. It is difficult to find a convincing explanation for this result, except for either a misspecification of our parameters (the share of housing in particular, which is obtained from an estimation and not actually observed), or a lack of appropriate controls for the quality of life.

To check our assumptions on the parameters of equation (7), we perform the same pattern of regressions, using the differential of expected wages as an explanatory variable instead of the difference in available income. If our model is correct, we should find an estimate of approximately 0.53, which corresponds to the share of households' income that comes from wages. Results are reported in table 9.

Again, our initial regression yields results that are lower than expected and even negative when no control is included. This negative coefficient suggests that the correlation between quality of life and expected wages is very negative, and stronger than the correlation between quality of life and available income. This result could be explained by the fact that our measure of available income includes a lot of elements that are not directly determined by quality of life (pensions, taxes, external income...), while wages should be more responsive to quality of life differences. Not including quality of life in our equation with expected wages should then lead to a stronger negative bias than with available income.

When including controls for amenities in columns 2 and 3, the results are still significantly different from the value of 0.53 we should expect. This is probably due to the same issues described above, in particular the incompleteness of our set of amenities. This time, repeating the analysis for

Table 9: Housing price and expected wage by Urban Areas

	<i>Dependent variable:</i>					
	0.325 * differential housing price			share housing * differential housing price		
	(1)	(2)	(3)	(4)	(5)	(6)
differential expected wage	-0.137** (0.056)	0.138*** (0.050)	0.146*** (0.050)	-0.086 (0.063)	0.143** (0.063)	0.162** (0.063)
Natural amenities	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>N</i>	<i>Y</i>	<i>Y</i>
Artificial amenities	<i>N</i>	<i>N</i>	<i>Y</i>	<i>N</i>	<i>N</i>	<i>Y</i>
Observations	608	606	606	198	198	198
R <sup>2</sup>	0.010	0.405	0.434	0.009	0.390	0.417
Adjusted R <sup>2</sup>	0.008	0.393	0.420	0.004	0.350	0.369

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Rents and housing costs are net of education effects  
Artificial amenities include the number of universities, cinemas, and doctors per capita.  
Natural amenities include dummies for proximity to the sea or an ocean,  
as well as climate variables

a variable share of housing leads to results that are not very different from the previous ones, and still significantly below our expected result of 0.53.

Those results however, while not particularly encouraging, do not necessarily mean that our chosen parameters are wildly incorrect. It is still possible that by adding some relevant amenities and improving the way we control for quality of life we would obtain higher coefficients.

## 5.2 Quality of Life indexes

After this test our chosen parametrisation, and despite the remaining uncertainty about the correctness of our parameters, we now turn to computing quality of life indexes. using equations (5) and (7). In all of our indexes, we choose to exclude the three cities that share a border with Switzerland and are outliers in terms of available income (Morteau, the French parts of the urban areas of Basel and Geneva). Those cities have the highest available income out of all the urban areas in our sample, but this is due to a labour market effect (proximity with Switzerland) and not to a lower quality of life. Because the housing market is also affected by this high income, we exclude those cities even in our index computed from expected wages.

### Estimating quality of life from available income

We first compute quality of life according to equation (5):  $\widehat{Q}_c = s_H \widehat{p}_c^H - \widehat{y}_c$ , with a constant share  $s_H = 0.325$ . It would be cumbersome to report here the full results of the computation for the 605 urban areas of our sample, but the detailed table can be found in Appendix D. The 15 cities at the top and bottom of this index are reported in table 10. It is apparent that urban areas in southern France, where the weather is mild and the sea is near, are dominating the ranking together with urban areas in the mountain. At the bottom are found urban areas in more rural regions of France, with little natural amenities one could think of. This seems to be coherent with general expectations about quality of life in France.

Figure 1 allows us to better visualise the quality of life estimates. We plot the wages and housing prices differentials for all urban areas, with  $\widehat{p}_c$  on the vertical axis and  $\widehat{y}_c$  on the horizontal axis. The dotted blue line corresponds to the results of our preferred regression, column 3 in table 8. The solid line represents all the combinations of income and housing price such that  $\widehat{Q}_c = 0$ , i.e.

Table 10: Quality of Life in Urban Areas, computed with income and constant share of housing

$$\widehat{Q}_c = 0.325 \times \text{housing} - \text{income}$$

	city	$\widehat{Q}_c$	housing	income
1	Saint-Tropez	0.511	1.828	0.083
2	Chamonix-Mont-Blanc	0.401	1.158	-0.024
3	Sainte-Maxime	0.364	1.202	0.027
4	Bormes-les-Mimosas - Le Lavandou	0.358	1.248	0.048
5	Cavalaire-sur-Mer	0.340	1.147	0.033
6	La Flotte	0.328	1.193	0.060
7	Morzine	0.322	1.211	0.071
8	Menton - Monaco (partie française)	0.322	1.041	0.016
9	Le Grau-du-Roi	0.319	0.795	-0.061
10	Marseillan	0.317	0.751	-0.072
11	Cogolin	0.306	0.927	-0.005
12	Agde	0.303	0.667	-0.086
13	Fréjus	0.291	0.854	-0.013
14	Nice	0.285	0.759	-0.039
15	Saint-Cyprien	0.258	0.602	-0.062
...				
590	Vittel	-0.186	-0.255	0.103
591	Commentry	-0.188	-0.524	0.017
592	Beaumont-de-Lomagne	-0.190	-0.583	0.0004
593	Thouars	-0.191	-0.550	0.012
594	La Souterraine	-0.195	-0.740	-0.045
595	Nogent	-0.198	-0.587	0.007
596	Guéret	-0.199	-0.621	-0.003
597	Gourin	-0.199	-0.478	0.043
598	Pouzauges	-0.199	-0.497	0.038
599	Mamers	-0.201	-0.623	-0.002
600	Decazeville	-0.209	-0.614	0.009
601	Mirecourt	-0.230	-0.738	-0.010
602	Neufchâteau	-0.240	-0.731	0.002
603	Clamecy	-0.242	-0.753	-0.003
604	Aubusson	-0.250	-1.041	-0.088
605	Gueugnon	-0.259	-0.579	0.071

quality of life is at the level of the national average, according to our parameters. It corresponds to the equation  $\bar{s}_H \hat{p}_c^H = \hat{y}_c$ . Cities above the solid line have a quality of life higher than average. The larger the distance between a city and the line, the higher the quality of life.

The graph illustrates the fact that, even if our parametrisation is significantly different from the actual regression line, it does not affect very strongly the quality of life results. Very few urban areas are in-between the two lines and would be considered to have quality of life positive in our estimation but negative if we used the results from the regression of housing costs on income. The discrepancy happens mainly for cities whose expected wage much above or below the average. Most of the cities that are at the very top and bottom of the ranking would likely stay the same, even if we used the coefficients from our regression.

Estimation of equation (5) using a variable share of housing, which only feasible for the 200 largest urban areas, yields a very close ranking. Once again, cities in Southern France, near the Mediterranean or Atlantic shore, score the highest, while urban areas at the bottom of the ranking are in central or North Eastern France. The 15 cities with the highest and lowest scores are reported in tables 11. To compare the results to those of table 10, one needs to keep in mind that the sample in the second table is much smaller, as it contains only 200 cities, out of which only 196 have all the data necessary to estimate a measure of quality of life. The fact that larger cities now

Table 11: Quality of Life in Urban Areas, computed with income and variable share of housing

$$\widehat{Q}_c = 0.325 \times \text{housing} - \text{income}$$

	City	$\widehat{Q}_c$	housing	share	income
1	Paris	0.258	0.661	0.394	0.002
2	Nice	0.225	0.709	0.273	-0.031
3	Marseille - Aix-en-Provence	0.171	0.418	0.299	-0.045
4	Beaucaire	0.166	0.141	0.105	-0.151
5	Montpellier	0.166	0.254	0.247	-0.103
6	Toulon	0.158	0.576	0.249	-0.015
7	Sète	0.146	0.479	0.158	-0.070
8	Arles	0.142	0.208	0.134	-0.114
9	Bayonne (partie française)	0.134	0.514	0.214	-0.025
10	Fréjus	0.134	0.804	0.160	-0.006
11	Narbonne	0.134	0.141	0.158	-0.111
12	Saint-Cyprien	0.127	0.553	0.131	-0.055
13	Avignon	0.126	0.233	0.241	-0.070
14	Menton - Monaco (partie française)	0.122	0.991	0.147	0.024
15	Berck	0.116	0.591	0.135	-0.037
...					
181	Châlons-en-Champagne	-0.063	-0.162	0.152	0.039
182	Longwy (partie française)	-0.067	-0.099	0.147	0.052
183	Thonon-les-Bains	-0.067	0.534	0.157	0.151
184	Montceau-les-Mines	-0.073	-0.415	0.124	0.022
185	Cluses	-0.075	0.391	0.159	0.137
186	Flers	-0.076	-0.519	0.122	0.012
187	Guéret	-0.076	-0.671	0.107	0.004
188	Nevers	-0.079	-0.395	0.162	0.015
189	Chaumont	-0.081	-0.426	0.121	0.029
190	Bar-le-Duc	-0.083	-0.462	0.109	0.032
191	Sarreguemines (partie française)	-0.086	-0.394	0.124	0.037
192	Tulle	-0.087	-0.556	0.106	0.028
193	Cognac	-0.090	-0.239	0.127	0.060
194	Sarrebourg	-0.093	-0.260	0.116	0.063
195	Montluçon	-0.098	-0.578	0.150	0.011
196	Pontarlier	-0.123	0.351	0.105	0.160

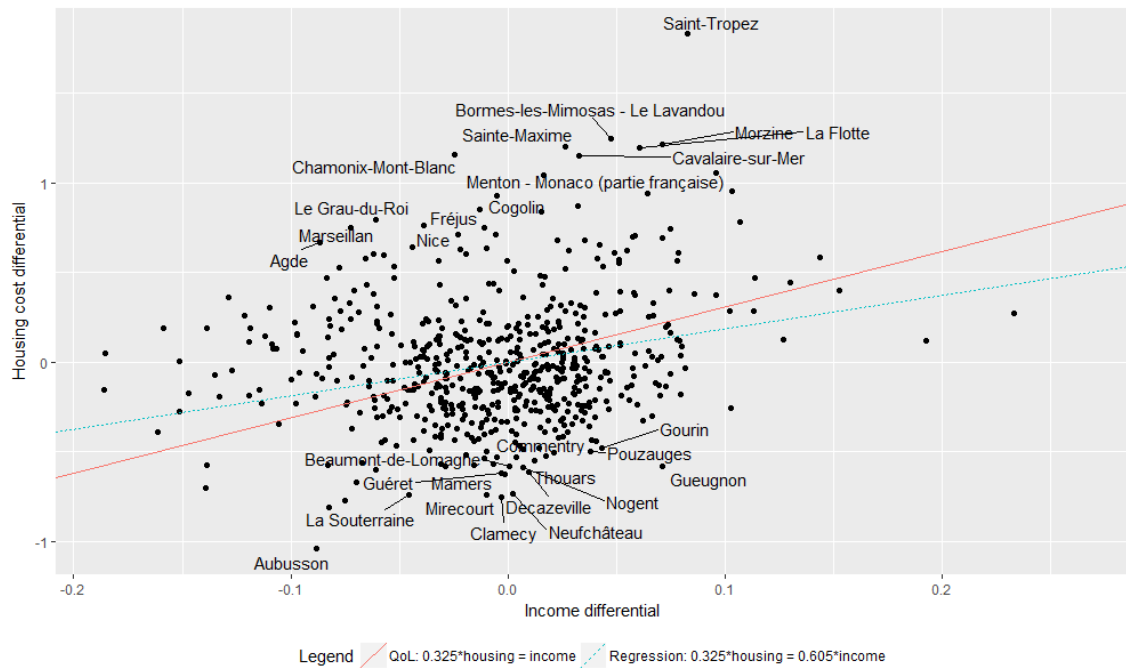


Figure 1: Quality of life: housing costs versus available income

appear at the top of the ranking is partly due to the mechanical effect of removing from the sample the small urban areas that topped the first index. In reality, as shown in figure 7 of Appendix C, when comparing the ranks of only the 200 largest cities under the two methods, the smaller cities are the ones that experience the biggest change in their ranking, and this change goes in both direction.

However, it is true that for the 10 largest cities, using a variable share of housing in expenditures increases the estimated quality of life. This is an automatic result of the way we compute the share as an increasing function of population. This method inflates the measure of total cost of housing for larger cities and hence the quality of life estimate. It is this effect that pulls Paris to the 1st row of the table. This index is still interesting in that it provides insight into how quality of life indexes might underestimate the quality of life in big cities by ignoring one of the way through which households pay more to live in them. However it is constructed in a way that makes it a weaker measure than the one with constant share of housing. Because it relies on a computation rather than a measurement of the share of housing in expenditure, it removes all the unexplained variation in the actual data. This means that this estimation of quality of life is not actually measured from observations on income and housing costs, but also inferred from city size. We do not allow in our computations for the possibility that a large city could have a low share of housing in expenditure, or reversely. For small cities in particular, imposing a share of housing dependent on population seems to incur dramatic changes that make the index unreliable as a measure of quality of life, and more of a thought experiment.

## An alternative index using expected wages

We now turn to estimation of equation (7), which allows us to compute quality of life from expected wages rather than income :  $\hat{Q}_c = \bar{s}_H \hat{p}_c^H - \bar{s}_w \hat{w}_c$ . The results of the first computation with a share of housing in expenditures constant across cities, and a share of wages in income of approximately 0.53 are reported in table 12.

The results are remarkably stable compared to the estimation based on available income: 24 cities are present in both tables 10 and 12, and none of them moves from the top to the bottom or reversely. It is again apparent that cities in sunny areas or high in the mountains have strong quality of life advantages, while urban areas in central France fare less well.

Table 12: Quality of Life in Urban Areas, computed with wage and constant share of housing

$$\widehat{Q}_c = 0.325 \times \text{housing} - 0.535 \times \text{expected wage}$$

	city	$\widehat{Q}_c$	housing	expected wage
1	Saint-Tropez	0.702	1.828	-0.201
2	Sainte-Maxime	0.500	1.202	-0.204
3	Bormes-les-Mimosas - Le Lavandou	0.476	1.248	-0.131
4	Cavalaire-sur-Mer	0.441	1.147	-0.127
5	La Flotte	0.435	1.193	-0.088
6	Ars-en-Ré	0.397	1.053	-0.101
7	Le Grau-du-Roi	0.396	0.795	-0.257
8	Agde	0.386	0.667	-0.316
9	Menton - Monaco (partie française)	0.368	1.041	-0.056
10	Morzine	0.363	1.211	0.057
11	Capbreton	0.363	0.708	-0.248
12	Chamonix-Mont-Blanc	0.353	1.158	0.044
13	Cogolin	0.352	0.927	-0.095
14	Quiberon	0.345	0.778	-0.171
15	Fréjus	0.344	0.854	-0.124
...				
590	Poligny	-0.193	-0.568	0.015
591	Mirecourt	-0.194	-0.738	-0.086
592	Beaumont-de-Lomagne	-0.198	-0.583	0.017
593	Gourin	-0.199	-0.478	0.081
594	Pouzauges	-0.201	-0.497	0.073
595	Torigny-les-Villes	-0.203	-0.301	0.197
596	Decazeville	-0.205	-0.614	0.009
597	Guéret	-0.205	-0.621	0.006
598	Tulle	-0.208	-0.506	0.081
599	La Souterraine	-0.208	-0.740	-0.060
600	Langeac	-0.218	-0.807	-0.082
601	Neufchâteau	-0.219	-0.731	-0.035
602	Clamecy	-0.231	-0.753	-0.025
603	Nogent	-0.242	-0.587	0.096
604	Gueugnon	-0.297	-0.579	0.203
605	Aubusson	-0.300	-1.041	-0.072

Figure 2 draws our estimated housing cost differential on the expected wage differentials. As before, the solid red line corresponds to the combinations of rents and expected wages which lead to an average quality of life, according to our equation (7). The other two lines correspond to the result of columns 3 and of table ??.

Finally, our last index of quality of life is based on expected wages differentials, and uses the variable share of housing in expenditures we have computed earlier. The best and worst ranked cities are reported in table 13. The results still seem coherent with general expectations about

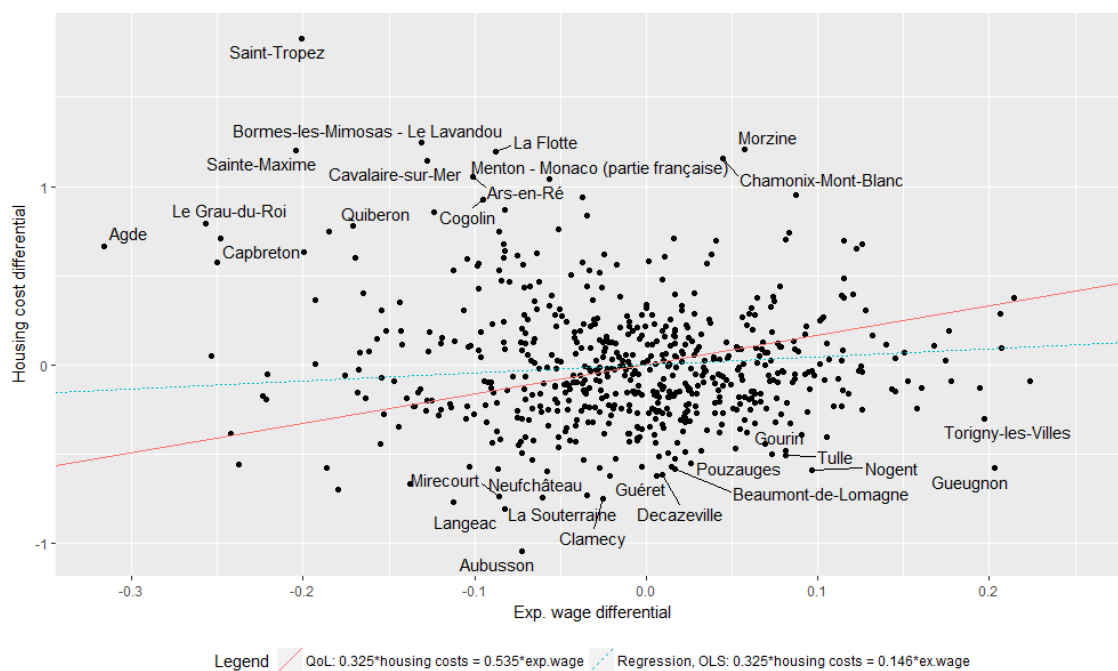


Figure 2: Quality of life: housing costs versus expected wage

quality of life in France, with cities on the shores over-represented in the top 15, and industrial or rural towns in the bottom part.

As before, this new index inflates the quality of life estimated for very large cities, and has a more uncertain effect on smaller urban areas, as illustrated in Figure 7 of appendix C. However, one needs again to keep in mind that this index is only computed for the largest 200 cities, for which we have been able to calculate a share of housing in expenditures. This means that smaller towns in the mountains for instance are automatically excluded, and that the large proportion of big cities in the table is partly due to this effect.

As explained previously, this imposed relationship between city size and share of housing can be considered a weakness of the index. For this reason, our preferred index is still the one that uses a constant share of housing. However, we recognise that using the average share of housing is not a perfect specification either, as it erases a part of the variation in housing expenditures. It is likely that our quality of life estimates are biased downwards for large cities when using this constant share, since it underestimates actual housing expenditures of households. But since the whole model is defined in terms of deviation from the average, considering only the deviation in prices for a given average share of housing expenditures should still provide a good estimate of quality of life, without "*forcing*" a relationship with city size as we do when we compute the variable share of housing.

Our quality of life index seems not to be too sensitive to the choice of expected wages or available income as a measure of income levels which is reassuring for the validity of our chosen parameters, and hence for the strength of our estimates. We verify whether this observation that the rankings

Table 13: Quality of Life in Urban Areas, computed with wage and variable share of housing

$$\widehat{Q}_c = \text{share} \times \text{housing} - 0.535 \times \text{expected wage}$$

	city	$\widehat{Q}_c$	housing	share	expected wage
1	Paris	0.242	0.661	0.394	0.034
2	Nice	0.211	0.709	0.273	-0.034
3	Fréjus	0.185	0.804	0.160	-0.106
4	Toulon	0.168	0.576	0.249	-0.046
5	Menton - Monaco (partie française)	0.166	0.991	0.147	-0.039
6	Saint-Cyprien	0.154	0.553	0.131	-0.152
7	Marseille - Aix-en-Provence	0.149	0.418	0.299	-0.045
8	Bayonne (partie française)	0.139	0.514	0.214	-0.054
9	Montpellier	0.136	0.254	0.247	-0.137
10	Sète	0.126	0.479	0.158	-0.095
11	La Teste-de-Buch - Arcachon	0.124	0.629	0.141	-0.066
12	Bordeaux	0.119	0.390	0.281	-0.017
13	Berck	0.115	0.591	0.135	-0.065
14	Royan	0.108	0.503	0.128	-0.081
15	La Rochelle	0.104	0.457	0.198	-0.026
...					
181	Chalon-sur-Saône	-0.069	-0.267	0.176	0.042
182	Saint-Lô	-0.070	-0.229	0.130	0.075
183	Longwy (partie française)	-0.070	-0.099	0.147	0.104
184	Nevers	-0.070	-0.395	0.162	0.012
185	Cognac	-0.072	-0.239	0.127	0.079
186	Lons-le-Saunier	-0.074	-0.241	0.136	0.077
187	Le Creusot	-0.077	-0.382	0.115	0.062
188	Montceau-les-Mines	-0.080	-0.415	0.124	0.053
189	Niort	-0.080	-0.201	0.183	0.080
190	Sarrebouurg	-0.083	-0.260	0.116	0.099
191	Dole	-0.084	-0.133	0.141	0.121
192	Guéret	-0.084	-0.671	0.107	0.023
193	Montluçon	-0.087	-0.578	0.150	-0.0002
194	Chaumont	-0.092	-0.426	0.121	0.076
195	Flers	-0.100	-0.519	0.122	0.069
196	Tulle	-0.112	-0.556	0.106	0.099

are stable is correct by computing the correlations between rankings in all four indexes, reported in table 14. The very high correlations seem to justify our choice of parameters and confirm that, when weighted correctly, available income and expected wages are broadly equivalent and both relevant to the study of households' location choices. In particular, the correlation between rankings in our two preferred indexes (wage and income with constant share of housing in expenditures) is very high, at 0.961.

## 6 The determinants of Quality of Life

Based on theory of amenities by Rosen (1979) and Roback (1982) and following the method of Albouy (2008), we can now perform a second-step estimation to find out the valuation of certain amenities by households. The model is obtained from Albouy (2008).

Recall that we defined quality of life to be an index of amenities, of the form  $Q_c = \tilde{Q}(A_c^k)$ . If we observed all the relevant amenities, our quality of life estimate  $\hat{Q}_c = -\frac{1}{y} \frac{\partial E}{\partial Q_c} dQ_c$  could then be expressed as a function of amenities which could be estimated by regression of the following



Table 14: Correlation matrix between QoL rankings (Urban Areas)

		Income		Wage	
Share:		Variable	Constant	Variable	Constant
Income	Variable	1	0.913	0.828	0.767
	Constant	–	1	0.867	0.961*
Wage	Variable	–	–	1	0.942
	Constant	–	–	–	1

*Note:* \*This correlation was computed on the full sample of all urban areas. All other correlations are based on the subsample of 200 largest cities, because indexes based on variable shared of housing are only available for those 200 urban areas.

equation:

$$\hat{Q}_c = \sum_k \pi^k A_c^k + \mu^k$$

where  $\pi^k = -\frac{1}{y} \frac{\partial E}{\partial Q_c} \frac{\partial \hat{Q}}{\partial A^k}$  represents the valuation of each amenity by households.

But in reality, quality of life depends on a very high number of amenities, many of them unobservable. A simple OLS regression will then yield result that are likely to suffer from strong bias, and cannot be directly interpreted as the monetary valuation of an amenity.

Nevertheless, such a regression could still be informative, and it would be reassuring if the coefficient on amenities at least had the sign that would be expected from general assumptions of quality of life.

We perform this second-step regression using our two preferred indexes of quality of life: income and wages, with a constant share of housing expenditures. The reasons why these specifications seem stronger to us were already exposed above. Furthermore, using them allows us to perform our regression on the full sample of urban areas, and not only on the 200 largest cities. Working on the restricted sample could prove particularly particularly since it will exclude urban areas where land development is complicated by some external characteristic, which could also be correlated with quality of life: for instance most urban areas high in the mountain are not in the subsample of 200 largest cities.

We control for two types of amenities: natural and artificial ones. Our natural amenities include climate variables that measure temperatures and precipitations in winter. We expect winter temperatures to have a positive coefficient, which would traduce preference for warmer winters. Rains should have a negative coefficient. We include the maximum altitude and slope as control for being in the mountain. In theory, we expect the maximum altitude to be attractive to households and have a positive effect on quality of life, while slope could have a negative effect due to the increased difficulty of living in such an area. But it could also be argued that altitude means colder temperatures and isolation, while slope signifies proximity to the mountains which is enough to improve quality of life. In that case the coefficients would be reversed.

We include controls for geography in the form of dummies for sharing a border with a neighbouring country (Switzerland, Belgium, Luxembourg, Germany or Spain). While these dummies

are theoretically intended to capture labour or housing market effects, they are very likely to capture other geographical characteristics (being in or close to the Alps for Switzerland for instance), and their coefficient is complicated to predict.

We also control for proximity to the main bodies of water in France (Mediterranean Sea, Atlantic Ocean, and British Channel), in two different ways: distance to the shore, or dummy for being on the shore. The distance variable is likely to capture a lot of climatic characteristics. Distance to the Mediterranean Sea for instance could broadly be interpreted as proximity to southern France and its mild climate. The dummy on the other hand might be too restrictive: urban areas that do not have a direct access to the beach but are in close proximity to it might still benefit from it in their quality of life.

Artificial amenities are more problematic to select and interpret, as they are highly endogenous. We chose to use three variables, for three types of amenities: the number of cinema rooms per thousand inhabitant for cultural amenities, the number of universities per thousand inhabitants for educational amenities, and the number of general practitioners for health related amenities. Our measure of universities does not only include public *universités*, but the number of higher education establishment in general (including business and engineering schools which are not considered universities in France).

We fully acknowledge that this selection is likely to be too restricted, and that a lot of potentially measurable amenities would deserve to be included: criminality rates, number of restaurants and bar, air quality, density of the transport network, number of parks... The list of omitted variables is very long. We would have liked to be able to include more, but did not have access to the necessary data. However, we were also wary of including too many variables which might be collinear and decrease the precision of our estimates.

Results of the second-step regression are reported in tables 15 (for the quality of life estimate based on income) and 16 (for the quality of life estimate based on expected wage).

We first include the climatic and geographic characteristics of urban area alone, in column 1 of both tables. Rain and temperature are both significant and have the expected sign meaning that households do value areas with milder winter. Coefficients for slope and altitude are imprecise and non-significant, which probably translates the balance between enjoying the landscapes in the mountain, and being isolated from other cities. Those variables alone already explain 10 to 15% of the variance across urban areas.

Artificial amenities, introduced on their own in column 2, have less explanatory power, and coefficients that are not all going in the expected direction. Cinemas and doctors per thousand both have the expected positive sign which implies that households value cultural offer and easy accessibility to health services. Universities however have a strong significant negative effect on our estimates of quality of life, which does not go well with our previous expectation that households should value easy access to education. But the result could be explained by the endogeneity of artificial amenities. It is possible that more skilled households sort into cities with more educational offer, or that cities with highly skilled inhabitants value education more and create more universities. If unobserved skills are positively correlated with our imprecise measure of education, then such cities should have both higher available income (or higher expected wages) and more universities. Since a high income leads to a decrease in estimated quality of life, this could explain why educational facilities are negatively correlated with quality of life. Another potential

explanation could argue that urban areas where there is a large number of universities benefit from positive externalities of learning, with university students or graduates sharing the skills they learned with their coworkers, family or neighbours. This would again inflate available income and wages through unobserved skills, and lower the quality of life estimate.

Combining climate and amenities in column 3 does not significantly change the findings on the valuation of those amenities.

We then introduce purely geographical variables in columns 4 to 9: dummies for sharing a border with another country, and distance or dummies for being on the shore. The estimated valuation of distance to the main bodies of water is much less precise than the coefficients on the dummies for being on the shore. In general, distance to the shore only matters for the Atlantic (column 4 of table 16 is the only exception, with people valuing distance to the British Channel). Using distance also makes the winter rains become insignificant in columns 5 and 6 of both tables, which suggests that the distance variable indeed captures some climate characteristics.

Our preferred explanatory variable is hence dummies for being on the shore, which have much stronger and clearer coefficients, and also have the advantage of having more than twice the explanatory power on variation in quality of life across cities. Using dummies show that people highly value close proximity to the shore, with a strong preference for the Mediterranean sea, followed by the Atlantic and the British Channel.

The dummy for sharing a border with Switzerland is strongly positive and significant. This is probably due to proximity to the Alps, especially since the labour market effect of being near Switzerland should imply higher income, and hence lower quality of life. Except for Switzerland, when quality of life is computed from expected wages, sharing a border with another country does not significantly impact quality of life (columns 7 to 9 of table 16). Indeed, our measure of wages only concerns salaries from French firms and hence does not take into account the income of cross-border workers.

This income from households living in France but working across the border is captured in the measure of quality of life from available income. This might explain the negative impact of sharing the border with Germany, in columns 7 to 9 of table 15, since the high income of cross-border workers would decrease the quality of life estimate. The negative coefficient could also simply capture the potential unattractiveness of the Rhine region. The positive coefficient on the Belgium/Luxembourg dummy is harder to explain. While wages in Belgium might not be much higher than in France, and cross-border workers might not bias the estimate so much, there are a large amount of people working in Luxembourg and living in France with the income they earn there. However, there are only 14 urban areas that share a border with Belgium and Luxembourg, and it is possible that they all have very positive amenities that we do not measure and that are hence captured in the coefficient for the dummy.

Introducing geographical variables in the form of dummies changes our findings on climate and artificial amenities only marginally. Slope becomes significant in table 15, but has a weak effect on quality of life. Other variables keep their signs and their values do not experience dramatic changes.

Overall, our findings suggest that households strongly value mild winter and proximity to the shore and the Alps, as well as cultural offer and access to health services. All coefficients have the "correct" sign and are reassuring towards the quality of our estimates of quality of life, except for

universities, whose obtained valuation might be explained by endogeneity issues.

Table 15: Predictive power of amenities on Quality of Life (computed from income)

	<i>Dependent variable:</i>								
	(1)	(2)	(3)	(4)	$\widehat{QoL}$ Distance	(6)	(7)	Dummy	(9)
Maximum altitude	0.00003 (0.00004)		0.00002 (0.00004)		-0.00004 (0.00004)	-0.00004 (0.00004)		0.00000 (0.00004)	-0.00001 (0.00004)
Slope	0.0001* (0.00005)		0.0001** (0.00005)		0.0001*** (0.00005)	0.0001*** (0.00005)		0.0001** (0.00004)	0.0001** (0.00004)
Rain, winter	-0.001*** (0.0003)		-0.001*** (0.0003)		0.0004 (0.0004)	0.0003 (0.0004)		-0.002*** (0.0003)	-0.002*** (0.0003)
Temperature, winter	0.019*** (0.003)		0.019*** (0.003)		0.036*** (0.003)	0.036*** (0.003)		0.009*** (0.003)	0.009*** (0.002)
Universities per thousand		-0.209** (0.090)	-0.177** (0.083)			-0.107 (0.076)			-0.138* (0.071)
Cinemas per thousand		0.087** (0.036)	0.084** (0.034)			0.102*** (0.032)			0.088*** (0.030)
Doctors per thousand		0.032*** (0.009)	0.028*** (0.009)			0.021*** (0.008)			0.024*** (0.007)
Dist. British Channel				0.00002 (0.0001)	-0.00004 (0.0001)	-0.00005 (0.0001)			
Dist. Mediterranean				-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)			
Dist. Atlantic				0.0001** (0.00003)	0.0003*** (0.00004)	0.0003*** (0.00004)			
Dummy British Channel							0.058*** (0.019)	0.076*** (0.018)	0.081*** (0.018)
Dummy Mediterranean							0.283*** (0.021)	0.241*** (0.021)	0.243*** (0.021)
Dummy Atlantic							0.110*** (0.015)	0.140*** (0.016)	0.136*** (0.016)
Dummy Switzerland				0.042 (0.036)	0.113*** (0.032)	0.090*** (0.032)	0.094*** (0.031)	0.102*** (0.031)	0.080*** (0.030)
Dummy Belgium/Luxembourg				0.041 (0.036)	0.022 (0.032)	0.025 (0.032)	0.034 (0.031)	0.063** (0.030)	0.068** (0.029)
Dummy Germany				-0.086** (0.041)	-0.086** (0.037)	-0.077** (0.037)	-0.058* (0.035)	-0.073** (0.033)	-0.064** (0.033)
Dummy Spain				0.105** (0.043)	0.094** (0.038)	0.082** (0.038)	0.068* (0.038)	0.027 (0.035)	0.011 (0.035)
R <sup>2</sup>	0.150	0.042	0.179	0.111	0.295	0.317	0.314	0.410	0.431
Adjusted R <sup>2</sup>	0.144	0.037	0.170	0.101	0.282	0.301	0.306	0.399	0.417

Note:

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table 16: Predictive power of amenities on Quality of Life (computed from expected wage)

	<i>Dependent variable:</i>								
	(1)	(2)	(3)	(4)	$\widehat{QoL}$ Distance	(6)	(7)	Dummy	(9)
Maximum altitude	0.00005 (0.00005)		0.00004 (0.00005)		-0.00001 (0.00005)	-0.00001 (0.00005)		0.00001 (0.00004)	0.00000 (0.00004)
Slope	0.0001 (0.0001)		0.0001 (0.0001)		0.0001 (0.0001)	0.0001 (0.0001)		0.0001 (0.00004)	0.0001 (0.00004)
Rain, winter	-0.001** (0.0003)		-0.001*** (0.0003)		0.0002 (0.0004)	0.0001 (0.0004)		-0.002*** (0.0003)	-0.002*** (0.0003)
Temperature, winter	0.017*** (0.003)		0.017*** (0.003)		0.038*** (0.004)	0.038*** (0.004)		0.005** (0.003)	0.005** (0.003)
Universities per thousand		-0.319*** (0.097)	-0.295*** (0.093)			-0.193** (0.084)			-0.225*** (0.073)
Cinemas per thousand		0.098** (0.039)	0.096** (0.038)			0.100*** (0.035)			0.086*** (0.031)
Doctors per thousand		0.030*** (0.010)	0.026*** (0.010)			0.020** (0.009)			0.021*** (0.008)
Dist. British Channel				0.0002** (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)			
Dist. Mediterranean				0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)			
Dist. Atlantic				0.00002 (0.00003)	0.0003*** (0.00005)	0.0003*** (0.00004)			
Dummy British Channel							0.066*** (0.019)	0.086*** (0.018)	0.092*** (0.018)
Dummy Mediterranean							0.319*** (0.021)	0.290*** (0.021)	0.292*** (0.021)
Dummy Atlantic							0.166*** (0.015)	0.204*** (0.017)	0.199*** (0.016)
Dummy Switzerland				0.143*** (0.039)	0.222*** (0.036)	0.198*** (0.036)	0.203*** (0.032)	0.205*** (0.031)	0.181*** (0.031)
Dummy Belgium/Luxembourg				-0.002 (0.040)	-0.024 (0.036)	-0.020 (0.035)	0.007 (0.032)	0.028 (0.030)	0.033 (0.030)
Dummy Germany				-0.042 (0.045)	-0.049 (0.041)	-0.038 (0.041)	0.009 (0.035)	-0.014 (0.034)	-0.004 (0.034)
Dummy Spain				0.098** (0.046)	0.092** (0.042)	0.080* (0.042)	0.055 (0.038)	0.024 (0.036)	0.007 (0.036)
R <sup>2</sup>	0.094	0.031	0.119	0.136	0.328	0.345	0.300	0.345	0.362
Adjusted R <sup>2</sup>	0.088	0.026	0.109	0.126	0.316	0.330	0.292	0.333	0.346

*Note:*

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

## Conclusion

Computing a quality of life index, and estimating the valuation of amenities households necessarily involves many simplifications. While non-academic literature is brimming with such rankings of the best places to live, to study or to work, it is complicated to create a theory-grounded index that yields results coherent with the popular literature.

This paper adapts the methodology of Albouy (2008) and applies it to French data. We find that using a direct measure of available income or computing an expected wage taking into account unemployment and taxes both produce plausible quality of life indexes, which are coherent with general notions on quality of life. Cities in Southern France or in close proximity to the mountains fare best, while urban areas in rural isolated regions rank lowest in our indexes.

Our results seem to suggest that natural amenities are such as climate and geographical locations are the strongest determinants of quality of life. Artificial amenities, while significant, do not seem to explain a large part of the variation in quality of life across cities. However this result might be due to endogeneity issues and could be improved by replicating the analysis with more complete data on amenities.

On the way to computing those quality of life indexes, we obtained wages and rent gradients that were coherent with the previous literature on the subject. We also tried to estimate how net wages evolved with city size, and found a decreasing relationship which might be a sign pointing towards French cities being oversized. Further research on the subject would be needed to confirm that result.

Overall, this paper is a first try at computing a quality of life index on French data using hedonic methods. It could be greatly improved by using more detailed data, particularly on housing prices for which we only have a very raw measure.

The model could also be extended to examine household heterogeneity in observable characteristics such as education or life-cycle value differently wages, rents and amenities.

## References

- Albouy, David (2008). *Are big cities bad places to live? Estimating quality of life across metropolitan areas*. Working paper 14472, National Bureau of Economic Research.
- Albouy, David and Bert Lue (2015). “Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life”. *Journal of Urban Economics* 89, pp. 74–92.
- Berger, Mark C. and Glenn C. Blomquist (1992). “Mobility and destination in migration decisions: The roles of earnings, quality of life, and housing prices”. *Journal of Housing Economics* 2.1, pp. 37–59.
- Berger, Mark C., Glenn C. Blomquist, and Klara Sabirianova Peter (2008). “Compensating differentials in emerging labor and housing markets: Estimates of quality of life in Russian cities”. *Journal of Urban Economics* 63.1, pp. 25–55.
- Berger, Mark C., Glenn C. Blomquist, and Werner Waldner (1987). “A revealed-preference ranking of quality of life for metropolitan areas”. *Social Science Quarterly* 68.4, p. 761.
- Blomquist, Glenn C., Mark C. Berger, and John P. Hoehn (1988). “New estimates of quality of life in urban areas”. *The American Economic Review*, pp. 89–107.
- Buettner, Thiess and Alexander Ebertz (2009). “Quality of life in the regions: results for German Counties”. *The annals of regional science* 43.1, pp. 89–112.
- Chen, Yong and Stuart S. Rosenthal (2008). “Local amenities and life-cycle migration: Do people move for jobs or fun?” *Journal of Urban Economics* 64.3, pp. 519–537.
- Cheshire, Paul C. and Stefano Magrini (2006). “Population growth in European cities: weather matters—but only nationally”. *Regional studies* 40.1, pp. 23–37.
- Colombo, Emilio, Alessandra Michelangeli, and Luca Stanca (2014). “La Dolce Vita: Hedonic estimates of quality of life in Italian cities”. *Regional Studies* 48.8, pp. 1404–1418.
- Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon (2008). “Spatial wage disparities: Sorting matters!” *Journal of Urban Economics* 63.2, pp. 723–742.
- (2012). “The costs of agglomeration: Land prices in French cities”.
- Combes, Pierre-Philippe and Laurent Gobillon (2015). “The empirics of agglomeration economies”. In: *Handbook of regional and urban economics*. Vol. 5. Elsevier, pp. 247–348.
- Handbury, Jessie and David E Weinstein (2014). “Goods prices and availability in cities”. *The Review of Economic Studies* 82.1, pp. 258–296.
- Harris, John R. and Michael P. Todaro (1970). “Migration, unemployment and development: a two-sector analysis”. *The American economic review* 60.1, pp. 126–142.
- Henderson, J Vernon (1974). “The sizes and types of cities”. *The American Economic Review* 64.4, pp. 640–656.



- Prix Immobilier France : Prix au m<sup>2</sup> par ville* / *Immobilier.notaires.fr* (2018). URL: <https://www.immobilier.notaires.fr/fr/prix-immobilier> (visited on 05/21/2018).
- Revenus des ménages - Tableaux de l'économie française* / *Insee* (2018). URL: <https://www.insee.fr/fr/statistiques/3303428?sommaire=3353488> (visited on 05/17/2018).
- Roback, Jennifer (1982). "Wages, Rents, and the Quality of Life". *Journal of Political Economy* 90.6, pp. 1257–1278. ISSN: 0022-3808.
- Rosen, Sherwin (1979). "Wage-based indexes of urban quality of life". *Current issues in urban economics* 3, pp. 324–345.
- Rosenthal, Stuart S and William C Strange (2008). "The attenuation of human capital spillovers". *Journal of Urban Economics* 64.2, pp. 373–389.
- Tiebout, Charles M (1956). "A pure theory of local expenditures". *Journal of political economy* 64.5, pp. 416–424.

## A Visualisation of the wage and rent gradients

This appendix presents graphically the results of our regressions of rents, wages and income on population. The name of the cities in the top and bottom percentile in terms of rents (resp. wages and income) are represented on the graph.

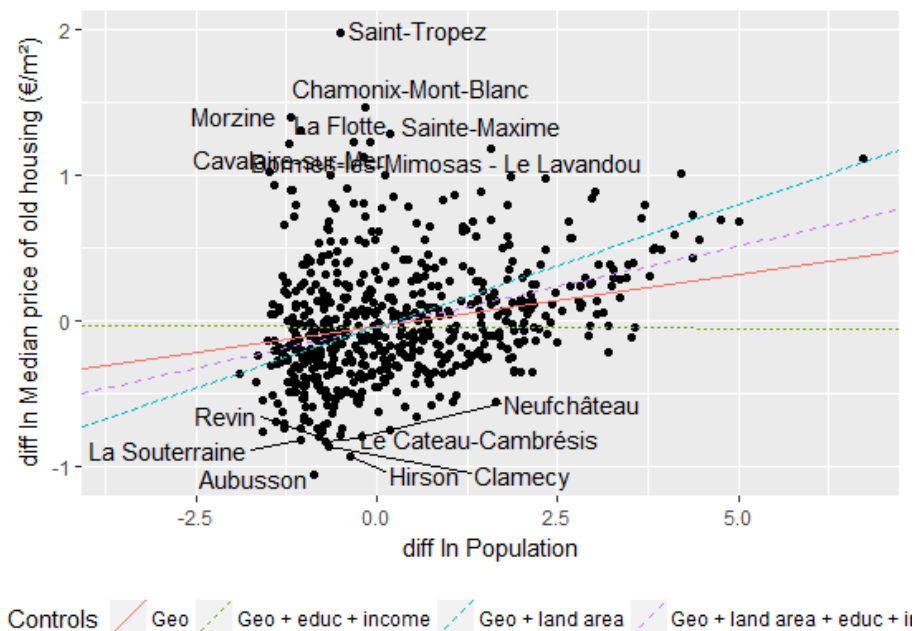


Figure 3: Housing price and city size

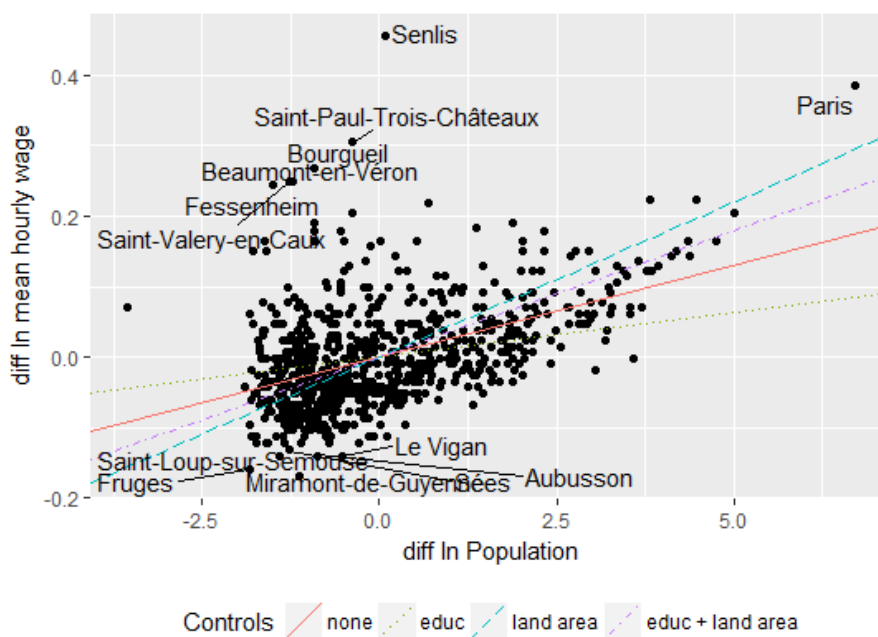


Figure 4: Mean wage and city size

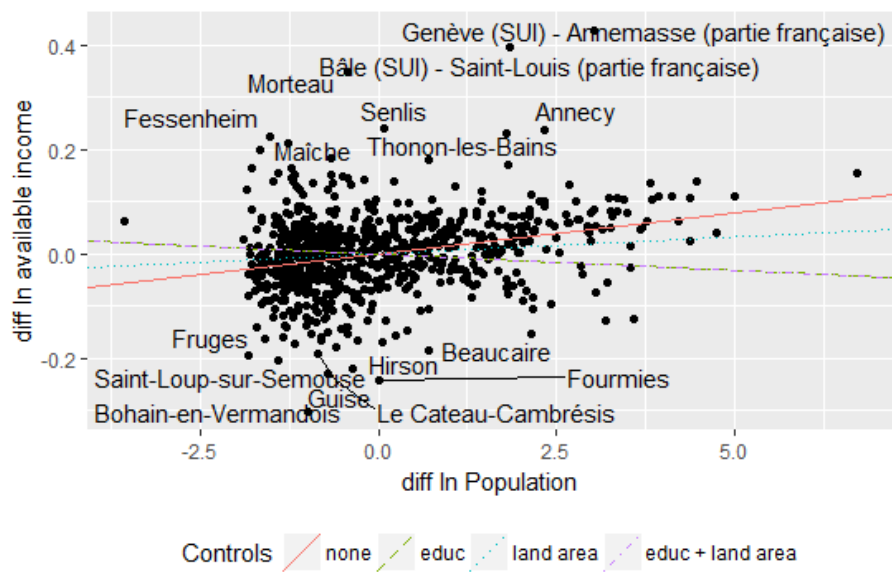


Figure 5: Available income an city size

The two lines in figure 5 with control for education and for land area and education have such close coefficients that they are indistinguishable from each other on the graph.

## B Further insights into the bell curve

This appendix is a complement to the bell curve analysis in section 4. It provides evidence that while rents exhibit at most a log-linear relationship with city size, the relationship between log mean wage and log population is slightly convex.

Table 17: Quadratic and Cubic terms in the wage equation (Urban Areas)

	<i>Dependent variable:</i>					
	Fringe adjustment			Land area controlled		
	(1)	(2)	(3)	(4)	(5)	(6)
log Population	0.013*** (0.002)	-0.069*** (0.017)	-0.031 (0.107)	0.034*** (0.003)	-0.036** (0.017)	-0.004 (0.103)
square log Population		0.004*** (0.001)	0.0004 (0.010)		0.003*** (0.001)	0.0003 (0.010)
cube log Population			0.0001 (0.0003)			0.0001 (0.0003)
ln Land area				-0.026*** (0.003)	-0.025*** (0.003)	-0.025*** (0.003)
Education	0.806*** (0.063)	0.801*** (0.062)	0.800*** (0.062)	0.860*** (0.061)	0.852*** (0.060)	0.852*** (0.060)
Observations	759	759	759	759	759	759
R <sup>2</sup>	0.375	0.394	0.394	0.423	0.436	0.436
Adjusted R <sup>2</sup>	0.373	0.392	0.391	0.420	0.433	0.432

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 18: Quadratic and Cubic terms in the housing price equation (Urban Areas)

	<i>Dependent variable:</i>					
	log Median price of old housing per square meter			Land area controlled		
	(1)	(2)	(3)	(4)	(5)	(6)
log Population	0.017* (0.010)	-0.124 (0.093)	0.896 (0.676)	0.156*** (0.019)	0.108 (0.092)	0.825 (0.639)
Square log Population		0.007 (0.004)	-0.086 (0.061)		0.002 (0.004)	-0.063 (0.058)
Cube log Population			0.003 (0.002)			0.002 (0.002)
log Land area				-0.163*** (0.019)	-0.162*** (0.019)	-0.161*** (0.019)
log Income	2.407*** (0.249)	2.401*** (0.249)	2.411*** (0.249)	2.351*** (0.235)	2.350*** (0.235)	2.357*** (0.235)
Education	2.138*** (0.486)	2.100*** (0.486)	2.075*** (0.486)	2.436*** (0.460)	2.421*** (0.461)	2.402*** (0.461)
Geography	Y	Y	Y	Y	Y	Y
Observations	608	608	608	608	608	608
R <sup>2</sup>	0.602	0.603	0.605	0.647	0.647	0.648
Adjusted R <sup>2</sup>	0.591	0.592	0.593	0.636	0.636	0.636

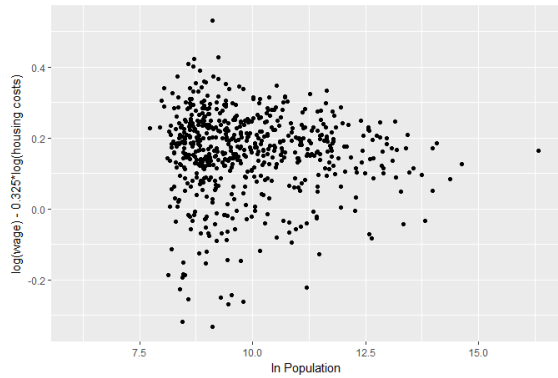
Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

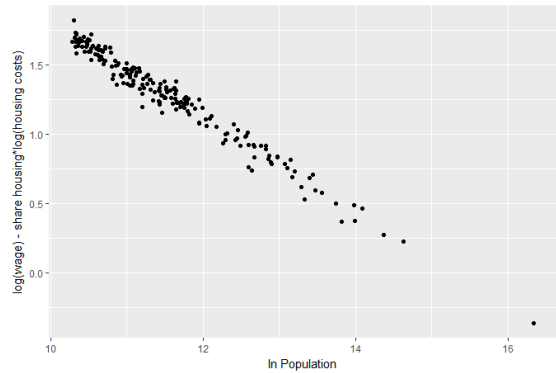
Housing price of an Urban Area corresponds to the mean of the housing prices of the Urban Units within the area, weighted by population. Controlling for geography as distance from France's neighbouring countries, seas, oceans and main rivers.

Figure 6 graphically represents the net wage and net expected wage per city on population. It illustrates both the slightly decreasing nature of the relationship, and the way using a variable share of housing removes a large portion of the variation from the data, for reasons presented in section 4.

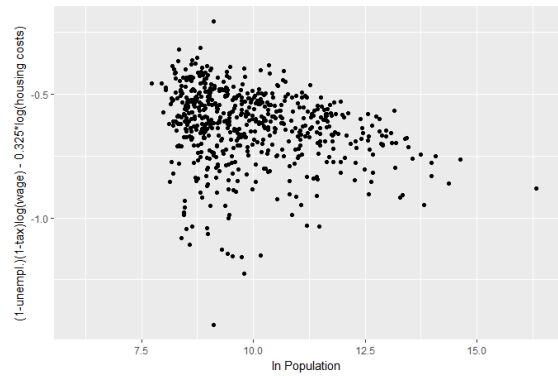
Figure 6: Bell curve: graphic representation



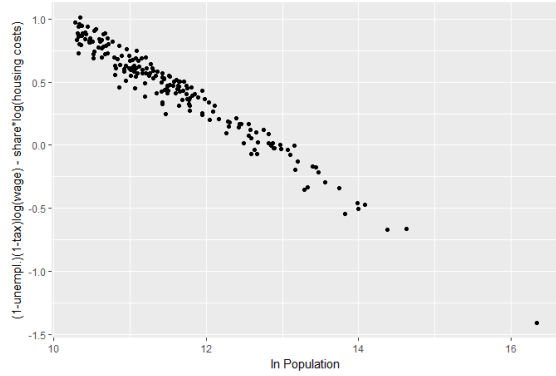
(a) Wage and constant share of housing in expenditures



(b) Wage and variable share of housing in expenditures (200 largest urban areas)



(c) Expected wage and constant share of housing in expenditures



(d) Expected wage and variable share of housing in expenditures (200 largest urban areas)

Finally, table 19 presents evidence that using a variable share of housing in expenditure unveils a slightly concave relationship between net *expected* log wages and log population.

Table 19: Bell curve: net expected wage and city size (Urban Areas)

<i>Dependent variable:</i>								
(1-tax)(1-unempl.)*ln(mean wage) – $s_w$ *ln(median housing price)								
	Cst share (0.325)		Variable share		Cst share (0.325)		Variable share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In Population	0.027 (0.051)	-0.411 (0.371)	-0.199** (0.080)	-0.522 (0.830)	-0.059 (0.051)	-0.392 (0.357)	-0.263*** (0.075)	-0.868 (0.770)
Square ln Population	-0.002 (0.002)	0.037 (0.033)	-0.007** (0.003)	0.019 (0.065)	-0.001 (0.002)	0.029 (0.032)	-0.006* (0.003)	0.042 (0.061)
Cube ln Population		-0.001 (0.001)		-0.001 (0.002)		-0.001 (0.001)		-0.001 (0.002)
Land Area controlled	<i>N</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
Observations	608	608	198	198	608	608	198	198
R <sup>2</sup>	0.055	0.058	0.962	0.962	0.125	0.127	0.967	0.967
Adjusted R <sup>2</sup>	0.052	0.053	0.961	0.961	0.121	0.121	0.967	0.967

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

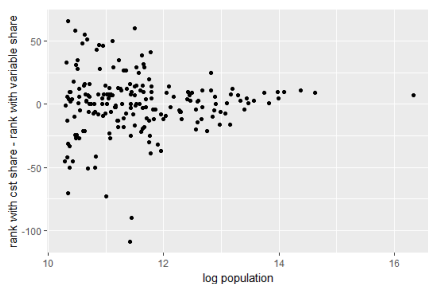
Housing price of an Urban Area corresponds to the mean of the housing prices of the Urban Units within the area, weighted by population.

Housing prices, wages, tax rate and unemployment are net of education.

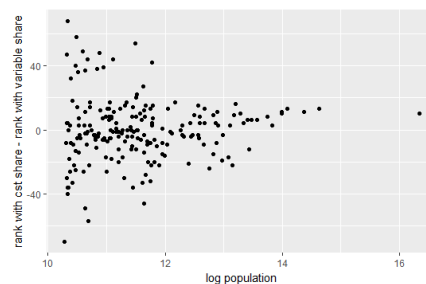
## C Quality of life: difference between rankings

This appendix complements the analysis in section 5. It shows that using a variable or a constant share of housing incurs the most dramatic changes in ranking for the smaller cities in the panel, and that larger cities are only slightly advantaged by using a higher share of housing.

A point being above the horizontal axis means that the city in question went up in the ranking when using the variable share of housing.



(a) Using available income



(b) Using expected wage

Figure 7: Changes in the quality of life rankings, with constant or variable share of housing

## D Quality of life: full rankings across Urban Areas

This appendix presents the quality of life ranking of all French urban areas for which we have data, according to the methodology developed in section 5. Cities are ordered based on their ranking in the specification from income and with a constant share of housing in expenditure. The ranks in the specifications with the constant share of housing are out of 605. With a variable share of housing, 196 urban areas are ranked.

Table 20: Quality of Life in Urban Areas

city	Constant share of housing				Variable share of housing			
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Saint-Tropez	0.511	1	0.702	1				
Chamonix-Mont-Blanc	0.401	2	0.353	12				
Sainte-Maxime	0.364	3	0.500	2				
Bormes-les-Mimosas - Le Lavandou	0.358	4	0.476	3				
Cavalaire-sur-Mer	0.340	5	0.441	4				
La Flotte	0.328	6	0.435	5				
Morzine	0.322	7	0.363	10				
Menton - Monaco (partie française)	0.322	8	0.368	9	0.122	14	0.166	5
Le Grau-du-Roi	0.319	9	0.396	7				
Marseillan	0.317	10	0.343	16				
Cogolin	0.306	11	0.352	13				
Agde	0.303	12	0.386	8				
Fréjus	0.291	13	0.344	15	0.134	10	0.185	3
Nice	0.285	14	0.274	24	0.225	2	0.211	2
Saint-Cyprien	0.258	15	0.287	23	0.127	12	0.154	6
Dives-sur-Mer	0.256	16	0.290	21	0.067	32	0.099	16
Aigues-Mortes	0.254	17	0.289	22				
Capbreton	0.253	18	0.363	11				
Port-la-Nouvelle	0.252	19	0.320	19				
Berck	0.252	20	0.252	27	0.116	15	0.115	13
Noirmoutier-en-l'Île	0.251	21	0.328	17				
Banyuls-sur-Mer	0.250	22	0.249	28				
Sète	0.250	23	0.232	34	0.146	7	0.126	10
Ars-en-Ré	0.247	24	0.397	6				
Uzès	0.246	25	0.221	37				
L'Île-d'Yeu	0.241	26	0.325	18				
Paris	0.237	27	0.222	35	0.258	1	0.242	1
Vaison-la-Romaine	0.237	28	0.198	43				
Toulon	0.226	29	0.238	32	0.158	6	0.168	4
Saint-Rémy-de-Provence	0.225	30	0.191	50				
Beaucaire	0.220	31	0.138	72	0.166	4	0.082	22
Carnac	0.217	32	0.313	20				
Le Luc	0.216	33	0.241	29				
Bayonne (partie française)	0.215	34	0.222	36	0.134	9	0.139	8
Montpellier	0.209	35	0.181	57	0.166	5	0.136	9
Abondance	0.208	36	0.264	26				
Arles	0.205	37	0.121	83	0.142	8	0.055	36
Marseille - Aix-en-Provence	0.205	38	0.186	53	0.171	3	0.149	7
Brignoles	0.204	39	0.191	49				
Pézenas	0.202	40	0.152	67				
Nyons	0.201	41	0.219	39				
Clermont-l'Hérault	0.199	42	0.128	80				
Bourg-Saint-Maurice	0.197	43	0.153	66				
Apt	0.195	44	0.192	47				
Valréas	0.191	45	0.128	79				
Creil	0.186	46	0.133	76	0.111	17	0.056	35
La Teste-de-Buch - Arcachon	0.186	47	0.265	25	0.046	43	0.124	11
Saint-Malo	0.183	48	0.192	48	0.068	30	0.075	25
Lunel	0.181	49	0.138	73	0.102	24	0.057	33
Narbonne	0.181	50	0.143	71	0.134	11	0.094	17
Samoëns	0.174	51	0.182	56				
Draguignan	0.172	52	0.178	59	0.083	27	0.087	19
Thônes	0.170	53	0.185	54				
Aime-la-Plagne	0.170	54	0.146	70				
Briançon	0.170	55	0.077	130				
Avignon	0.169	56	0.130	78	0.126	13	0.085	20
Sallanches	0.169	57	0.165	61	0.014	73	0.008	77
Saint-Brevin-les-Pins	0.167	58	0.197	44				
La Rochelle	0.162	59	0.188	52	0.080	28	0.104	15
Embrun	0.161	60	0.123	81				
Salernes	0.160	61	0.157	63				
Noyon	0.160	62	0.132	77				
Bollène	0.160	63	0.119	85				
Ganges	0.156	64	0.113	90				
Pornic	0.154	65	0.204	42				
Forcalquier	0.154	66	0.105	94				
Saint-Vincent-de-Tyrosse	0.151	67	0.179	58				
Cadenet	0.151	68	0.084	122				
Saint-Jean-de-Monts	0.150	69	0.239	30				
Bordeaux	0.150	70	0.161	62	0.109	19	0.119	12
Barcelonnette	0.149	71	0.065	150				
Crest	0.149	72	0.105	95				
Mimizan	0.148	73	0.215	40				



Table 20: Quality of Life in Urban Areas

city	Constant share of housing				Variable share of housing			
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Nîmes	0.147	74	0.114	88	0.112	16	0.076	24
Quiberon	0.146	75	0.345	14				
Les Sables-d'Olonne	0.145	76	0.207	41	0.019	67	0.078	23
Port-Saint-Louis-du-Rhône	0.142	77	0.095	107				
Soustons	0.142	78	0.183	55				
Béziers	0.141	79	0.088	118	0.111	18	0.056	34
Villard-de-Lans	0.140	80	0.101	102				
Saint-Nazaire	0.139	81	0.151	69	0.061	34	0.071	27
Le Vigan	0.136	82	0.041	188				
Salon-de-Provence	0.136	83	0.110	93	0.058	36	0.030	51
Lille (partie française)	0.136	84	0.097	105	0.107	20	0.065	30
Saint-Pierre-sur-Dives	0.136	85	0.151	68				
Provins	0.134	86	0.122	82				
Saint-Pierre-d'Oléron	0.134	87	0.238	31				
Lyon	0.133	88	0.120	84	0.105	22	0.090	18
Perpignan	0.132	89	0.113	89	0.106	21	0.085	21
Alès	0.130	90	0.092	111	0.103	23	0.063	31
Bessan	0.130	91	0.070	142				
Biscarrosse	0.129	92	0.219	38				
Royan	0.129	93	0.232	33	0.006	84	0.108	14
Oraison	0.128	94	0.103	98				
Boulogne-sur-Mer	0.127	95	0.104	96	0.091	25	0.065	29
Dinard	0.125	96	0.155	65	0.018	69	0.045	41
Manosque	0.120	97	0.083	124	0.068	31	0.029	52
Saint-Hilaire-de-Riez	0.119	98	0.192	46				
Pithiviers	0.116	99	0.103	99				
Douai - Lens	0.114	100	0.057	165	0.090	26	0.030	50
Lézignan-Corbières	0.113	101	0.060	159				
Die	0.111	102	0.102	100				
Dreux	0.111	103	0.094	109	0.054	39	0.035	47
Parentis-en-Born	0.111	104	0.134	75				
Pierrelatte	0.109	105	0.057	164				
Vernon	0.109	106	0.087	119	0.049	41	0.025	55
Annecy	0.106	107	0.165	60	0.009	78	0.066	28
Sisteron	0.104	108	0.037	193				
Nantes	0.103	109	0.089	115	0.066	33	0.051	37
Beaurepaire	0.096	110	0.091	113				
Honfleur	0.095	111	0.076	132				
Calais	0.094	112	0.065	147	0.071	29	0.041	44
Auray	0.091	113	0.112	91				
Céret	0.091	114	0.112	92				
Bagnols-sur-Cèze	0.091	115	0.036	194				
Prades	0.090	116	0.063	152				
Reims	0.089	117	0.092	112	0.045	46	0.046	40
Aubenas	0.088	118	0.080	128	0.058	37	0.048	39
La Tremblade	0.085	119	0.156	64				
Saint-Valery-en-Caux	0.081	120	0.032	196				
Rennes	0.081	121	0.065	149	0.045	45	0.027	53
Gap	0.080	122	0.051	174	0.048	42	0.017	64
Montdidier	0.080	123	0.091	114				
Vannes	0.079	124	0.099	104	0.032	56	0.049	38
Louviers	0.079	125	0.060	160	0.037	49	0.015	66
Bagnères-de-Luchon	0.079	126	0.050	175				
Challans	0.078	127	0.096	106				
Bellegarde-sur-Valserine	0.078	128	0.136	74				
Doullens	0.078	129	0.076	135				
Langon	0.077	130	0.062	154				
Chambéry	0.076	131	0.079	129	0.023	62	0.023	56
Saint-Père-en-Retz	0.076	132	0.066	144				
Amiens	0.075	133	0.073	137	0.039	48	0.036	46
Libourne	0.075	134	0.086	120	0.035	51	0.044	42
Compiègne	0.074	135	0.075	136	0.017	70	0.016	65
Amélie-les-Bains-Palalda	0.074	136	0.081	127				
Toulouse	0.073	137	0.062	153	0.046	44	0.034	48
Sélestat	0.072	138	0.083	123				
Abbeville	0.071	139	0.072	138	0.040	47	0.039	45
Saint-Omer	0.071	140	0.024	213	0.052	40	0.002	84
Avesnes-sur-Helpe	0.071	141	0.056	166				
Yvetot	0.070	142	0.070	141				
Strasbourg (partie française)	0.069	143	0.099	103	0.032	54	0.060	32
Falaise	0.068	144	0.049	177				
Dieulefit	0.068	145	0.018	223				
Valdahon	0.067	146	0.086	121				
Bourg-Saint-Andéol	0.067	147	0.020	219				
Laudun-l'Ardoise	0.067	148	-0.017	319				
Dunkerque	0.066	149	0.041	186	0.032	55	0.005	79
Nogent-sur-Seine	0.066	150	-0.001	267				
Feurs	0.065	151	0.032	199				
Granville	0.064	152	0.088	117	-0.014	104	0.007	78
Fécamp	0.064	153	0.072	139				
Valenciennes (partie française)	0.064	154	-0.003	274	0.061	35	-0.008	104
Ugine	0.064	155	0.008	241				
Dol-de-Bretagne	0.064	156	0.045	181				
Tours	0.063	157	0.058	161	0.027	60	0.020	61
Aiguillon	0.062	158	-0.007	281				
Montélimar	0.062	159	0.032	197	0.035	50	0.003	83
Angers	0.061	160	0.054	170	0.030	57	0.021	58

Table 20: Quality of Life in Urban Areas

city	Constant share of housing				Variable share of housing			
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Gaillac	0.060	161	0.022	216				
Montauban	0.060	162	0.043	185	0.034	53	0.015	69
Joigny	0.059	163	0.027	207				
Gérardmer	0.059	164	0.076	133				
Lesparre-Médoc	0.058	165	0.104	97				
Marennes	0.058	166	0.116	86				
Caen	0.058	167	0.066	146	0.021	65	0.027	54
Saint-Just-en-Chaussée	0.057	168	0.076	134				
Caudry	0.055	169	0.048	179				
Favergeres-Seythenex	0.055	170	0.065	148				
Tarare	0.054	171	0.041	187				
Bayeux	0.051	172	0.072	140				
Rochefort	0.050	173	0.066	145	0.020	66	0.034	49
Pont-Saint-Esprit	0.050	174	-0.011	301				
Thionville	0.050	175	0.038	190	0.009	79	-0.005	98
Grenoble	0.050	176	0.025	212	0.022	63	-0.005	97
Saint-Marcellin	0.049	177	0.016	228				
Le Havre	0.049	178	0.060	158	0.007	83	0.015	67
Carentan les Marais	0.049	179	-0.018	320				
Béthune	0.048	180	-0.005	279	0.028	59	-0.028	129
Romans-sur-Isère	0.048	181	0.020	221	0.028	58	-0.002	90
Caussade	0.047	182	0.028	203				
Rouen	0.047	183	0.055	169	0.013	76	0.018	62
Vitré	0.047	184	0.028	205	-0.021	118	-0.043	152
Château-Arnoux-Saint-Auban	0.047	185	0.028	204				
Thonon-les-Bains	0.046	186	0.189	51	-0.067	183	0.074	26
Armentières (partie française)	0.046	187	0.014	232	0.021	64	-0.013	113
Revel	0.046	188	0.007	245				
Neufchâtel-en-Bray	0.046	189	0.061	155				
Castillon-la-Bataille	0.045	190	-0.002	269				
Castelsarrasin	0.045	191	-0.008	286				
Bagnères-de-Bigorre	0.045	192	0.007	242				
Dax	0.045	193	0.081	126	0.007	82	0.041	43
Ancenis	0.045	194	0.005	252				
Boën	0.045	195	-0.009	290				
Paimpol	0.044	196	0.053	171				
Roye	0.044	197	0.077	131				
Rethel	0.042	198	0.023	214				
Miramont-de-Guyenne	0.042	199	0.032	198				
Friville-Escarbotin	0.042	200	0.052	172				
Beauvais	0.042	201	0.046	180	0.002	90	0.004	80
Machecoul-Saint-Même	0.041	202	0.031	200				
Argelès-Gazost	0.041	203	0.003	258				
Chartres	0.040	204	0.058	162	-0.017	110	-0.001	87
Senlis	0.039	205	0.067	143				
Concarneau	0.039	206	0.083	125				
Gamaches	0.039	207	0.043	184				
Maubeuge (partie française)	0.039	208	-0.002	271	0.058	38	0.015	70
Albertville	0.039	209	0.021	218	-0.012	101	-0.033	137
Pauillac	0.039	210	0.049	178				
Saint-Vaast-la-Hougue	0.038	211	0.058	163				
Sarzeau	0.038	212	0.195	45				
Beauvoir-sur-Mer	0.038	213	0.089	116				
Vienne	0.037	214	0.020	222	-0.012	100	-0.032	136
Dijon	0.036	215	0.056	167	0.001	92	0.018	63
Fourmies	0.036	216	0.004	255				
Lorient	0.035	217	0.050	176	0.002	89	0.015	68
La Mure	0.033	218	-0.002	270				
Soissons	0.032	219	0.039	189	0.015	71	0.020	60
Besançon	0.030	220	0.017	225	0.013	75	-0.002	88
Lure	0.030	221	-0.014	310				
Valence	0.029	222	0.011	238	0.014	72	-0.007	101
Troyes	0.027	223	0.044	183	0.007	81	0.021	57
La Voulte-sur-Rhône	0.026	224	0.003	259				
Le Neubourg	0.026	225	0.061	157				
La Réole	0.026	226	-0.035	353				
Bédarieux	0.023	227	-0.002	272				
Lavaur	0.022	228	-0.027	337				
La Loupe	0.022	229	0.011	236				
Saint-Paul-Trois-Châteaux	0.022	230	0.007	243				
Verneuil-sur-Avre	0.021	231	0.0004	265				
Orbec	0.021	232	-0.047	377				
Hazebrouck	0.020	233	-0.011	300				
Castelnaudary	0.020	234	-0.006	280				
Pons	0.020	235	-0.008	288				
Château-Thierry	0.019	236	0.037	192	-0.018	112	-0.002	93
Dieppe	0.017	237	0.006	251	-0.016	107	-0.029	133
Arras	0.017	238	0.011	237	0.004	85	-0.004	96
Gournay-en-Bray	0.017	239	0.028	206				
Haguenau	0.017	240	0.064	151	-0.046	164	-0.001	86
Montbrison	0.016	241	-0.003	277				
Belley	0.016	242	0.016	230				
Les Herbiers	0.015	243	-0.003	275				
Saint-Amand-les-Eaux	0.015	244	-0.033	349	0.014	74	-0.036	143
Metz	0.014	245	0.023	215	-0.010	98	-0.004	95
Thann - Cernay	0.013	246	0.045	182	-0.035	144	-0.006	99
Cluses	0.013	247	0.102	101	-0.075	185	0.011	72

Table 20: Quality of Life in Urban Areas

city	Constant share of housing				Variable share of housing			
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Questembert	0.011	248	0.030	202				
Semur-en-Auxois	0.011	249	-0.037	358				
Saint-Seurin-sur-l'Isle	0.011	250	0.026	209				
Saumur	0.011	251	0.002	262	0.009	80	-0.002	91
Beaune	0.010	252	0.017	227	-0.025	124	-0.020	119
Clermont-Ferrand	0.010	253	0.015	231	-0.015	105	-0.012	112
Toul	0.010	254	-0.023	329				
Lisieux	0.009	255	0.004	254	-0.007	97	-0.013	114
Mont-de-Marsan	0.009	256	0.027	208	-0.014	102	0.003	82
Albi	0.008	257	0.017	226	0.003	87	0.010	73
Feuquières-en-Vimeu - Fressenneville	0.007	258	-0.009	292				
Saintes	0.007	259	0.007	244	-0.001	94	-0.003	94
Les Andelys	0.006	260	0.031	201				
Lannion	0.005	261	0.002	261	-0.005	96	-0.010	107
Bergerac	0.004	262	-0.011	298	0.010	77	-0.007	102
Beaupréau-en-Mauges	0.003	263	-0.038	359				
Orléans	0.003	264	0.013	234	-0.023	121	-0.015	116
Évreux	0.003	265	0.008	240	-0.017	109	-0.014	115
La Roche-sur-Yon	0.002	266	-0.002	268	-0.014	103	-0.020	120
Mende	0.002	267	-0.011	299				
Montreuil-Bellay	0.002	268	-0.014	309				
Graulhet	0.002	269	-0.022	328				
Hesdin	0.001	270	-0.003	276				
Chauny	-0.001	271	-0.014	312				
Millau	-0.001	272	-0.025	333				
Forges-les-Eaux	-0.001	273	0.006	250				
Cherbourg-en-Cotentin	-0.001	274	-0.016	314	-0.027	130	-0.044	154
Étain	-0.002	275	-0.009	289				
Salies-de-Béarn	-0.002	276	-0.005	278				
Montmirail	-0.002	277	0.002	263				
Limoux	-0.003	278	-0.017	318				
Lourdes	-0.003	279	0.025	210				
Péronne	-0.003	280	0.014	233				
Romilly-sur-Seine	-0.004	281	0.021	217				
Issoire	-0.004	282	-0.007	283				
Sens	-0.004	283	0.025	211	-0.029	132	-0.002	89
Bernay	-0.005	284	0.007	247				
Saint-Vallier	-0.006	285	-0.025	334				
Tournon-sur-Rhône	-0.006	286	-0.013	307	-0.016	108	-0.025	126
Agon-Coutainville	-0.006	287	0.055	168				
Pont-Audemer	-0.006	288	-0.015	313	-0.034	142	-0.045	156
La Roche-Chalais - Saint-Aigulin	-0.006	289	-0.044	373				
Carcassonne	-0.007	290	-0.036	354	0.034	52	0.004	81
Charleville-Mézières	-0.007	291	-0.032	347	0.002	88	-0.024	123
Villeneuve-sur-Lot	-0.007	292	-0.022	327	0.019	68	0.002	85
Saint-Pol-de-Léon	-0.008	293	-0.010	296				
Pont-l'Abbé	-0.008	294	0.020	220				
Vendôme	-0.009	295	-0.009	294	-0.032	136	-0.035	142
Luçon	-0.009	296	0.007	246				
Nancy	-0.010	297	0.004	256	-0.023	122	-0.012	109
Ham	-0.010	298	0.003	260				
Marckolsheim	-0.010	299	0.094	110				
La Bruffière	-0.010	300	-0.031	345				
Montaigu	-0.011	301	-0.023	331				
Lunéville	-0.011	302	-0.019	322				
Eu	-0.012	303	0.00002	266	-0.044	159	-0.034	140
Châteaubriant	-0.012	304	-0.049	383				
Longué-Jumelles	-0.013	305	-0.039	360				
Plancoët	-0.013	306	-0.013	306				
Albert	-0.014	307	-0.027	338				
Doué-la-Fontaine	-0.015	308	-0.009	291				
Montargis	-0.015	309	0.0004	264	-0.022	119	-0.008	105
Colmar	-0.015	310	0.038	191	-0.043	158	0.008	75
Poitiers	-0.016	311	-0.024	332	-0.018	113	-0.028	130
Saint-Hilaire-du-Harcouët	-0.016	312	-0.054	399				
Gannat	-0.016	313	-0.045	375				
Marmande	-0.017	314	-0.031	346	-0.0001	93	-0.017	118
Le Mans	-0.018	315	-0.023	330	-0.034	143	-0.042	149
Épernay	-0.019	316	0.012	235	-0.036	147	-0.007	103
La Ferté-Bernard	-0.019	317	-0.034	350				
Modane	-0.020	318	-0.079	458				
Évron	-0.020	319	-0.059	414				
Soufflenheim	-0.020	320	0.061	156				
Lillebonne	-0.020	321	-0.016	317				
Commercy	-0.021	322	-0.014	311				
Castres	-0.021	323	-0.044	370	-0.004	95	-0.029	131
Montpon-Ménéstérol	-0.021	324	-0.012	302				
Rosporden	-0.022	325	-0.032	348				
Sablé-sur-Sarthe	-0.022	326	-0.030	342	-0.040	156	-0.051	166
Pontarlier	-0.023	327	0.115	87	-0.123	196	0.013	71
Baugé-en-Anjou	-0.023	328	-0.068	444				
Sedan	-0.023	329	-0.026	335	0.026	61	0.021	59
Cholet	-0.024	330	-0.036	356	-0.036	146	-0.050	165
Auxerre	-0.025	331	-0.008	285	-0.040	154	-0.025	125
Coutances	-0.026	332	-0.043	367				
Laval	-0.026	333	-0.057	410	-0.033	141	-0.066	178
Quimper	-0.027	334	-0.019	323	-0.017	111	-0.012	110

Table 20: Quality of Life in Urban Areas

city	Constant share of housing			Variable share of housing				
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Guebwiller	-0.027	335	0.005	253	-0.035	145	-0.006	100
Solesmes	-0.027	336	-0.016	315				
Penmarch	-0.027	337	0.016	229				
Laon	-0.028	338	-0.019	321	0.003	86	0.010	74
Loches	-0.028	339	-0.013	304				
Fougères	-0.029	340	-0.055	402	-0.033	140	-0.062	175
Valognes	-0.029	341	-0.066	435				
Bourg-en-Bresse	-0.029	342	-0.029	340	-0.046	165	-0.048	160
Lamballe	-0.031	343	-0.042	363				
Périgueux	-0.031	344	-0.013	308	-0.027	129	-0.012	111
Montbéliard	-0.031	345	-0.030	341	-0.036	149	-0.038	145
Vire Normandie	-0.032	346	-0.056	404	-0.036	148	-0.062	176
Pau	-0.032	347	-0.049	384	-0.032	135	-0.051	167
Chemillé-en-Anjou	-0.032	348	-0.070	445				
Migennes	-0.033	349	-0.009	295				
Saint-Florentin	-0.033	350	0.003	257				
Venarey-les-Laumes	-0.033	351	-0.056	406				
Tarascon-sur-Ariège	-0.034	352	-0.088	481				
Argentan	-0.034	353	-0.008	287				
Muzillac	-0.034	354	-0.013	305				
Malestroit	-0.034	355	-0.052	388				
Mourenx	-0.035	356	-0.052	389				
Agen	-0.035	357	-0.049	382	-0.025	125	-0.041	148
Saint-Affrique	-0.035	358	-0.059	415				
Cambrai	-0.035	359	-0.036	355	0.001	91	-0.002	92
Tréguier	-0.036	360	-0.034	352				
Ploërmel	-0.036	361	-0.029	339				
Blois	-0.036	362	-0.031	344	-0.047	167	-0.043	153
Vic-en-Bigorre	-0.037	363	-0.020	325				
Saint-Dizier	-0.037	364	-0.043	366	-0.020	115	-0.028	128
Loireauxence	-0.037	365	-0.079	457				
Delle (partie française)	-0.037	366	0.052	173				
Barbezieux-Saint-Hilaire	-0.038	367	-0.073	451				
Oyonnax	-0.038	368	-0.053	392	-0.026	128	-0.043	151
Lamotte-Beuvron	-0.038	369	-0.021	326				
Dole	-0.038	370	-0.083	464	-0.037	151	-0.084	191
Tournus	-0.039	371	-0.043	365				
Brive-la-Gaillarde	-0.039	372	-0.068	441	-0.028	131	-0.059	172
Morcenx	-0.039	373	-0.009	293				
Brou	-0.040	374	-0.003	273				
Vic-Fezensac	-0.040	375	-0.101	502				
Saint-Étienne	-0.041	376	-0.056	405	-0.046	163	-0.064	177
Douarnenez	-0.041	377	-0.011	297				
Crozon	-0.041	378	-0.012	303				
Château-Gontier	-0.041	379	-0.078	455				
Chantonnay	-0.041	380	-0.072	450				
Oloron-Sainte-Marie	-0.042	381	-0.053	393				
Belfort	-0.042	382	-0.068	443	-0.020	116	-0.048	161
Chinon	-0.042	383	-0.065	433				
Dinan	-0.042	384	-0.026	336				
Avranches	-0.043	385	-0.048	380				
Contres	-0.043	386	-0.020	324				
Valence	-0.043	387	-0.063	427	0.014	72	-0.007	101
Saint-Sever	-0.044	388	-0.008	284				
Beaumont-le-Roger	-0.044	389	0.009	239				
Le Puy-en-Velay	-0.045	390	-0.068	442	-0.019	114	-0.045	155
Pont-à-Mousson	-0.045	391	-0.061	419				
Roanne	-0.046	392	-0.054	395	-0.037	150	-0.046	157
Rodez	-0.046	393	-0.067	439	-0.033	139	-0.056	170
Baud	-0.046	394	-0.063	428				
Le Cateau-Cambrésis	-0.048	395	-0.087	476				
Verdun	-0.048	396	-0.050	385	-0.033	137	-0.037	144
Charlieu	-0.049	397	-0.052	387				
Saint-Brieuc	-0.049	398	-0.044	369	-0.045	162	-0.042	150
Tergnier	-0.049	399	-0.074	452				
Surgères	-0.049	400	0.007	248				
Tonneins	-0.050	401	-0.063	429				
Brest	-0.050	402	-0.041	361	-0.046	166	-0.039	147
Sarrebruck (ALL) - Forbach (partie française)	-0.050	403	-0.044	371	-0.025	126	-0.021	121
Saint-Jean-d'Angély	-0.050	404	-0.043	368				
Tarbes	-0.051	405	-0.054	394	-0.025	127	-0.030	135
Neuf-Brisach	-0.051	406	-0.007	282				
Creutzwald	-0.053	407	-0.045	374				
Pamiers	-0.054	408	-0.056	408	-0.012	99	-0.016	117
Legé	-0.054	409	-0.066	437				
Chauvigny	-0.054	410	-0.114	527				
Mulhouse	-0.055	411	0.018	224	-0.062	178	0.008	76
Alençon	-0.055	412	-0.062	420	-0.039	152	-0.048	162
Vichy	-0.055	413	-0.056	407	-0.030	133	-0.034	139
Auch	-0.055	414	-0.064	431	-0.015	106	-0.026	127
Mauléon	-0.055	415	-0.124	540				
Saint-Quentin	-0.055	416	-0.059	413	-0.024	123	-0.029	132
Mauges-sur-Loire	-0.056	417	-0.112	523				
Sainte-Sigolène	-0.056	418	-0.047	379				
Segré	-0.057	419	-0.058	412				
Redon	-0.057	420	-0.058	411				
Autun	-0.057	421	-0.086	473				

Table 20: Quality of Life in Urban Areas

city	Constant share of housing			Variable share of housing				
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
La Bresse	-0.058	422	-0.072	449				
Saint-Dié-des-Vosges	-0.059	423	-0.044	372	-0.022	120	-0.009	106
Locminé	-0.059	424	-0.063	430				
Longwy (partie française)	-0.061	425	-0.062	424	-0.067	182	-0.070	183
Château-du-Loir	-0.061	426	-0.048	381				
La Guerche-de-Bretagne	-0.062	427	-0.084	467				
Périers	-0.063	428	-0.125	541				
Saint-Lô	-0.063	429	-0.089	483	-0.042	157	-0.070	182
Louhans	-0.064	430	-0.076	453				
Niort	-0.064	431	-0.083	465	-0.059	174	-0.080	189
Mayenne	-0.064	432	-0.072	448				
Sézanne	-0.065	433	-0.030	343				
Limoges	-0.065	434	-0.071	447	-0.053	171	-0.061	174
Bourgueil	-0.065	435	-0.149	568				
Quimperlé	-0.065	436	-0.060	418				
Bonneval	-0.065	437	-0.037	357				
Montréjeau	-0.065	438	-0.054	396				
Remiremont	-0.066	439	-0.057	409				
Cahors	-0.067	440	-0.055	401	-0.021	117	-0.011	108
Lons-le-Saunier	-0.067	441	-0.094	493	-0.045	161	-0.074	186
Pontivy	-0.067	442	-0.034	351				
Saint-Céré	-0.068	443	-0.105	510				
Saverne	-0.068	444	-0.055	403				
Ornans	-0.068	445	-0.066	436				
Châlons-en-Champagne	-0.068	446	-0.041	362	-0.063	181	-0.038	146
Angoulême	-0.069	447	-0.062	421	-0.055	173	-0.050	164
Aubigny-sur-Nère	-0.069	448	-0.062	425				
Bourges	-0.069	449	-0.053	390	-0.061	176	-0.047	158
Courtenay	-0.069	450	0.006	249				
Champagnole	-0.069	451	-0.066	438				
Saint-Avold (partie française)	-0.070	452	-0.060	416	-0.033	138	-0.024	124
Blaye	-0.070	453	-0.115	528				
Carmaux	-0.070	454	-0.052	386				
Sainte-Maure-de-Touraine	-0.071	455	-0.087	477				
Baume-les-Dames	-0.071	456	-0.102	504				
Châteauroux	-0.075	457	-0.066	434	-0.061	177	-0.053	169
Figeac	-0.076	458	-0.108	514				
La Flèche	-0.077	459	-0.064	432				
Essarts en Bocage	-0.077	460	-0.107	513				
Vesoul	-0.077	461	-0.084	468	-0.044	160	-0.053	168
Plouhinec - Audierne	-0.078	462	-0.047	378				
Parthenay	-0.079	463	-0.093	489				
Mortagne-sur-Sèvre	-0.079	464	-0.094	491				
Chalon-sur-Saône	-0.079	465	-0.084	466	-0.063	180	-0.069	181
Châteaudun	-0.080	466	-0.054	400				
Nérac	-0.080	467	-0.111	520				
Sully-sur-Loire	-0.084	468	-0.085	471				
Luxeuil-les-Bains	-0.084	469	-0.118	533				
Varennes-sur-Allier	-0.084	470	-0.086	474				
Fleurance	-0.084	471	-0.105	509				
Orthez	-0.084	472	-0.062	426				
Descartes	-0.085	473	-0.086	472				
Châtellerault	-0.085	474	-0.090	484	-0.063	179	-0.069	180
Brioude	-0.085	475	-0.111	519				
Vitry-le-François	-0.086	476	-0.071	446	-0.047	168	-0.033	138
Hagetmau	-0.087	477	-0.060	417				
Reichshoffen - Niederbronn-les-Bains	-0.087	478	-0.016	316				
Moulins	-0.087	479	-0.078	456	-0.053	172	-0.047	159
Villefranche-de-Rouergue	-0.087	480	-0.090	486				
Joinville	-0.087	481	-0.106	512				
Hirson	-0.088	482	-0.131	549				
Gien	-0.088	483	-0.081	461				
Selles-sur-Cher	-0.089	484	-0.042	364				
Mazamet	-0.090	485	-0.095	496				
Avallon	-0.090	486	-0.099	499				
Saint-Aignan	-0.091	487	-0.081	463				
Fleury-sur-Andelle	-0.092	488	-0.053	391				
Fontenay-le-Comte	-0.093	489	-0.085	469				
Saint-Junien	-0.093	490	-0.102	506				
Épinal	-0.094	491	-0.089	482	-0.052	170	-0.049	163
Gourdon	-0.095	492	-0.088	478				
Arbois	-0.096	493	-0.131	548				
Salbris	-0.097	494	-0.046	376				
Argenton-sur-Creuse	-0.098	495	-0.111	518				
Bressuire	-0.098	496	-0.116	530				
Foix	-0.098	497	-0.094	492				
Châteaulin	-0.098	498	-0.080	459				
Langres	-0.099	499	-0.091	488				
Saint-Girons	-0.099	500	-0.124	539				
La Verrie	-0.099	501	-0.128	542				
Aire-sur-l'Adour	-0.099	502	-0.108	515				
Saint-Pourçain-sur-Sioule	-0.099	503	-0.081	462				
Mauléon-Licharre	-0.099	504	-0.148	567				
Nogent-le-Rotrou	-0.100	505	-0.067	440				
Bruyères	-0.100	506	-0.103	508				
Bogny-sur-Meuse	-0.102	507	-0.090	487				
Mortagne-au-Perche	-0.102	508	-0.133	552				

Table 20: Quality of Life in Urban Areas

city	Constant share of housing				Variable share of housing			
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Revin	-0.103	509	-0.130	546				
Le Thillot	-0.105	510	-0.088	480				
Le Creusot	-0.105	511	-0.131	550	-0.048	169	-0.077	187
Lalinde	-0.105	512	-0.097	498				
Montrichard	-0.105	513	-0.054	397				
Digoïn	-0.105	514	-0.116	532				
Morlaix	-0.106	515	-0.102	503	-0.032	134	-0.029	134
Saint-Maixent-l'École	-0.106	516	-0.116	529				
Aurillac	-0.107	517	-0.113	524	-0.061	175	-0.068	179
Villedieu-les-Poêles-Rouffigny	-0.108	518	-0.137	556				
Carhaix-Plouguer	-0.109	519	-0.103	507				
Romorantin-Lanthenay	-0.109	520	-0.090	485				
Issoudun	-0.110	521	-0.085	470				
Saint-Jean-de-Maurienne	-0.111	522	-0.145	564				
Vierzon	-0.112	523	-0.093	490	-0.039	153	-0.022	122
Loudéac	-0.113	524	-0.116	531				
Thiviers	-0.113	525	-0.106	511				
Cognac	-0.114	526	-0.094	494	-0.090	193	-0.072	185
Lavelanet	-0.114	527	-0.054	398				
Saint-Pol-sur-Ternoise	-0.115	528	-0.135	554				
Saint-Laurent-sur-Sèvre	-0.116	529	-0.164	575				
Montbard	-0.116	530	-0.100	501				
Guer	-0.117	531	-0.132	551				
La Ferté-Macé	-0.117	532	-0.146	565				
Saint-Fulgent	-0.117	533	-0.121	537				
Paray-le-Monial	-0.118	534	-0.120	536				
Pontorson	-0.119	535	-0.109	517				
Nevers	-0.120	536	-0.109	516	-0.079	188	-0.070	184
Guingamp	-0.121	537	-0.129	543				
Saint-Gaudens	-0.121	538	-0.113	526	-0.040	155	-0.035	141
Cosne-Cours-sur-Loire	-0.121	539	-0.088	479				
Chauffailles	-0.123	540	-0.145	563				
Mirande	-0.124	541	-0.121	538				
Sarrebourg	-0.124	542	-0.112	522	-0.093	194	-0.083	190
La Charité-sur-Loire	-0.125	543	-0.099	500				
Loudun	-0.126	544	-0.112	521				
Mussidan	-0.127	545	-0.119	534				
Ligny-en-Barrois	-0.127	546	-0.080	460				
Le Blanc	-0.127	547	-0.152	570				
Bar-sur-Aube	-0.130	548	-0.078	454				
Saint-James	-0.131	549	-0.102	505				
Saint-Amand-Montrond	-0.131	550	-0.095	495				
Jarny	-0.132	551	-0.136	555				
Condom	-0.133	552	-0.163	574				
Montceau-les-Mines	-0.134	553	-0.138	558	-0.073	184	-0.080	188
Nueil-les-Aubiers	-0.134	554	-0.187	586				
Sancerre	-0.137	555	-0.062	422				
Brassac-les-Mines	-0.137	556	-0.087	475				
La Gacilly	-0.139	557	-0.130	545				
Condé-en-Normandie	-0.140	558	-0.119	535				
Lesneven	-0.141	559	-0.152	569				
Sarreguemines (partie française)	-0.142	560	-0.113	525	-0.086	191	-0.059	173
Égletons	-0.143	561	-0.175	581				
Chaumont	-0.144	562	-0.153	571	-0.081	189	-0.092	194
Maïche	-0.144	563	0.095	108				
Tonnerre	-0.147	564	-0.143	561				
Vouziers	-0.148	565	-0.171	578				
Raon-l'Étape	-0.148	566	-0.062	423				
Melle	-0.151	567	-0.168	576				
Poligny	-0.154	568	-0.193	590				
Hauts de Biemme	-0.154	569	0.036	195				
Domfront en Poiraise	-0.154	570	-0.146	566				
Châtillon-sur-Seine	-0.155	571	-0.130	544				
Flers	-0.157	572	-0.180	583	-0.076	186	-0.100	195
Bar-le-Duc	-0.159	573	-0.131	547	-0.083	190	-0.057	171
Pouancé	-0.160	574	-0.134	553				
Souillac	-0.160	575	-0.143	560				
Saint-Claude	-0.162	576	-0.138	557				
Torigny-les-Villes	-0.164	577	-0.203	595				
Saint-Yrieix-la-Perche	-0.165	578	-0.170	577				
Landivisiau	-0.168	579	-0.153	572				
Nontron	-0.168	580	-0.140	559				
Lannemezan	-0.170	581	-0.173	580				
Bellac	-0.171	582	-0.173	579				
Rostrenen	-0.175	583	-0.190	587				
Montluçon	-0.176	584	-0.162	573	-0.098	195	-0.087	193
Pont-de-Buis-lès-Quimerch	-0.179	585	-0.184	585				
Decize	-0.179	586	-0.143	562				
Langeac	-0.180	587	-0.218	600				
La Châtre	-0.184	588	-0.181	584				
Tulle	-0.185	589	-0.208	598	-0.087	192	-0.112	196
Vittel	-0.186	590	-0.096	497				
Commentry	-0.188	591	-0.179	582				
Beaumont-de-Lomagne	-0.190	592	-0.198	592				
Thouars	-0.191	593	-0.193	589				
La Souterraine	-0.195	594	-0.208	599				
Nogent	-0.198	595	-0.242	603				

Table 20: Quality of Life in Urban Areas

city	Constant share of housing				Variable share of housing			
	QoL: inc	rank	QoL: wage	rank	QoL: inc	rank	QoL: wage	rank
Guéret	-0.199	596	-0.205	597	-0.076	187	-0.084	192
Gourin	-0.199	597	-0.199	593				
Pouzauges	-0.199	598	-0.201	594				
Mamers	-0.201	599	-0.191	588				
Decazeville	-0.209	600	-0.205	596				
Mirecourt	-0.230	601	-0.194	591				
Neufchâteau	-0.240	602	-0.219	601				
Clamecy	-0.242	603	-0.231	602				
Aubusson	-0.250	604	-0.300	605				
Gueugnon	-0.259	605	-0.297	604				

## E Results at the Urban Unit level

This appendix reproduces all the previous results, using data at the Urban Unit level. As explained in section 2, this is the scale at which we obtained our housing prices estimates. As a result, our urban area prices only correspond to a mean of some of the urban units they contain, the ones where enough transactions happened. Because we are concerned that this discrepancy between the geographic scale of our rent information and the rest of our data might introduce some bias, we repeated all our estimations using the sample of urban units which are at the center of an urban area. Other non-central urban units are excluded to avoid spatial autocorrelation between our observations.

Most of the results are unchanged when using this geographic scale. When there is some discrepancy with the urban area results we signal it and try to explain it. Tables are inserted in the same order as in the main part of our report.

### First step regressions

#### Rent estimates

Table 21: Housing price and city size (across central Urban Units)

	<i>Dependent variable:</i>					
	ln Median price of old housing per square meter					
	Fringe adjustment			Land area controlled		
	(1)	(2)	(3)	(4)	(5)	(6)
ln Population	0.095*** (0.010)	0.071*** (0.009)	0.028** (0.011)	0.091*** (0.017)	0.081*** (0.015)	0.035** (0.016)
ln Income			2.760*** (0.418)			2.752*** (0.418)
Education		2.146*** (0.171)	1.369*** (0.203)		2.161*** (0.172)	1.383*** (0.204)
ln Land area				0.008 (0.026)	-0.019 (0.023)	-0.015 (0.022)
Geography	Y	Y	Y	Y	Y	Y
Observations	605	594	594	605	594	594
R <sup>2</sup>	0.481	0.592	0.621	0.481	0.593	0.621
Adjusted R <sup>2</sup>	0.468	0.581	0.610	0.467	0.581	0.609

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Controlling for geography as slope and maximum altitude, as well as dummies for border with France's neighbouring countries, seas, oceans and main rivers.

This first table on housing prices is one where using the urban unit level does incur some changes. Our estimation of the population elasticity is lower now, at 3.5% in the last column when it was 11.2% in table 1 for Urban Areas. Furthermore, the land area is not significant anymore. This could be simply explained by the fact that by definition, central urban areas do not correspond to the actual city. The housing market of a city should be larger than its central



area. Hence the extensive margin explanation makes little sense here: extending the boundaries of a central urban unit should not significantly affect the prices since the housing market in which prices are determined is already larger than the urban unit. This would also explain why the population elasticity is not sensitive to whether we control for land area or not: even when we include land area, it does not actually correspond to the boundaries that would be pushed back to adjust to the higher demand for housing.

## Wages and income

Table 22: Wage and density across Central Urban Units

<i>Dependent variable:</i>				
ln Mean hourly wage				
	(1)	(2)	(3)	(4)
log density	0.039*** (0.003)	0.022*** (0.003)	0.033*** (0.003)	0.022*** (0.003)
Education		0.881*** (0.053)		0.810*** (0.062)
log Land Area			0.027*** (0.003)	0.007** (0.003)
Observations	748	748	748	748
R <sup>2</sup>	0.167	0.391	0.256	0.395
Adjusted R <sup>2</sup>	0.166	0.389	0.254	0.393

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 23: Wage and city size (across Urban Units central to an Urban Area)

<i>Dependent variable:</i>				
ln Mean hourly wage				
	Fringe adjustment		Land area controlled	
	(1)	(2)	(3)	(4)
ln Population	0.030*** (0.002)	0.014*** (0.002)	0.033*** (0.003)	0.022*** (0.003)
Education		0.776*** (0.061)		0.810*** (0.062)
ln Land area			-0.006 (0.005)	-0.015*** (0.004)
Observations	748	748	748	748
R <sup>2</sup>	0.254	0.385	0.256	0.395
Adjusted R <sup>2</sup>	0.253	0.383	0.254	0.393

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 24: Available income and city size (across Urban Units central to a Urban Area)

<i>Dependent variable:</i>				
In Median available income				
	Fringe adjustment		Land area controlled	
	(1)	(2)	(3)	(4)
In Population	0.011*** (0.002)	-0.016*** (0.002)	-0.001 (0.004)	-0.020*** (0.003)
Education		1.360*** (0.060)		1.343*** (0.061)
In Land area			0.022*** (0.005)	0.007* (0.004)
Observations	749	749	749	749
R <sup>2</sup>	0.033	0.425	0.055	0.428
Adjusted R <sup>2</sup>	0.032	0.424	0.053	0.425

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

The results for wages and income are very similar to the ones obtained for urban areas. Again, the elasticity of available income with respect to income is not clear, but the effect of education seems quite precisely estimated.

We use the results of the last columns of each table to compute rents, wages and income net of the education effect.

## Unemployment and tax rate

Table 25: Unemployment and city size across central Urban Units

<i>Dependent variable:</i>						
Unemployment rate						
	Fringe adjustment			Land area controlled		
	(1)	(2)	(3)	(4)	(5)	(6)
log Population	0.016*** (0.001)	0.064*** (0.011)	0.138* (0.078)	0.021*** (0.002)	0.030* (0.015)	0.338*** (0.088)
square log Population		-0.002*** (0.001)	-0.009 (0.007)		-0.0005 (0.001)	-0.030*** (0.008)
cube log Population			0.0002 (0.0002)			0.001*** (0.0003)
Land Area				-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Education	-0.559*** (0.037)	-0.560*** (0.037)	-0.561*** (0.037)	-0.554*** (0.037)	-0.555*** (0.037)	-0.554*** (0.036)
Observations	760	760	760	760	760	760
R <sup>2</sup>	0.247	0.266	0.267	0.275	0.276	0.288
Adjusted R <sup>2</sup>	0.245	0.263	0.263	0.273	0.272	0.283

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 26: Tax rate and city size across central urban units

<i>Dependent variable:</i>			
Tax rate			
	(1)	(2)	(3)
log Population	0.006*** (0.0004)	0.001 (0.0004)	0.001*** (0.0004)
Education		0.252*** (0.012)	0.173*** (0.015)
log income			0.045*** (0.006)
Observations	748	748	748
R <sup>2</sup>	0.192	0.492	0.532
Adjusted R <sup>2</sup>	0.190	0.491	0.530

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## Bell curve

Table 27: Bell curve: net wage and city size (central Urban Units)

<i>Dependent variable:</i>								
	Cst share (0.325)		*ln(mean wage) – $s_w$ *ln(median housing price) Variable share		Cst share (0.325)		Variable share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Population	-0.002 (0.043)	0.041 (0.314)	-0.292*** (0.056)	-0.109 (0.580)	-0.001 (0.043)	0.047 (0.310)	-0.297*** (0.056)	-0.263 (0.579)
Square ln Population	-0.0001 (0.002)	-0.004 (0.029)	-0.002 (0.002)	-0.016 (0.047)	0.001 (0.002)	-0.004 (0.028)	-0.001 (0.002)	-0.004 (0.046)
Cube ln Population		0.0001 (0.001)		0.0004 (0.001)		0.0001 (0.001)		0.0001 (0.001)
Land Area controlled	<i>N</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
Observations	598	598	199	199	598	598	199	199
R <sup>2</sup>	0.002	0.002	0.973	0.973	0.030	0.030	0.974	0.974
Adjusted R <sup>2</sup>	-0.002	-0.003	0.973	0.973	0.025	0.023	0.973	0.973

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## Index of quality of life

### Regressions of rents on revenues

### Quality of life from income

### Quality of life from expected wage

Table 28: Housing price and available income by central Urban Units

	<i>Dependent variable:</i>					
	0.325 * differential housing price			share housing * differential housing price		
	(1)	(2)	(3)	(4)	(5)	(6)
differential available income	0.421*** (0.078)	0.506*** (0.066)	0.503*** (0.068)	0.203*** (0.065)	0.234*** (0.060)	0.230*** (0.064)
Natural amenities	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>N</i>	<i>Y</i>	<i>Y</i>
Artificial amenities	<i>N</i>	<i>N</i>	<i>Y</i>	<i>N</i>	<i>N</i>	<i>Y</i>
Observations	598	594	594	199	199	199
R <sup>2</sup>	0.046	0.458	0.468	0.048	0.425	0.433
Adjusted R <sup>2</sup>	0.045	0.447	0.454	0.043	0.388	0.386

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Rents and housing costs are net of education effects

Artificial amenities include the number of universities, cinemas, and doctors per capita.

Natural amenities include dummies for proximity to the sea or an ocean, as well as climate variables

Table 29: Housing price and expected wage by central Urban Units

	<i>Dependent variable:</i>					
	0.325 * differential housing price			share housing * differential housing price		
	(1)	(2)	(3)	(4)	(5)	(6)
differential expected wage	-0.028 (0.055)	0.160*** (0.046)	0.146*** (0.048)	0.069 (0.056)	0.152*** (0.049)	0.147*** (0.053)
Natural amenities	<i>N</i>	<i>Y</i>	<i>Y</i>	<i>N</i>	<i>Y</i>	<i>Y</i>
Artificial amenities	<i>N</i>	<i>N</i>	<i>Y</i>	<i>N</i>	<i>N</i>	<i>Y</i>
Observations	598	594	594	199	199	199
R <sup>2</sup>	0.0004	0.414	0.427	0.008	0.409	0.417
Adjusted R <sup>2</sup>	-0.001	0.402	0.412	0.003	0.371	0.369

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Rents and housing costs are net of education effects

Artificial amenities include the number of universities, cinemas, and doctors per capita.

Natural amenities include dummies for proximity to the sea or an ocean, as well as climate variables

Table 30: Quality of Life in central Urban Units, computed with income and constant share of housing

$$\widehat{Q}_c = 0.325 \times \text{housing} - \text{income}$$

	City	QoL	housing	income
1	Saint-Tropez	0.512	1.861	0.093
2	Chamonix-Mont-Blanc	0.414	1.226	-0.015
3	Sainte-Maxime	0.359	1.221	0.038
4	Bormes-les-Mimosas - Le Lavandou	0.345	1.246	0.060
5	Cavalaire-sur-Mer	0.334	1.165	0.044
6	Menton - Monaco (partie française)	0.328	1.093	0.027
7	Morzine	0.326	1.253	0.081
8	La Flotte	0.325	1.220	0.071
9	Le Grau-du-Roi	0.324	0.839	-0.051
10	Marseillan	0.299	0.738	-0.059
11	Nice	0.298	0.811	-0.035
12	Agde	0.291	0.669	-0.074
13	Fréjus	0.290	0.884	-0.002
14	Cogolin	0.285	0.905	0.009
15	Paris	0.284	0.801	-0.024
...				
580	Vittel	-0.196	-0.245	0.116
581	Bellac	-0.196	-0.607	-0.001
582	Decize	-0.203	-0.462	0.053
583	Nogent	-0.205	-0.607	0.008
584	Beaumont-de-Lomagne	-0.211	-0.604	0.014
585	Mamers	-0.213	-0.636	0.006
586	La Souterraine	-0.213	-0.754	-0.032
587	Mirecourt	-0.213	-0.717	-0.020
588	Aubusson	-0.214	-1.036	-0.123
589	Clamecy	-0.214	-0.814	-0.050
590	Pouzauges	-0.214	-0.503	0.051
591	Commentry	-0.214	-0.557	0.034
592	Neufchâteau	-0.219	-0.746	-0.024
593	Gourin	-0.222	-0.506	0.058
594	Decazeville	-0.226	-0.629	0.021
595	Gueugnon	-0.280	-0.607	0.083

Table 31: Quality of Life in central Urban Units, computed with income and variable share of housing

	city	QoL	housing	share	income
1	Paris	0.303	0.794	0.386	0.004
2	Nice	0.224	0.804	0.270	-0.007
3	Montpellier	0.196	0.350	0.231	-0.116
4	Marseille - Aix-en-Provence	0.176	0.500	0.294	-0.029
5	Narbonne	0.156	0.207	0.131	-0.128
6	Toulon	0.151	0.661	0.245	0.011
7	Nîmes	0.149	0.159	0.191	-0.118
8	Béziers	0.147	-0.049	0.157	-0.155
9	Beaucaire	0.134	0.166	0.105	-0.117
10	Lyon	0.133	0.451	0.296	0.001
11	Lille (partie française)	0.131	0.246	0.274	-0.064
12	Bayonne (partie française)	0.130	0.618	0.203	-0.004
13	Strasbourg (partie française)	0.126	0.286	0.235	-0.059
14	Sète	0.123	0.536	0.158	-0.038
15	Avignon	0.120	0.309	0.234	-0.048
...					
182	Moulins	-0.055	-0.263	0.116	0.025
183	Châteauroux	-0.055	-0.211	0.139	0.026
184	Pont-à-Mousson	-0.057	-0.116	0.094	0.046
185	Saint-Avold (partie française)	-0.057	-0.245	0.111	0.030
186	Thann - Cernay	-0.060	0.173	0.107	0.079
187	Cognac	-0.064	-0.253	0.098	0.039
188	Guebwiller	-0.064	0.006	0.103	0.065
189	Châtelleraut	-0.064	-0.228	0.119	0.037
190	Saint-Hilaire-de-Riez	-0.065	0.584	0.096	0.121
191	Le Creusot	-0.070	-0.339	0.109	0.033
192	Haguenau	-0.070	0.253	0.137	0.105
193	Thonon-les-Bains	-0.077	0.614	0.148	0.168
194	La Bresse	-0.083	-0.102	0.094	0.073
195	Montceau-les-Mines	-0.097	-0.393	0.117	0.051
196	Cluses	-0.097	0.460	0.156	0.169
197	Montluçon	-0.098	-0.529	0.135	0.026

Table 32: Quality of Life in central Urban Units, computed with wage and constant share of housing

$$\widehat{Q}_c = 0.325 \times \text{housing} - 0.535 \times \text{expected wage}$$

	City	QoL	housing	exp. wage
1	Saint-Tropez	0.700	1.861	-0.177
2	Sainte-Maxime	0.493	1.221	-0.180
3	Bormes-les-Mimosas - Le Lavandou	0.461	1.246	-0.105
4	Cavalaire-sur-Mer	0.433	1.165	-0.103
5	La Flotte	0.430	1.220	-0.063
6	Le Grau-du-Roi	0.399	0.839	-0.235
7	Ars-en-Ré	0.395	1.089	-0.077
8	Capbreton	0.381	0.796	-0.230
9	Menton - Monaco (partie française)	0.376	1.093	-0.039
10	Agde	0.373	0.669	-0.291
11	Chamonix-Mont-Blanc	0.366	1.226	0.061
12	Morzine	0.363	1.253	0.082
13	Fréjus	0.341	0.884	-0.100
14	Quiberon	0.333	0.784	-0.146
15	Cogolin	0.331	0.905	-0.068
...				
580	Clamecy	-0.193	-0.814	-0.134
581	Pont-de-Buis-lès-Quimerch	-0.197	-0.569	0.023
582	Tulle	-0.197	-0.490	0.071
583	Bellac	-0.198	-0.607	0.001
584	Commentry	-0.200	-0.557	0.035
585	Rostrenen	-0.203	-0.766	-0.087
586	Decazeville	-0.211	-0.629	0.013
587	Nueil-les-Aubiers	-0.215	-0.441	0.133
588	Pouzauges	-0.217	-0.503	0.100
589	Beaumont-de-Lomagne	-0.220	-0.604	0.044
590	Gourin	-0.223	-0.506	0.109
591	Langeac	-0.227	-0.791	-0.057
592	La Souterraine	-0.227	-0.754	-0.034
593	Aubusson	-0.246	-1.036	-0.169
594	Nogent	-0.256	-0.607	0.110
595	Gueugnon	-0.317	-0.607	0.224

Table 33: Quality of Life in central Urban Units, computed with wage and variable share of housing

$$\widehat{Q}_c = \text{share} \times \text{housing} - 0.535 \times \text{expected wage}$$

	City	QoL	housing	share	exp. wage
1	Paris	0.275	0.794	0.386	0.058
2	Nice	0.213	0.804	0.270	0.007
3	Agde	0.194	0.662	0.097	-0.243
4	Fréjus	0.168	0.877	0.160	-0.052
5	Toulon	0.162	0.661	0.245	0.0001
6	Montpellier	0.160	0.350	0.231	-0.148
7	Menton - Monaco (partie française)	0.151	1.086	0.144	0.010
8	Marseille - Aix-en-Provence	0.150	0.500	0.294	-0.006
9	Bayonne (partie française)	0.139	0.618	0.203	-0.026
10	Saint-Cyprien	0.130	0.601	0.131	-0.096
11	Bordeaux	0.126	0.459	0.267	-0.007
12	La Rochelle	0.116	0.527	0.174	-0.045
13	Lyon	0.113	0.451	0.296	0.038
14	Strasbourg (partie française)	0.110	0.286	0.235	-0.081
15	Narbonne	0.110	0.207	0.131	-0.155
...					
182	Albertville	-0.052	0.195	0.118	0.140
183	Mazamet	-0.053	-0.386	0.096	0.030
184	Dole	-0.056	-0.119	0.104	0.082
185	Cognac	-0.056	-0.253	0.098	0.059
186	Hazebrouck	-0.057	0.012	0.098	0.108
187	Saint-Amand-les-Eaux	-0.057	-0.029	0.110	0.100
188	Fougères	-0.058	-0.098	0.098	0.090
189	Brive-la-Gaillarde	-0.058	-0.153	0.148	0.066
190	Chaumont	-0.062	-0.417	0.093	0.043
191	Longwy (partie française)	-0.068	-0.069	0.124	0.110
192	Saint-Étienne	-0.068	-0.246	0.225	0.024
193	Pont-à-Mousson	-0.072	-0.116	0.094	0.114
194	Montluçon	-0.075	-0.529	0.135	0.008
195	Le Creusot	-0.088	-0.339	0.109	0.095
196	La Bresse	-0.096	-0.102	0.094	0.162
197	Montceau-les-Mines	-0.097	-0.393	0.117	0.095

Table 34: Correlation matrix between QoL rankings (central Urban Units)

		Income		Wage	
Share:		Variable	Constant	Variable	Constant
Income	Variable	1	0.850	0.833	0.721
	Constant	–	1	0.865	0.953
Wage	Variable	–	–	1	0.896
	Constant	–	–	–	1

Table 35: Predictive power of amenities on Quality of Life in central Urban Units (computed from income)

	<i>Dependent variable:</i>								
					$\widehat{QoL}$ Distance		Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Maximum altitude	0.00005 (0.00004)		0.00004 (0.00004)		-0.00002 (0.00004)	-0.00003 (0.00004)		0.00001 (0.00003)	0.00000 (0.00003)
Slope	0.0001 (0.00004)		0.0001 (0.00004)		0.0001** (0.00004)	0.0001** (0.00004)		0.0001* (0.00004)	0.0001* (0.00004)
Rain, winter	-0.001*** (0.0003)		-0.001*** (0.0003)		0.001 (0.0004)	0.0004 (0.0004)		-0.002*** (0.0003)	-0.002*** (0.0003)
Temperature, winter	0.015*** (0.003)		0.016*** (0.003)		0.034*** (0.003)	0.035*** (0.003)		0.005** (0.003)	0.006** (0.003)
Universities per thousand		-0.072 (0.066)	-0.045 (0.064)			0.045 (0.059)			0.024 (0.056)
Cinemas per thousand		0.041 (0.034)	0.056* (0.033)			0.067** (0.030)			0.061** (0.029)
Doctors per thousand		0.016* (0.009)	0.017* (0.009)			0.012 (0.008)			0.016** (0.008)
Dist. British Channel				0.00001 (0.0001)	-0.0001 (0.0001)	-0.00004 (0.0001)			
Dist. Mediterranean				-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)			
Dist. Atlantic				0.0001*** (0.00003)	0.0003*** (0.00004)	0.0004*** (0.00004)			
Dummy British Channel							0.069*** (0.021)	0.087*** (0.020)	0.089*** (0.020)
Dummy Mediterranean							0.291*** (0.023)	0.259*** (0.023)	0.264*** (0.023)
Dummy Atlantic							0.104*** (0.016)	0.139*** (0.018)	0.140*** (0.017)
Dummy Switzerland				0.071* (0.039)	0.137*** (0.036)	0.126*** (0.036)	0.126*** (0.035)	0.120*** (0.034)	0.109*** (0.035)
Dummy Belgium/Luxembourg				0.037 (0.042)	0.016 (0.037)	0.019 (0.037)	0.042 (0.037)	0.059* (0.035)	0.064* (0.035)
Dummy Germany				-0.070 (0.045)	-0.071* (0.042)	-0.067 (0.042)	-0.039 (0.039)	-0.054 (0.038)	-0.046 (0.038)
Dummy Spain				0.107** (0.044)	0.115*** (0.040)	0.109*** (0.040)	0.063 (0.040)	0.047 (0.038)	0.037 (0.038)
Observations	594	598	594	598	594	594	598	594	594
R <sup>2</sup>	0.115	0.010	0.126	0.115	0.290	0.302	0.272	0.347	0.358
Adjusted R <sup>2</sup>	0.109	0.005	0.116	0.105	0.277	0.285	0.263	0.334	0.343

Note:

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01



Table 36: Predictive power of amenities on Quality of Life in central Urban Units (computed from wages)

	<i>Dependent variable:</i>								
					$\widehat{QoL}$		Dummy		
	(1)	(2)	(3)	(4)	Distance	(6)	(7)	(8)	(9)
Maximum altitude	0.0001 (0.00004)		0.0001 (0.00004)		0.00001 (0.00004)	0.00000 (0.00004)		0.00002 (0.00003)	0.00001 (0.00003)
Slope	0.00002 (0.00005)		0.00002 (0.00005)		0.00005 (0.00005)	0.0001 (0.00005)		0.00004 (0.00004)	0.00004 (0.00004)
Rain, winter	-0.001** (0.0003)		-0.001** (0.0003)		0.0003 (0.0004)	0.0002 (0.0004)		-0.002*** (0.0003)	-0.002*** (0.0003)
Temperature, winter	0.015*** (0.003)		0.015*** (0.003)		0.035*** (0.004)	0.036*** (0.004)		0.003 (0.003)	0.004 (0.003)
Universities per thousand		-0.152** (0.070)	-0.125* (0.070)			-0.011 (0.064)			-0.023 (0.056)
Cinemas per thousand		0.052 (0.036)	0.065* (0.036)			0.063* (0.033)			0.058** (0.029)
Doctors per thousand		0.014 (0.010)	0.014 (0.010)			0.010 (0.009)			0.013* (0.008)
Dist. British Channel				0.0002* (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)			
Dist. Mediterranean				0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)			
Dist. Atlantic				0.00003 (0.00003)	0.0003*** (0.00005)	0.0003*** (0.00005)			
Dummy British Channel							0.078*** (0.021)	0.098*** (0.020)	0.100*** (0.020)
Dummy Mediterranean							0.332*** (0.023)	0.309*** (0.023)	0.313*** (0.023)
Dummy Atlantic							0.163*** (0.016)	0.203*** (0.017)	0.203*** (0.017)
Dummy Switzerland				0.176*** (0.041)	0.251*** (0.039)	0.238*** (0.039)	0.235*** (0.034)	0.227*** (0.034)	0.215*** (0.035)
Dummy Belgium/Luxembourg				-0.010 (0.044)	-0.032 (0.040)	-0.030 (0.040)	0.007 (0.036)	0.019 (0.035)	0.023 (0.035)
Dummy Germany				-0.041 (0.048)	-0.051 (0.045)	-0.045 (0.045)	0.008 (0.039)	-0.013 (0.038)	-0.005 (0.038)
Dummy Spain				0.100** (0.047)	0.110** (0.043)	0.104** (0.044)	0.050 (0.039)	0.039 (0.037)	0.029 (0.038)
Observations	594	598	594	598	594	594	598	594	594
R <sup>2</sup>	0.080	0.014	0.094	0.111	0.266	0.273	0.378	0.431	0.439
Adjusted R <sup>2</sup>	0.074	0.009	0.083	0.101	0.253	0.256	0.371	0.420	0.425

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01