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BIG-CITY LIFE (DIS)SATISFACTION? THE EFFECT OF URBAN LIVING ON SUBJECTIVE WELL-BEING

by David Loschiavo*

Abstract

This paper investigates the effect of big-city life on individuals' well-being. Combining data on Italian municipalities' characteristics with individual-level survey data, I find that city size negatively affects subjective well-being. This association is not driven by omitted variable bias or by spatial sorting of citizens. Commute time accounts for most of the differences in subjective well-being among cities of different size. There is suggestive evidence that the negative effect of commuting on well-being is caused by reduced time availability for fostering personal relationships and engaging in leisure activities. This finding suggests that interventions reducing the amount of time people spend in an unpleasant state can spur agglomeration economies and their contribution to aggregate productivity and growth.

JEL Classification: D60, I3, R23, R41, H54, J61.
Keywords: subjective well-being, urbanization, commute time.

Contents

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1 Introduction*

According to traditional analysis of agglomeration, urban concentration enhances productivity, which, in turn, spurs national economic growth.[1] However, at individual level urbanization not only provides many benefits but also comes with substantial costs. The overall effect on subjective well-being (SWB) is unclear and is debated in the literature. Importantly, the existence of differentials in SWB among cities of different size may lower the contribution of agglomeration economies to aggregate growth if such differentials limit the number of workers willing to move in high productivity cities in response to a localized labour demand shock (i.e. the *local employment elasticity*).

Against this background, Italy has a milder (relative to other countries) pattern of agglomeration and its main urban areas economies make a lower contribution to national value added (Accetturo *et al.* (2019)). There is limited population mobility with migration responding weakly to local changes in employment and wages (see Brunello *et al.* (2001); Ciani *et al.* (2017)).[2] Despite differentials in productivity between urban and non-urban areas that are in line with those of other comparable countries, urban wage premia are lower in Italy (Lamorgese and Petrella (2018)). Rigid housing supply elasticity has been found to hamper agglomeration processes by effectively limiting the number of workers who have access to such high productivity (Accetturo *et al.* (2018)).

Congestion may also play an important role in affecting local employment elasticity and Italian urban agglomeration. According to the INRIX 2018 Global Traffic Scorecard, eight of the top ten cities in the world ranked by hours lost in congestion are European. Among them, Italian cities are among the slowest.[3] Since congestion correlates with city age, it is no surprise that European cities place among the slowest globally. Dense cores, narrow roads and complex road networks make older European cities ill-suited for mobility. Surprisingly enough, research on congestion's drag on employment and productivity growth has focused mainly on US cities, with less attention devoted to Europe.[4] Italy is indeed a particularly interesting country to analyse due to the strong presence of historical and artistic amenities and urban constrained topographies. Such constraints limit a city's expansion to a shape deemed ideal for minimizing within-city trips and for building

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[1]Several mechanisms have been postulated. See, for instance, Rosenthal and Strange (2001); Ellison *et al.* (2010); Chaney *et al.* (2012).

[2]A reduced propensity to move can also be explained by the familistic culture in Italy (Alesina and Ichino (2009)) or by the dynastic nature of professional occupations (Mocetti (2016)).

[3]Rome ranks first in Europe and second globally; 5 out of the 16 most congested European cities are Italian (Rome (1), Milan (6), Florence (10), Naples (13), Turin (16)).

[4]A remarkable exception is Broersma and van Dijk (2008) who find that slow productivity growth in The Netherlands during the 1990s was concentrated in the economic core regions and explained by negative congestion effects overruling positive agglomeration advantages.

cost-effective transport networks (Harari (2017)), thus negatively affecting SWB via increased commute times.

This analysis is motivated by the relatively low degree of agglomeration in Italy and, consequently, the weaker contribution of agglomeration economies to aggregate productivity and growth. It aims to show that commute time, by negatively affecting SWB, lessens the attractiveness of big cities and therefore may be an important determinant of low local employment elasticity. Indeed, there is some evidence that big-city life can lower the well-being of residents (see Section 2) and so, by affecting workers' location choices across cities, prevent or slow down agglomeration processes. As a matter of fact, urbanization is a source of both amenities and disamenities. When the sources of urban attractiveness prevail, local labour demand shocks may boost a city's growth. Conversely, when disamenities prevail, the ability of local areas to grasp the benefits of a positive shock may be hindered. It follows that big cities' characteristics and their capacity to attract skilled workers are likely to have relevant effects on aggregate economic growth.

Results of the analysis show that urbanization negatively affects individuals' well-being, even after taking into account heterogeneity of living conditions within cities (Section 5). Estimations yield a happiness (negative) premium with respect to city size of -0.059 (Section 6). Commute time accounts for most of the differences in SWB among cities of different size, as it proxies a fundamental determinant of SWB: the reduced availability of time for big-city dwellers to build and foster personal relationships (Section 4). An IV strategy and a coefficient stability analysis *à la Altonji* tackle unobserved heterogeneity concerns (Section 7.1); a Heckman selection model (Section 7.2) shows that results are not driven by spatial sorting of citizens. Results are insensitive to different definitions of city size variable, to the presence of endogenous amenities, to the relative income hypothesis and to different types of individual and city income shocks (Section 7.3).

Congestion may negatively impact the economic growth of metropolitan areas through three channels: the monetary costs of congestion-induced travel delays; when congestion slows metropolitan growth and limits agglomeration economies; and the fiscal burdens stemming from public-sector congestion mitigation policies. This work highlights another potential channel, which reinforce the second channel, for the relevance of congestion as a constraint on growth: the sizable negative effect of commute time on SWB. It is argued that increased commute times force big-city dwellers to spend relatively more of their time in a state of tension and stress rather than engaging in leisure activities and fostering personal relationships. This, in turn, limits the attractiveness of big cities, slows labour mobility and hampers agglomeration economies. Such a channel is of great policy interest since it helps to determine local policies, such as transport infrastructure investments and local taxation. For instance, Hymel (2009) find that high initial levels of traffic congestion dampen subsequent employment growth in large US metropolitan areas and, consequently, that increasing the efficiency of public infrastructure can spur local economies. Agrawal and Hoyt (2018) show how local income tax differentials can have a large effect on commuting times.

Overall, the analysis suggests that policy makers interested in increasing urbanization as a driver of aggregate growth may enhance individual well-being through interventions that reduce the amount of time people spend in an unpleasant state.

In particular, congestion taxes, investment in public transportation and flextime work arrangements may reduce the amount of time spent commuting, thus increasing well-being and the attractiveness of big cities.

2 Related literature

This paper relates to different strands of literature. First, it builds on the literature on resource misallocation across cities and its effects on aggregate growth. Hsieh and Moretti (2019) have recently shown that spatial misallocation of labour, due to constraints on housing supply in the most productive US cities, has lowered aggregate growth by the striking figure of almost 50 per cent in the last half century. However, by enabling people to separate workplace and residence, efficient commuting may facilitate the allocation of workers to productive locations even in the presence of inelastic housing supply. For example, Monte *et al.* (2018) show how empirically-observed improvements in commuting technologies across US counties generate sizable welfare gains. This work contributes to this literature by showing that negative effects of long commute times on SWB can lower big cities' attractiveness and, therefore, impede the efficient allocation of resources across cities.

This work also adds to both the growing strands of literature on urban and happiness economics. Indeed, big cities offer better job, income and consumption opportunities, thus positively affecting the SWB of their inhabitants. However, an adverse effect on SWB could stem from increased living costs, congestion, pollution, work pressure, and a lower willingness among people to cooperate and support each other. On the whole, the impact of urbanization on SWB appears to be ultimately an empirical question. According to urban economics literature, people in big cities are not only richer but also happier (Glaeser (2011); Albouy (2008)). However, Diamond (2016) has shown that benefits stemming from living in urban areas are easily grasped by skilled individuals who are able to better enjoy the amenities that are relatively more important or affordable to them than to those less educated. On the contrary, studies in the field of happiness economics find that urbanization generally reduces SWB (for instance, Berry and Okulicz-Kozaryn (2011); Easterlin *et al.* (2011); Winters and Li (2017)). Glaeser *et al.* (2016) show that residents of declining cities in the US appear less happy than others. Previous studies on Italian data confirm that quality of life varies substantially across space (Colombo *et al.* (2014)). To the best of my knowledge, this is the first paper that systematically addresses the potential bias in the relationship between urbanization and SWB stemming from the unobserved heterogeneity and spatial sorting of citizens.

This work also relates to studies on the relevance of commute time for SWB. Stutzer and Frey (2008) show that the length and difficulty of a person's commute may play a much bigger role in her happiness than whatever benefits she may derive from a longer commute. Lucas and Heady (2002) also find evidence that commuting stress is correlated with sleep quality, health and problems at work. According to the study of the Office for National Statistics (2014) commuters are more likely to be anxious, dissatisfied and have a lower sense that their activities are worthwhile even if they are paid more than those who do not have to travel to work.[5] This analysis contributes to this strand of literature by showing how commute time affects SWB not only because of health and stress issues but also via a reduced time for building and fostering personal relationships.

3 Data and overview of spatial disparities in SWB

Data sources The data used in the analysis are obtained from different sources. The primary one is the *Banca d'Italia's Survey on Household Income and Wealth* (SHIW), which collects information on demographics, income, assets, and loans for a representative sample of Italian households and is carried out biennially. The survey includes approximately 8,000 households, distributed over about 350 Italian municipalities. The sampling is in two stages: first m unicipalities a re c hosen from different strata from throughout Italy and then households are randomly chosen from registry œce records within each chosen municipality.

From 2004 to 2010, the SHIW asked half of the sample the following question: "Considering all the aspects of your life, how happy would you say you are? Please score on a scale from 1 to 10, where 1 means *extremely unhappy* and 10 *extremely happy*, and the intermediate numbers serve to graduate the response". Since 2012, the question has been asked to all respondents. The sample used in the analysis consists of the seven waves 2004-2016 for a total of approximately 36,000 observations (21,500 individuals). For the purposes of this paper, it is important to underline that the SHIW confidentially r eports i ndividuals' c ity o f r esidence (there are 452 cities in the sample used for this analysis). This makes it possible to match the individual data with local information at city level.

Data at city level are drawn from other sources. Crime rate, Commute time, City Connectivity, Unemployment Rate and Value Added are from *Italian National Institute of Statistics* (ISTAT - Istituto nazionale di statistica). House prices are from The Italian Revenue Agency (AdE - Agenzia delle Entrate). Data on environmental variables are from the *Italian National Agency for New Technologies, Energy and Sustainable Economic Development* (ENEA - Agenzia nazionale per le nuove tecnologie, l'energia e lo sviluppo economico sostenibile). Data on tax and income records at city level are from the *Italian Ministry of Economy and Finance* (MEF). Variable definitions and descriptive statistics (Table A1) are presented in the Appendix A.

Evidence presented in the next Section 4 is drawn on the Italian leg of the Eurostat's EU-SILC survey (*EU-Statistics on Income and Living Conditions*), that in its *2013 Ad-hoc module on Subjective Well-Being* collected data on different dimensions of SWB (life satisfaction, happiness, and the sense of purpose in life), individual satisfaction with commute time, personal relationships and time use. This survey, although richer in the dimensions of quality of life considered, cannot be used for the main analysis of this paper due to the confidentiality l imitation on the city of residence of respondents.

[5]However, behind such apparently sub-optimal choices there could be a countervailing indirect effect since commuters could be sacrificing t hemselves for t he h appiness of o ther m embers of the family in living far from the commuter workplace.

Overview of spatial disparities in SWB To provide a first glance at who/where are the happy people in Italy, Table 1 describes SWB levels for different groups by reporting the mean level of the happiness score for each characteristic. The data show that women report themselves as noticeably less happy than men. There is a negative effect from age, with the highest level of happiness reported in the 35-to-44 years age category and some evidence of a mild U-shape. Interestingly, and perhaps unexpectedly, the highly educated (with college degrees) are less satisfied than those with high school qualification, who are in turn more satisfied than those with no or few qualifications. Individuals who work as employees are slightly happier than those who are self-employed; while the lowest level of hap-piness is reported by those in a non-working status. These are averages across a heterogeneous group and the presence of both retired and unemployed in the latter category is particularly likely to confound the average score. As an economist would predict, SWB rises with quartiles of income and wealth. The mean level of the happiness score does vary somewhat across geographical areas (it is higher in North Italy than in the southern regions); most likely reflecting spatial differences in per capita income. A primary aim of the paper is to explore the idea that city size has a relevant effect on SWB: the bottom of Table 1 shows the existence of differences in average levels of happiness by city size with the highest level of SWB occurring in medium-sized cities and the lower mean level in the biggest cities.

A preliminary descriptive analysis of city-level happiness is further provided by showing how happy the happiest cities are relative to the least happy, and how these differences compare with the average values of other selected variables relevant for the following econometric analysis. The top panel of Table 2 documents large differences in average happiness between the top and bottom quintiles of its distribution, from an average of 5.9 in the least happy quintile to 7.9 in the top quintile. The inter-quintile difference is also highly significant. The top and bottom quintiles also differ significantly with regard to the other variables: commute times and population size are significantly lower in the happiest communities while house prices are significantly higher in the bottom quintiles of the distribution of happiness. These findings suggest that life is significantly less happy in urban areas.

To further explore the issue, in the bottom panel of Table 2 a direct comparison of happiness in the urban and non-urban samples is presented, to see how, on average, happiness and other relevant variables differ between the two types of cities.[6] The average gap between urban and non-urban happiness is about 0.3 points on a scale of 0 to 10: a difference highly significant in statistical terms and that those familiar with the literature on SWB will recognize as substantial. As expected, house prices and population size are significantly higher in the urban areas. Average commute times are 34 minutes in the non-urban areas, compared to 40 minutes in the urban areas. Despite being in line with previous studies,[7]

[6] The distinction between urban and non-urban typology is based on the Eurostat's methodology that classifies the degree of urbanization of an area into 3 levels: 'Densely populated area'; 'Intermediate area'; and 'Thinly-populated area'. For the sake of simplicity, I have aggregate the last two typologies in the non-urban category while adopting the first typology for the urban category. The population threshold between these two categories is 50,000 inhabitants.

[7] A recent work by Helliwell *et al.* (2018) finds very similar differences in happiness and commute time between Canadian urban and rural communities.

this difference in commute time may not appear striking at first glance. However, the effect of commuting on SWB depends not only on the time and the distance involved but also on the interaction with other factors that may cause emotional and physical stress. In particular, the quality of commuting is often negatively correlated with its length. Systematic public transportation and congestion-related travel delays make commuting more stressful because people feel like they are not in control of their time and are under considerable time pressure to get to their job. The strain of commuting is also increased by environmental factors like noise, overcrowded transports and pollution, which are typically associated with bigger cities.

Overall, these results document the existence of spatial disparities in levels of SWB and that the top quintile cities have lower commute times, smaller population size and house prices, all of which are features of non-urban rather than urban life. In fact, when splitting the sample into non-urban and urban parts, life is found to be indeed less happy in the cities.

Following this preliminary look at the happiness data and some of the related determinants, the next section provides suggestive evidence of how time availability, as proxied by commute time, is an important determinant of SWB.

4 Big-city life and allocation of time

Why should big-city residents be less happy? According to Wirth (1938), one of many potential reasons is "the relative absence of intimate personal acquaintanceship". Characteristically, big-city dwellers are exposed to unceasing external contacts with numbers of persons that are nevertheless impersonal and transitory.[8]

In addition to this, big-city dwellers are dependent upon more people for the satisfaction of their life-needs than are residents of smaller cities. It follows that their acquaintances tend to be of a self-serving nature: the role they play in each other's lives is often a means to their own ends. This utilitarian nexus tends to displace inter-personal relations and is enhanced by the higher cost of living of larger cities. Finally, the exposure to a more competitive environment where there is a lower willingness among people to cooperate and support each other may reduce happiness.

According to social psychology literature, close relationships are indeed a fundamental determinant of individual health and well-being. Those who keep warm and lasting relationships with family, friends, and the community are happier than loners (see Distel *et al.* (2015)) and those with strong social support experienced less mental deterioration as they aged (Vaillant (2003)). More recently, Clark *et al.* (2018) find that, contrary to the conventional wisdom, income inequality accounts for only a small percentage of the variance in happiness across the population; the critical factors being instead their social relationships and their mental and physical health.

[8]It is often said that the big cities are characterized by secondary rather than primary contacts: typically, physical contacts are close but social contacts are distant (Wirth (1938)).

As the quality of personal relationships is not easily observed by the econometrician, the simple consideration that building and maintaining close and good relationships require time helps us in looking for an observed "proxy" control. Big-city dwellers typically face increased congestion, longer workdays and greater commute time. This causes a reduction of the time available for fostering personal relationships and leisure activities and a higher opportunity cost of time in big cities. On average, big-city dwellers spend relatively more of their time in activities that are associated not with greater happiness, but with higher tension and stress. Therefore, commute time is the observed "proxy" control[9] that, supported by the following evidence, I assume to be negatively correlated with the time available for developing and enriching personal relationships and happiness-generating activities.

A *prima facie* evidence of the relevance of commute time for several dimensions of SWB is provided in Table 3. Columns 1, 4, and 7 show that, after controlling for a bevy set of individual characteristics, the effect on SWB of a one standard deviation increase in the self-reported satisfaction with commute time accounts for as much as 45 to 80 per cent of one standard deviation increase in income (another important determinant of SWB). Once satisfaction with personal relationships and time use are also taken into account, it becomes evident that the strongest effect on SWB stems from the former, whose effect on SWB accounts, in terms of standardized coefficients, for as much as 1.3 to 5 times the effect of one standard deviation increase in income (see Table 3). Since happiness will be the dimension of SWB used in this work, it is worth noting that this result holds true regardless of the measure of well-being adopted (happiness, life satisfaction or eudamonia).[10] Table 4 complements this suggestive evidence by showing how satisfaction with commute time strongly correlates with, and has a sizable effect on, satisfaction with personal relationships and with time use, thus supporting the choice of the former as a "proxy" variable for the latter.

In line with these findings, I proxy the opportunity cost of time by using commute time (city mean values) to argue that the negative effect of living in big cities is largely explained by the reduced availability of time for their inhabitants. In fact, when I add data on commute time into the analysis, the coefficient of city size dulls substantially both in magnitude and statistical significance.

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[9]In Angrist and Pischke (2008) it is shown how a proxy control, that is, the inclusion of variables that might partially control for omitted factors, but are themselves affected by the variable of interest, it is an improvement on no control at all.

[10]Happiness is often referred to as hedonic well-being since respondents tend to answer how they are feeling right at the instant of the interview. Life satisfaction is considered a cognitive/evaluative measure because in answering individuals tend to make an evaluation about how well their life is going with respect their initial goals. Last, there are eudemonic measures (declaration that life has a meaning) that can be thought of as reflecting Maslow's hierarchy of needs. The different well-being measures are actually sharply different from each other and, as such, it is not a priori clear which one of them is closest to what really matters to people. However, the well-being measures may be quite strongly correlated with each other as shown by previous studies (see Clark (2016)) but, as it stands, are also clear from the results reported in Table 3.

5 Effects of urbanization on well-being

Let us assume that the level of happiness reported by individual i in city c at time t is given by:

$$h_{ict} = log(pop_{ct}) + \mathbf{x}'_{it}\beta + \mathbf{z}'_{ct-1}\gamma + \epsilon_{ict}, \tag{1}$$

where urbanization is measured by the size of the city as expressed by the log of its population $log(pop_{ct})$, $\mathbf{x}_{it}$ is a vector of time-varying individual characteristics expected to have a significant explanatory power according to the related literature. More specifically, they include a gender dummy, age, age squared, dummies for educational attainment and marital status, household size, dummies for employment status, the logs of equivalised income and equivalised net wealth. $\mathbf{z}_{ct-1}$ is a vector of time-varying location-specific features that may affect individual well-being. They include city's house prices, natural amenities (degree days[11] and altitude), commute time, inter-city connectivity,[12] county crime rate, unemployment rate and value added. ϵ_{ict} denotes the error term. Estimations of equation (1) also include year and month of interview, and macro-area geo dummies.

A first hypothesis to test is whether there are systematic differences in happiness levels across Italian cities of different size, both before controlling for individual and location characteristics and after including these controls. To facilitate a comparison with previous studies on SWB, I estimate equation (1) by means of a pooled ordered probit. To account for the complex sampling design in the SHIW, in all the regressions variance is estimated using Jackknife Repeated Replications (JRR) replicated weights.[13] In the following sections, the sources of bias potentially arising from estimating such an equation will be addressed.

Results reported in Table 5 show that city size has a negative and statistically significant effect on self-reported happiness. Estimated coefficients of all other control variables confirm all the main determinants of happiness highlighted by the literature (see Appendix B for coefficient discussion). The city size coefficient estimates do vary somewhat across specifications. Interestingly, the magnitude of the coefficient increases both when individual (Columns 2 to 3) and location controls (Columns 4 to 7) are included, suggesting that studies not controlling for individual characteristics or city features may produce inaccurate results. In particular, the biggest variation in coefficient magnitude occurs when housing values are included among controls. In urban economics, higher house prices are a revealed signal of higher quality of life. Consistently, conditioning on house prices significantly lowers the coefficient on the city size (from -0.022 to -0.055) since it partials out the effect of better local amenities in bigger cities.

In addition to this, when commute time is added to the city level variables, the city-size negative effect greatly decreases in magnitude and statistical significance

[11]Heating degree days express how cold winters are in each specific city. This measure is preferred to annual average temperatures because it better reflects how much the temperature varied within a year. For a more in-depth explanation see the variable's definition in Appendix A.

[12]The index expresses the intensity of worker flows among cities. The greater the index the higher the intensity of inter-city flows. For further details, see Appendix A.

[13]Faiella (2008) shows how ignoring SHIW sampling design can affect the results of statistical inference and suggests, as a strategy for unbias variance estimation, the use of JRR method.

(see Table 5 Column 6), suggesting that part of the negative effect of city size depends on this variable. Table 6 shows that the latter result holds not only when I include commute time together with the other city-level covariates but also in isolation, when I sequentially augment the regression in Table 5 Column 3, with each of the variables measuring socioeconomic conditions of municipalities where the individual resides.

The augmented specification of Table 5 Column 6 will be the baseline since, when comparing the estimated models in Table 5 and Table 6, I find that the introduction of the additional regressors delivers the highest values for Pseudo R2 and the lowest ones for AIC and BIC, confirming the superior performance of the full specification in terms of goodness of fit.

It is worth noting that, despite the number of regressors used, the variance inflation factor (VIF) does not reveal multicollinearity problems. In particular, the variables of interest, population size and commute time do not have high VIFs, being respectively 3.33 and 3.40, well below the threshold of 10 usually adopted in the literature to conclude that multicollinearity is a problem (Gujarati (1988)). In addition to this, an adjusted Wald test rejects, at a confidence level of 99.9 per cent, the null hypothesis that the estimated coefficients of population size and commute time are jointly equal to zero. Multicollinearity does not pose a serious problem for at least two other reasons: i) the regression coefficients are individually significant (see Columns 5 and 7 of Table 5 and Columns 7 and 9 of Table 6); and ii) the estimates and their standard errors are not very sensitive to changes in the data.[14] On the other hand, dropping one of the two variables of interest from the model may cause a specification bias since omitting a variable may seriously mislead as to the true values of the parameters.

Overall, the negative relationship between urbanization and self-reported happiness is strongly significant and robust to various specifications and only controlling for commute time causes the relationship to weaken both in magnitude and statistical significance.

Results are in line with the urban morphologies of most of the biggest Italian cities. In fact, with few exceptions they are prevalently monocentric but, at the same time, they face different geographic (steep terrain or proximity to sea coasts) and historical/artistic (implying restrictive regulations on vertical limits for buildings) constraints. Such constraints prevent them from taking a circular expansion path, which is considered by urban planners the ideal one for minimizing within-city trips and for constructing cost-effective transport networks. It follows that the spatial layout of cities is forced towards a less compact development pattern, which, in turn, can cause longer within-city distances. Consistently, Manzoli and Mocetti (2016) find that most of the large house prices differentials between Italian urban and non-urban areas is explained by the higher prices of urban central areas and that the house price gradient is steeper when the average commute time is longer. Thus, the strong tourism attractiveness of Italian city centres and the evidence that consumers are paying a premium for living in central areas (in terms of a higher house price-to-income ratio) to reduce within-city trips[15] may explain

[14] This is confirmed by the numerous sample splits presented in the following sections.

[15] Harari (2017) using Indian data finds also evidence that consumers are paying a premium

the existence of large house price differentials even in the presence of low agglomeration and labour mobility. The following section provides additional insights on this.

Heterogeneity of living conditions within cities This section of the paper considers amendments of the previous model to handle individual heterogeneity in living conditions inside the city. In particular, information reported by the interviewer on the respondents' house of residence location (centre vs outskirts), on the quality of the building where they live (luxury vs deteriorated) as well as on the quality of their neighbourhood (luxury vs deteriorated) are exploited. Columns 1 and 2 of Table 7 show that including these indicators among individual controls does not affect previous results. Furthermore, results of the regressions run only on the sub-sample of individuals living in the city centre show that for those individuals the effect of agglomeration on SWB is not statistically different from zero (see Columns 3 and 4 of Table 7). Indeed, Italian cities are predominantly monocentric and so people living in city centres experience on average shorter within-city trips. Hence, by showing that people living in city centre are not negatively affected by city size, these results provide additional evidence that commute time is an important determinant of big-city dwellers' lower SWB.

6 Big-city negative premium

One potential issue with the estimations of the previous sections is that they are performed on micro-data and include aggregated (specifically, city-level) variables. As shown by Moulton (1990) and Combes *et al.* (2008), this one-step procedure may be problematic since it can create very large biases in the standard error for the coefficients on aggregate explanatory variables. To address the issue,[16] I adopt a two-stage estimation procedure that has been widely used in urban literature when estimating the effect of urbanization on wage premia (see, among others, Moretti (2004) and De la Roca and Puga (2017)) and that yields standard errors that account for the grouped structure of the data. For this, in the first stage, I estimate a pooled ordered probit regression of self-reported happiness on individual characteristics and city fixed effects. Hence, the regression-adjusted mean happiness in city c at time t, $\widehat{\sigma_c}$, is obtained from the following first-stage regression:

$$h_{ic} = \sigma_c + \mathbf{x}_i^{'}\beta + d_t + d_m + \epsilon_{ic}, \tag{2}$$

where $\mathbf{x}_i^{'}$ is a vector of individual characteristics, d_t and d_m are respectively year and month of interview dummies, and σ_c is a set of city-time dummies that can be interpreted as a vector of adjusted city average happiness. This equation is estimated by a pooled ordered probit and results are reported in Column 1 of Table 8.

for living in more compact cities, in terms of lower wages and higher housing rents/prices.

[16] Clustering standard errors at the city level is not sufficient to avoid this pitfall since individuals can move between areas.

In the second stage, the estimated city fixed effects $\hat{\sigma_c}$ are used as dependent variable and are regressed on the log of the city population, controlling for city characteristics $\mathbf{z}_c^{'}$ and macro-area fixed effects m_a:

$$\widehat{\sigma_c} = log(pop_c) + \mathbf{z}_c^{'}\gamma + m_a + \eta_{ic}, \tag{3}$$

All the regressions are weighted by the number of observations per city to account for differences in the precision of the first stage estimates. This weighted two-stage procedure gives rise to estimates that are numerically very close to one-step estimates: Table 8 Columns 2 to 4 show pooled-OLS happiness (negative) premia with respect to city size which are equivalent to the relevant coefficients obtained by the single-stage estimations of Table 5 Columns 3 to 5. In particular, estimates of the specification with the full set of location-specific controls yield a happiness (negative) premium with respect to city size of -0.059 (Column4), which is very close to the one-stage estimate of -0.050. In addition to this, when commute time is added among city-level variables, the city-size negative premium decreases both numerically and in statistical significance (see Table 8 Column 5), confirming that actually a good part of the negative effect of city size depends on this variable.

7 Identification issues and sensitivity analysis

In this section, other sources of bias potentially affecting results, such as unobserved heterogeneity and spatial sorting of individuals across cities, will be addressed. Furthermore, the last subsection is devoted to examine the sensitivity of findings when alternative measures of urbanization are used and the role of endogenous amenities, the reference income hypothesis and aggregate and individuals' income shocks are taken into account.

7.1 Addressing the endogeneity of city size

A first issue with estimating the effect of city size on SWB is that people living in big cities might differ from other people along unobservable dimensions. Furthermore, an omitted variable bias could also arise if some city characteristics simultaneously influence SWB and attract individuals to the city, thus increasing its size. In order to tackle these potential sources of bias, I adopt two identification strategies: I first provide instrumental variables (IV) estimates; then I follow the Altonji *et al.* (2005) approach and use selection on observables to assess the bias from unobservables.

IV estimates City size is instrumented by historical population in 1921.[17] The hypothesis of lack of correlation between long-lagged population size and current economic phenomena is commonly made in the urban economics literature (see, for instance, Ciccone and Hall (1996); Combes *et al.* (2008)).

The validity of this instrument rests on the hypothesis that the early patterns of agglomeration in Italy did not reflect factors which both significantly contribute

[17]The year 1921 was chosen to avoid a strong reduction in the number of cities included in the sample. In fact, Italy's first census year was 1861 but, at that time, many cities included in the sample did not exist or they changed the extension of their area over time.

to SWB nowadays and are not accounted for by the model (as it would be if natural amenities were not controlled for), but have a lingering influence mainly through the legacy of agglomeration. On the contrary, if historical population is correlated with the SWB level of the city, it will not give an estimate of the agglomeration effect. Indeed, it is reasonable to assume that modern societies have changed so much that it is unlikely that the variables relevant for SWB at the beginning of the 20th century still matter today. This identifying assumption can be also defended on the grounds that industrialization in Italy did not begin until the 1890s, and that the biggest wave of industrialization, which came with the first congestion problems in bigger cities (see Ciani *et al.* (2017)), occurred only in the 1950s.

Table 9 gives the first and second stages of IV estimations. The first-stage results in Panel B show that the instrument is significant. It is also strong. The F-statistic for weak identification exceeds all critical values proposed by Stock and Yogo (2005). The LM test confirms the instrument is relevant as it rejects the null hypothesis that the model is underidentified. Lastly, according to the endogeneity test, the data do not reject the use of OLS.

Overall, I found endogeneity concerns to be of small practical importance. Indeed, estimates document that instrumenting leaves almost unchanged the coefficient of happiness (negative) premium with respect to city size. This holds true for all the specifications with sequentially increasing controls (Columns 1 to 3). The reduction in the magnitude and statistical significance of the city size coefficient when commute time is plugged into estimations is also confirmed (Column 4).

Bias from unobservables and coefficient stability Since the validity of an instrument is always disputable, it is possible to adopt another identification strategy under the assumption that selection on observables can be used to assess the potential bias from unobservables (Altonji *et al.* (2005)). For this, one needs to look for a measure of how strong selection on unobservables, relative to selection on observables, must be to explain away the full estimated effect of city size. This measure can be calculated by first considering two regressions: one with a restricted set of control variables, and one with a full set of controls. If selection on observables is proportional to selection on unobservables, then the changes in the coefficient of interest between the two regressions provide information about the bias induced by excluding relevant characteristics. Oster (2017) has shown that coefficient stability analysis can be misleading if it ignores the fact that coefficient movements must be scaled by R^2 movements.[18] For this reason, a correction that takes into account the R^2 is proposed. This correction delivers a bound for the

[18] Oster (2017) shows that the following is a consistent estimator of the effect of α (e.g., city size) on the outcome variable (e.g., SWB):

$$\hat{\hat{\alpha}} = \hat{\alpha*} - (\hat{\alpha} - \hat{\alpha*}) \times \frac{R_{max} - R^*}{R^* - R}, \tag{4}$$

where $\hat{\alpha*}$ and R* are the coefficient estimate and R^2 from the regression including observable covariates, and $\hat{\alpha}$ and R are the coefficient and R^2 from the uncontrolled regression. In addition, R_{max} is the R^2 in a regression of the outcome variable on all observable and unobservable controls, which is clearly unknowable (given its reliance on unobservables) and must be obtained using one of the statistical approaches presented in the text.

coefficient of interest. The idea underlying the approach is that the increase in the R^2 across the uncontrolled and the controlled regressions captures the amount of variation in the dependent variable that is explained by the observed covariates. This, together with the maximum amount of variation that can be potentially explained R_{max}, gives rise to an estimate of the lower bound for the interval of coefficients. If this lower bound is negative, it would provide further evidence that the true causal effect of city size on SWB is indeed likely to be negative. To be cautious, I adopt different statistical assumptions regarding R_{max}, including the most conservative case of $R_{max} = 1$.[19]

Accordingly, the adjusted coefficients for the specification with full controls presented in Column 6 of Table 5 are reported in the last five columns of Table 10. The bounds confirm that the true effect of city size is negative, and possibly even larger than the estimates in Table 5. This holds true under different approaches to R_{max} and, most remarkably, even under the unrealistically conservative assumption of R_{max}=1.[20] Indeed, in the more realistic cases of Columns 3 and 4, the lower bounds are also numerically very close to the upper bound. Such results make it less likely that the estimated effects are fully driven by omitted variable bias.

Overall the analysis shows that, by exploiting instrumental variables and the *à la Altonji* approach, it is possible to provide robust results with respect to endogeneity concerns.

7.2 Sample selection

Another potential source of estimation bias may arise from not taking into account the sorting of individuals across cities, especially if cities of different size attract people who are disproportionately inclined to be more or less happy. As a matter of fact, urban dwellers are more likely to have moved recently, and less likely to have a sense of community belonging than are those in more rural areas. Individuals leaving small cities for bigger cities experience greater levels of congestion, pollution and distress. In addition to having to adapt to the latter negative factors, movers face other migration costs (such as breaking physical proximity with family and friends). Such costs may (at least temporarily) outweigh the benefits to the individual's well-being stemming from getting a new job or a higher income. If this is the case, the negative relationship between SWB and urbanization might then be transitory and driven by adaptation to big-city life.

Hence, in order to leave out temporary adaptation effects, I run the regressions on the sub-sample of stayers by exploiting, as in Guiso *et al.* (2015), the SHIW information on the place of birth and city of residence of individuals, to create an indicator variable denoting whether the individual lives in the same province where

[19] More in detail, I use all the approaches to R_{max} adopted in González and Miguel (2015) and based on different degrees of measurement error in the reported outcome variable (i.e., the survey–resurvey reliability ratio of an outcome variable), namely: (1) the Oster approach ($R_{max} = \min\{1.3R^*, 1\}$), (2) the González and Miguel approach (R_{max}=2R*–R), (3) and (4) the reliability ratio approaches based on McKenzie (2012) and Baird *et al.* (2008) (assuming R_{max}=0.5 and R_{max}=0.8, respectively), (5) and the most conservative case (R_{max}=1).

[20] R_{max}=1 implicitly assumes that there is exactly zero measurement error in the reported outcome variable. A case which seems implausible in most real-world applications.

she was born (stayer) or she has moved since her birth (mover). The coefficient of city size is unaffected, and it remains significantly different from zero at the 1 per ceb level (Table 11). This holds true both for the single-stage regression on happiness (Column 1) and for the two-stage estimation on regression-adjusted city average happiness (Column 2).

Furthermore, to deal with the fact that the stayers might be a selected sam-ple of the population, I adopt a Heckman selection model. Following Barone and Mocetti (2011) as exclusion restriction, I use an indicator variable that is equal to 1 if the individual has inherited the house where she lives and 0 otherwise. This exclusion restriction implies that, conditional on controls, the inheritance of the house of residence affects the probability of being a stayer but it is unrelated to SWB. Indeed, it is reasonable that the propensity to stay is higher for those who inherit their house of residence. Selling and buying houses are in fact typically as-sociated with relatively large search and sunk costs. Thus, homeowners face higher switching costs than do others, which, in turn, may negatively affect their propen-sity to move. A potential threat to the validity of such an exclusion restriction is whether having inherited the house of residence is related to an individual's SWB even after conditioning on covariates. Indeed, it seems unlikely that, once having controlled for individuals' income and wealth, inheritance of home of residence may directly affect SWB. Despite this, to make the exclusion restriction adopted even more defensible, I also add to the controls the inheritance of a secondary home so that the wealth effect of inheriting a house on SWB is partialled out.

Running the selection model, I find that the coefficient of the relevant indicator variable in the Heckman selection equation is statistically different from zero, and the sign is positive as expected. More importantly, the negative effect of living in big cities on individual well-being is confirmed (Column 3 of Table 11). This leads me to believe that much of the difference in happiness between cities of different size reflects more than the selection of unhappy people into unhappy places.[21] Comparison between relevant Columns of Table 11 and Table 12 confirms that the city-size negative effect on happiness is significantly dwarfed when commute time is plugged into regressions.

Overall, from these results it is possible to conclude that spatial sorting and transitory effects do not seem to be relevant issues in the data since city size is more strongly associated with the unhappiness of longer-term residents.[22] This evidence is also consistent with the fact that in Italy the risk that a selected subset of individuals move to the most agglomerated areas is reduced because of low labour mobility (see Section 1) and that the choice of location is strongly driven by other factors, such as family links, migration costs, and employment relationships.

[21]An alternative approach, commonly followed in the literature when dealing with spatial sorting of individuals on unobservables, is to adopt a panel fixed effects model.To identify all the effects involved in such a specification it would be necessary to have a very large number of observations with many stayers and large flows of movers between cities. Unfortunately, the SHIW panel sample size does not have enough observations for these two conditions to be met.

[22]Were the number of panel individuals large enough, it would possible to estimate a full specification of equation 1 allowing for a joint estimation of the static and dynamic components of the happiness premium of bigger cities while accounting for unobserved individual heterogeneity. This full specification would then make it possible to formally test the existence of a dynamic effect of life experience accumulated in bigger cities on subjective well-being.

7.3 Additional robustness checks

In this subsection, I further consider how sensitive the results presented in Section 5 are to additional specifications and robustness checks.

Results are insensitive to alternative clustering schemes. Estimates reported in Table 13 show that the effect of city size on happiness is unaffected when clustering standard errors both by individual (Columns 1 and 2) and by city (Columns 3 and 4) as well as when adopting two-way clustered standard errors by both individual and city (instead of clustering just by either of the two, see Columns 5 and 6).

Table 14 presents different approaches for measuring the extent of urbanization in lieu of the log of city population. A common agglomeration variable employed in urban economics studies is based on the Local Labour Market (LLM). LLMs are clusters of municipalities aggregated on the basis of residents' daily commuting flows to their place of work. The urban economics literature is increasingly basing empirical analysis on LLMs to avoid a geographical aggregation bias in contexts of imperfect labour mobility. However, LLMs are not particularly suited to be the spatial unit of this analysis because SHIW data do not enable us to distinguish whether individuals living in small cities of a big LLM actually commute or not. In addition to this, even when they are commuters, the negative impact on their SWB may be offset by the indirect effect of living in happier families if other family members do not have to commute to their workplaces and live in a place that is less congested and with an easier access to amenities. Despite this, as an additional check in Column 1 of Table 14, I have replaced for each individual the population size of the municipality of residence with the population size of the LLM in which she lives. In accordance with my expectations, the effect of LLM population size on SWB, albeit still negative and significant, is downward biased both in magnitude and statistical significance with respect to the use of administrative area population. Controlling for commute time in Column 2 causes the negative relationship between LLM size and SWB to disappear. It is worth noting that, since commute time is still measured at city level while population size now refers to the LLM, this result provides further evidence that previous findings were not driven by the fact that population size and commute time are referred to the same spatial unit.

To check for non-linearities in the definition of city size, I assign each city to one of four categories based on population groupings: small (0-20,000); medium (20, 001-40,000); large (40,001-500,000); very large (over 500,000). In the regression results, small cities are the excluded base group and coefficients for the size dummy variables are measured relative to this base group. Estimates reported in Column 3 of Table 14 show that the highest well-being occurs in the omitted base group (small cities) and generate coefficients that are all statistically significant and largely decreasing in urban size. Columns 4 confirms that controlling for commute time reduces the negative effect of city size and that the bigger the urban size, the larger the reduction. In Columns 5 and 6, besides city population size, city land area is included among controls. Since both variables are expressed in logs, this allows us to proxy the effect of density on SWB. Using a density measure produces rather similar results, albeit it slightly lowers the coefficient on city population size which nonetheless remains strongly significant.

Finally, to check if findings are driven by the unhappiness of one or some of the largest cities, I have also explored removing them from the sample. In particular, in Table 15 I sequentially exclude the three biggest Italian cities (Rome, Milan and Naples) and I find that such sample restrictions do not affect the city size coefficient.

The use of OPROBIT estimations is the common standard in the SWB literature. Even though OLS estimations make it easier to interpret the coefficients, the use of such an estimator is somewhat problematic since it assumes that the distances between the 10 satisfaction scores are all equal. Ordered models relax that assumption. Moreover, the technical correctness of an OPROBIT outweighs the simplicity of interpreting an OLS when the distribution of the outcomes is skewed, as is normally the case for SWB. Bearing this in mind, it is important to emphasize that in unreported estimations OLS models give the same results as OPROBIT models in terms of significance levels and predicted outcomes.

Value of amenities, endogenous amenities and the role of skill gap In the previous specifications, the value of amenities was approximated by the level of a city's house prices. In urban economics, the value of a city's amenities, in line with the standard revealed-preference approach, is usually considered proportional to the city's cost-of-living relative to its wage level. Hence, one may be worried that results are driven by incorrect amenity-value estimations. I replace house prices with a measure of value of amenities obtained, following Albouy (2008), by the willingness-to-pay (WTP) of a city's inhabitant. More specifically, to obtain the city average WTP, I subtract from imputed rents the average income after local and state taxes.[23] Adjusted amenity-value estimates reported in Columns 1 of Table 16 indicate that previous results are insensitive to such a change.

Diamond (2016) recently showed for US big cities that the increase in the proportion of college graduates raised local productivity and all workers' wages, but improved even more so the local amenities that matter to skilled workers. Such amenities may be considered endogenous since their supply tends to respond to the larger high-skill mix of big cities. Thus, the net welfare impacts of changes in a city's wages, rents, and endogenous amenities led to greater in well-being inequality between college and high school graduates that is larger than the increase in the college wage gap alone. In what follows, I check whether structural and significant differences between the two groups of individuals affect the relationship between agglomeration and SWB.

To this end, I estimate three different specifications. As a first exercise, I split the sample by education level, distinguishing college graduates from from those who did not graduate from college. I then run separate regressions on the two sub-samples (Columns 2 to 5 of Table 16). I then take it a step further and run regressions in which the log of city population is interacted with an indicator variable expressing individuals' highest educational attainment (Columns 6 and 7 of Table 16). Finally, in Columns 8 and 9 of Table 16 I adopt a different approach for measuring the extent of urbanization in lieu of the log of city population. Specifically, I assign each city to one of four categories based on population groupings:

[23]For a more in-depth explanation see the definition of the variable in Appendix A.

small (0-20,000); medium (20,001-40,000); large (40,001-500,000); very large (over 500,000). I then interact each of these categories with the indicator variable expressing the individuals' highest educational attainment.

Estimates of all specifications show that the negative effect of urbanization for college graduates is weaker and statistically less significant than for non-college graduates. This is in line with Diamond (2016) result according to which 'endogenous' amenities play a role in explaining a differentiated effect of agglomeration between skilled and unskilled individuals' SWB since the relative importance of certain amenities is different for different skill groups. Furthermore, Columns 3, 5, 7 and 9 confirm that, when commute time is plugged into estimations, the negative effect of urbanization decreases significantly for both skill groups.

Nevertheless, when comparing the effect of living in cities of different sizes for individuals within the same educational group (Columns 8 and 9), the highest well-being occurs in the omitted base group (college graduates living in small cities) and other groups' coefficients are largely decreasing in urban size and increasing in educational attainment. It follows that college graduates living in big cities experience a lower level of SWB with respect to individuals living in smaller cities with the same level of education. Overall, it appears that urbanization's amenities compensate skilled individuals more than unskilled ones for its disamenities, but they are probably not important enough to completely offset the negative effects of living in bigger cities for both skill groups.[24] From that, I conclude that the negative relationship between agglomeration and SWB fully exists even when the role of 'endogenous' amenities is taken into account.

Relative income hypothesis A long-standing tradition in economics maintains that SWB is mainly affected by relative rather than absolute level of income and wealth (see, for instance, Duesenberry (1949); Easterlin (1974); Ferrer-i Carbonell (2005); Luttmer (2005)). I therefore test the hypothesis that a person's position in the income and wealth distributions matters per se and, potentially, how sensitive the results on the effect of urbanization are to income comparisons.

For this, I adopt the following specification:

$$h_{ict} = log(pop_{ct}) + \mathbf{x}_{it}^{'}\beta + f(y_{imt}^{*})\delta + \mathbf{z}_{ct-1}^{'}\gamma + \epsilon_{ict}, \tag{5}$$

compared with equation 1, equation 5 now incorporates an additional term $f(y_{imt}^{*})$ that expresses the income of the reference group for individual i.[25] Thus, function $f(y_{imt}^{*})$ determines how reference group income influences individual well-being. Two basic specifications of this function are: $f(y_{imt}^{*}) = ln(y_{imt}^{*})$ (in model 1) and $f(y_{imt}^{*}) = \frac{ln(y_{ict})}{ln(y_{imt}^{*})}$ (in model 2), where y_{ict} denotes the income of individual i. Moreover, three additional models are estimated that, instead of the term $f(y_{imt}^{*})$, include: a dummy variable *richer* that is equal to 1 when an individual

[24]For an analysis of the role of amenities in worker location decisions and the differential change in the amenities that matter for skilled or unskilled workers across metropolitan areas in the United States, see Moretti (2013).

[25] For an explanation of how a reference group is calculated, see the definition of the variable in Appendix A.

earns more than the reference income; individuals' ranks in the income and wealth distributions; the degree of a city's income inequality.

Columns 1 and 2 of Table 17 presents the results for the first specification. The inclusion of the average equivalized income of the reference group does not change the household income coefficient significantly (see Column 5 of Table 17). Contrary to conventional wisdom, the average income of the reference group has a positive impact on SWB. There are two potential explanations for this result. First, according to the channel named "Tunnel Effect" by Hirschman and Rothschild (1973), a high reference income can have a welfare-enhancing "anticipatory feelings" effect. The idea is that individuals observing the high income of other people in their social circle interpret it as a sign that their own future income is likely to move in the same direction (Senik (2008)). Secondly, such a specification does not take into account the importance of relative income for SWB (i.e. the relevance of the distance between the individual's own and the reference group's income). To deal with this issue a second specification is adopted in which the average income of the reference group is substituted by the relative income expressed as the ratio between the individual's own income and the reference income. Results presented in Columns 3 and 4 of Table 17 show that the coefficient of the relative income is positive, indicating that the larger an individual's own income is in comparison to the reference group income, the happier the individual is.

Another hypothesis to test is that income comparisons are not symmetric (see, e.g., Duesenberry (1949)) because the happiness of individuals is negatively affected by an income below that of their reference group while individuals with an income above that of their reference group do not experience a positive impact on SWB. For this a third specification is estimated where a dummy variable *richer* is introduced when an individual earns more than the reference income. According to the hypothesis, the coefficient of the variable *richer* is expected to be non-significant. Results reported in Columns 5 and 6 of Table 17 show instead a significant and positive coefficient for the variable *richer*, contradicting the assumption that comparisons are only 'upwards'. This result is in line with evidence found on US individuals by McBride (2001) and it suggests the existence of what can be called a "getting ahead of the Joneses" channel according to which even wealthier individuals care about their social position, and their marginal utility rises when their relative wealth position advances.

Finally, Columns 7 and 8 of Table 17 report estimates of a specification in which the level of income and wealth have been replaced by the individuals' ranks in the income and wealth distributions. In both cases the omitted category is the first quartile. Results reveal a monotonic relationship between equivalised income and wealth ranks and the individuals' well-being. Unsurprisingly, the null of 0 on these coefficients can be rejected at any conventional level and the size of the income and wealth gradient is large: there is a large difference in the happiness point between individuals in the highest income/wealth quartiles and those in the lowest ones.

A number of empirical studies in experimental economics have identified fairness, inequity aversion, pure and impure altruism and reciprocity as some of the main departures from the purely self-regarding preference paradigm (see e.g. Fehr and Schmidt (1999)). Since income distribution in big cities is usually highly skewed, I test if previous findings may be driven by inequality aversion. In Columns

9 and 10 the Gini coefficient, expressing the city's degree of income inequality, is not significant and its introduction among controls does not alter previous results.

All in all, the inclusion of the income comparisons in the model does not alter the negative effect of city size on well-being: the relevant coefficient remains stable and strongly significant across all the specifications presented in Table 17 and controlling for commute time still greatly reduces its magnitude.

Individual and city income shocks According to social psychology litera-ture, individuals' memories are imperfect and susceptible to bias (Kahneman *et al.*(2003); Kahneman and Krueger (2006)). The self-evaluation of well-being is often dominated by the most recent experiences with unpleasant ones playing a bigger role than pleasurable episodes (see, for instance, the *focusing illusion* hypothesis of Kahneman *et al.* (2006)). As an economic counterpart of this, recent changes in an individual's income may influence self-reported happiness. To this end, I exploit some SHIW questions about (past or expected) individuals' income shocks to check if my results are driven by a systematic overestimation of the transitory circumstances on mood. Such questions have been included in the survey only since 2010 so the sample size is significantly reduced. Despite this, evidence re-ported in Table 18 confirms that results hold even when income shocks are taken into account.

In all columns the effect of city size on happiness holds both in terms of statistical significance and the negative sign of the coefficient, even though the size of it rises moderately with respect to the preferred specification of Table 5 Column 5.[26] Interestingly, according to the estimations, the effect of a shock to income (past or expected) is asymmetric: negative shocks affect individuals' well-being more than positive ones. This is in line with some well-known results in happiness economics and may be interpreted as backward- and forward-looking loss aversion.[27] More specifically, in Columns 1 and 2 a negative recent income shock (last year's income unusually low) has a sizable negative effect on an individual's happiness whereas the coefficient for a positive shock is not statistically different from zero. Columns 3 and 4 shows that this asymmetric pattern also emerges for decreasing and in-creasing expected income (current year income lower/higher than last year). I also control for the effect of an expected loss or gain in individuals' purchasing power. Results reported in Columns 5 and 6 confirm that a negative change in economic conditions has a significant impact on happiness that outweighs a positive one.

Finally, I also take into account the effect of income shocks at city level. Since in an area with a weak (strong) local economy there could be an increased (de-creased) perceived risk of becoming unemployed, which, in turn, may affect mood, in Columns 7 and 8 I check whether a shock to average income at city level (as expressed by its annual average rate of growth over the period 2004-2016) is causing unhappiness and I find previous results insensitive to such a change.

Overall, results on the negative effects of city size on happiness, as well as the attenuating effect of commute time, hold also when shocks to individual and aggregate income are taken into account.

[26]Most probably, this is due to the sampling variation.

[27]For example, according to the hedonic treadmill hypothesis, increases in the standard of living have almost no detectable effects on life satisfaction or happiness. Despite this, some negative changes in circumstances, such as unemployment, have a lasting effect.

8 Conclusion

I have examined the relationship between subjective well-being and urbanization. Using data on Italian cities, I find evidence that city size negatively affects individuals' happiness. This result holds when I control not only for a wide range of individual characteristics, but also for several location features at a finer partition of the territory than is usually done in the literature.

To the best of my knowledge, this is also the first work that systematically addresses the sources of bias potentially affecting the relationship between SWB and urbanization. First, to deal with the issue of a regression performed on micro units and including aggregated variables that may bias standard errors, I adopt a two-stage procedure allowing the estimation of a big-city negative well-being premium. Secondly, in order to tackle unobserved heterogeneity concerns, I also estimate the model by means of both a IV strategy and an *à la Altonji* approach and I find such concerns to be of small practical importance. Thirdly, I address the issue of spatial sorting of individuals and I find that much of the difference in happiness between cities of different size reflects more than the selection of unhappy people into unhappy places. In particular, results show that that city size is more strongly associated with unhappiness of longer-term residents, arguably suggesting the existence of a dynamic effect of life experience accumulated in bigger cities. Finally, I find that urbanization's amenities compensate skilled individuals more than unskilled ones for its disamenities, but the overall effect of living in bigger cities on SWB remains negative for both skill groups.

Controlling for commute time causes the relationship between SWB and city size to weaken both in magnitude and statistical significance. Supported by this result and by the evidence presented in Section 4, I interpret the negative relationship between urbanization and individuals' well-being as expressing the effect of reduced availability of time for big-city dwellers to engage in happiness-generating activities and foster personal relationships. I therefore argue that an important factor in explaining the negative relationship between city size and SWB is big-city inhabitants' constrained use of time as proxied by the length of commute time.

Bearing in mind the urban economics consensus on the leading role of big cities for aggregated economic growth, the implications of these results are particularly relevant in the case of Italy. A strong presence of different constraints limiting cities' expansion into an ideal shape for minimizing within-city trips and for more cost-effective transport networks may affect location choices across Italian cities. It follows that weak responsiveness of labour mobility to local positive shocks may hinder the ability of cities to grasp the benefits of these shocks for economic growth.

The findings of the analysis then suggest that policy makers interested in increasing urbanization as a driver of aggregate growth may enhance individual well-being through interventions that reduce the amount of time people spend in an unpleasant state. In particular, congestion taxes, investment in public transportation and flextime work arrangements may reduce the amount of time spent commuting, thus increasing well-being and the attractiveness of big cities.

Table 1: Happiness by social and economic characteristics

	Mean Happiness (1)	N
Sex		
Woman	6.614	15,732
Male	7.107	20,096
Age		
Less than 35 years	7.387	2,002
35 to 44 years	7.440	4,739
45 to 54 years	6.962	6,986
55 to 64 years	6.799	7,227
65 years or older	6.483	14,874
Education		
Primary school or without education	6.284	10,403
Junior high school	7.065	12,605
High school	7.422	8,909
Degree or more	7.308	3,911
Job status		
Employee	7.312	11,258
Self-employed	7.212	3,234
Non worker	6.560	21,336
Quartiles of equivalised income		
First quartile	6.516	7,435
Second quartile	6.774	9,467
Third quartile	6.995	9,449
Fourth quartile	7.323	9,477
Quartiles of equivalised net wealth		
First quartile	6.558	8,059
Second quartile	6.654	7,146
Third quartile	7.167	9,507
Fourth quartile	7.230	11,116
Geographical areas		
North West	7.214	8,738
North East	7.025	7,247
Centre	6.907	7,723
South	6.541	8,066
Islands	6.754	4,054
City size (2)		
Small city	6.929	9,609
Medium city	7.110	6,702
Large City	6.891	16,389
Very large city	6.731	3,128
Total	6.918	35,828

Source: *Survey of Household Income and Wealth*, 2004-2016 waves. Notes: (1) Means are calculated using sampling weights and refer to the whole sample.(2) City size: Small city is up to 20,000 inhabitants; Medium city population is over 20,000 and up to 40,000 inhabitants; Large city is over 40,000 and up to 500,000 inhabitants; Very large city is over 500,000 inhabitants.

Table 2: Spatial differences in SWB

	Difference between Top and Bottom Happiness Quintile Means		
	Top Quintile	Bottom Quintile	Difference
Happiness	7.914	5.871	2.043
	(0.000)	(0.000)	(0.000)
Mean Commute (minutes)	33.982	36.623	-2.640
	(0.000)	(0.001)	(0.000)
Log Population	9.504	10.289	-0.785
	(0.000)	(0.000)	(0.000)
Log house prices	7.244	7.033	0.212
	(0.000)	(0.000)	(0.001)

	Difference between Urban and Non-Urban Means		
Variable	Urban	Non-Urban	Difference
Happiness	6.734	7.007	-0.274
	(0.000)	(0.000)	(0.000)
Mean Commute (minutes)	39.844	34.108	5.736
	(0.000)	(0.001)	(0.000)
Log Population	11.448	9.410	2.038
	(0.000)	(0.000)	(0.000)
Log house prices	7.374	7.093	0.281
	(0.000)	(0.000)	(0.000)

P-values are reported in parentheses

Table 3: Effect of Satisfaction with Commuting on different dimensions of well-being

Dependent variable	Happiness			Life Satisfaction			Eudamonia		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Commuting (sat.)	0.066***	0.046***	0.027***	0.177***	0.112***	0.068***	0.180***	0.106***	0.085***
	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Relationsh. (sat.)		0.121***	0.094***		0.377***	0.314***		0.422***	0.394***
		(0.010)	(0.010)		(0.020)	(0.020)		(0.019)	(0.020)
Time use (sat.)			0.075***			0.165***			0.076***
			(0.007)			(0.014)			(0.014)
Income	0.105***	0.086***	0.084***	0.388***	0.328***	0.305***	0.223***	0.158***	0.151***
	(0.023)	(0.023)	(0.022)	(0.048)	(0.043)	(0.038)	(0.038)	(0.032)	(0.032)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10004	9995	9988	9606	9598	9592	9925	9919	9914

Note: Standardized coefficients, *** p<0.01, ** p<0.05, * p<0.1. All specifications are estimated using sampling weights with standard errors are corrected for heteroscedasticity. Individual controls are: sex, age, age squared, log of equivalised income, indicator variables for education attainment, household size, activity status, marital status and health conditions. Source: 2013 IT-SILC.

Table 4: Effect of Satisfaction with Commuting on Personal Relationships and Time use

Dependent variable	Relationships		Time Use
	(1)	(2)	(3)
	OLS	OLS	OLS
Commuting (satisf.)	0.176***	0.105***	0.334***
	(0.012)	(0.012)	(0.015)
Time use (satisf.)		0.213***	
		(0.013)	
Income	0.151***	0.127***	0.071
	(0.038)	(0.035)	(0.043)
Individual controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
N	10010	10003	10003

Note: Standardized coefficients, *** p<0.01, ** p<0.05, * p<0.1. All specifications are estimated using sampling weights with standard errors are corrected for heteroscedasticity. Individual controls are: sex, age, age squared, log of equivalised income, indicator variables for education attainment, household size, activity status, marital status and health conditions. Source: 2013 IT-SILC.

Table 5: Effects of urbanization on happiness - single stage estimations

	(1) OPROBIT	(2) OPROBIT	(3) OPROBIT	(4) OPROBIT	(5) OPROBIT	(6) OPROBIT	(7) OPROBIT
Log city size	-0.016***	-0.030***	-0.022***	-0.055***	-0.050***	-0.025**	
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.010)	
Commute time						-0.014***	-0.016***
						(0.004)	(0.002)
Sex		0.053***	0.043**	0.044**	0.046***	0.047***	0.042**
		(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Age		-0.036***	-0.045***	-0.045***	-0.045***	-0.045***	-0.046***
		(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age squared		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Elemen. school		-0.369***	-0.217***	-0.210***	-0.207***	-0.210***	-0.210***
		(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Middle school		-0.182***	-0.082***	-0.078***	-0.078***	-0.081***	-0.081***
		(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
University		0.190***	0.117***	0.117***	0.108***	0.109***	0.107***
		(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Self-employed		0.002	-0.077***	-0.076***	-0.075**	-0.074**	-0.076**
		(0.028)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Unemployed		-0.546***	-0.325***	-0.321***	-0.326***	-0.326***	-0.319***
		(0.048)	(0.054)	(0.054)	(0.054)	(0.053)	(0.054)
Retired		0.055**	0.027	0.028	0.030	0.029	0.030
		(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Household size		0.035***	0.045***	0.046***	0.046***	0.046***	0.046***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Married		0.427***	0.393***	0.395***	0.401***	0.400***	0.397***
		(0.020)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Income			0.093***	0.093***	0.092***	0.093***	0.093***
			(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Wealth			0.055***	0.054***	0.055***	0.054***	0.054***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
House prices				0.182***	0.196***	0.192***	0.142***
				(0.028)	(0.031)	(0.031)	(0.024)
Degree days					-0.033	0.010	0.020
					(0.049)	(0.049)	(0.048)
Altitude					0.006	0.004	0.013
					(0.008)	(0.008)	(0.008)
Crime rate					-0.182***	-0.158***	-0.176***
					(0.034)	(0.034)	(0.034)
Connectivity					-0.002***	-0.003***	
					(0.000)	(0.000)	
Value added					0.090***	0.073**	0.123***
					(0.034)	(0.034)	(0.035)
N	35828	35828	34812	34812	34797	34797	34797
Pseudo R2	0.007	0.038	0.045	0.046	0.047	0.047	0.047
Log likelihood	-68380.426	-66274.507	-63284.900	-63238.401	-63133.858	-63114.495	-63121.742
AIC	136818.851	132629.014	126653.801	126562.802	126363.717	126326.990	126339.483
BIC	137064.959	132968.473	127009.025	126926.484	126769.666	126741.397	126745.433

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. Reference categories: education = high school; marital status = single; employment status = employee. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 6: Effects of urbanization on happiness - single stage estimations

	(1) OPROBIT	(2) OPROBIT	(3) OPROBIT	(4) OPROBIT	(5) OPROBIT	(6) OPROBIT	(7) OPROBIT	(8) OPROBIT	(9) OPROBIT
Log city size	-0.055***	-0.021***	-0.019***	-0.015***	-0.025***	-0.019***	-0.025***	-0.003	
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	
Commute time								-0.011***	-0.012***
								(0.003)	(0.002)
House prices	0.182***								
	(0.028)								
Degree days		0.012							
		(0.036)							
Altitude			0.008						
			(0.006)						
Crime rate				-0.116***					
				(0.032)					
Value added					0.111***				
					(0.032)				
Unemployment rate						-0.148***			
						(0.034)			
Connectivity							-0.002***		
							(0.000)		
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34812	34797	34797	34812	34812	34802	34812	34812	34812
Pseudo R2	0.046	0.045	0.045	0.045	0.046	0.045	0.045	0.045	0.045
Log likelihood	-63238.401	-63248.937	-63247.586	-63270.269	-63246.649	-63241.83	-63277.876	-63271.216	-63271.277
AIC	126562.802	126583.874	126581.172	126626.538	126579.298	126569.7	126641.751	126628.432	126626.554
BIC	126926.484	126947.537	126944.836	126990.219	126942.980	126933.3	127005.433	126992.113	126981.778

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 7: Effects of urbanization on happiness - controlling for heterogeneity in location and housing quality

	(1) OPROBIT Whole sample	(2) OPROBIT Whole sample	(3) OPROBIT Only living in center	(4) OPROBIT Only living in center
Log city size	-0.047***	-0.023**	0.020	0.044
	(0.007)	(0.010)	(0.026)	(0.037)
Commute time		-0.013***		-0.011
		(0.004)		(0.010)
Center	-0.007	-0.006		
	(0.023)	(0.023)		
Outskirt	0.008	0.007		
	(0.018)	(0.018)		
Luxury neighborhood	0.070**	0.071**	0.050	0.053
	(0.034)	(0.034)	(0.059)	(0.059)
Deteriorate neighborhood	-0.228***	-0.229***	-0.268***	-0.273***
	(0.038)	(0.038)	(0.088)	(0.088)
Luxury house	0.099***	0.097***	0.002	-0.001
	(0.035)	(0.036)	(0.060)	(0.061)
Deteriorated house	-0.082**	-0.078**	-0.219**	-0.219**
	(0.032)	(0.032)	(0.094)	(0.094)
Individual controls	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes
N	34797	34797	4957	4957

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 8: Estimation of the city size well-being premium - two stage estimations

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Happiness	City Indicators coefficients of column (1)			
	OPROBIT	OLS			
Log city size		-0.026**	-0.065***	-0.059***	-0.031
		(0.010)	(0.018)	(0.016)	(0.021)
City indicators	Yes				
Sex	0.045**				
	(0.019)				
Age	-0.044***				
	(0.004)				
Age squared	0.000***				
	(0.000)				
Elementary school	-0.243***				
	(0.029)				
Middle school	-0.098***				
	(0.022)				
University	0.113***				
	(0.033)				
Self-employed	-0.083***				
	(0.030)				
Unemployed	-0.324***				
	(0.062)				
Retired	0.017				
	(0.025)				
Household size	0.050***				
	(0.012)				
Married	0.413***				
	(0.027)				
Income	0.088***				
	(0.014)				
Wealth	0.055***				
	(0.005)				
House prices			0.215***	0.226***	0.221***
			(0.075)	(0.082)	(0.083)
Degree days				-0.027	0.024
				(0.138)	(0.132)
Altitude				0.006	0.003
				(0.019)	(0.019)
Crime rate				-0.233***	-0.202**
				(0.079)	(0.082)
Connectivity				-0.003***	-0.003***
				(0.001)	(0.001)
Value added				0.156*	0.127
				(0.092)	(0.095)
Commute time					-0.015*
					(0.008)
Observations	34812	452	452	447	447
R2		0.13	0.16	0.21	0.22

Notes: Column (1) include year and month of interview indicators and is estimated using sampling weights. Columns (2) to (5) include geo (5 Macroareas: NW, NE, Center, South, Islands) indicators and are weighted by the number of observations per city. Reference categories: education = high school; marital status = single; employment status = employee. Coefficients are reported with robust standard errors in parenthesis, which are clustered at city level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 9: IV estimation of the city size well-being premium

	(1)	(2)	(3)	(4)
Panel A: Second stage estimates				
Dependent variable	City size premium	City size premium	City size premium	City size premium
Instrumented log city size	-0.023*	-0.079***	-0.062***	-0.029
	(0.012)	(0.017)	(0.016)	(0.024)
House prices		0.306***	0.213***	0.198***
		(0.061)	(0.075)	(0.075)
Degree days			-0.020	-0.002
			(0.080)	(0.080)
Altitude			-0.006	-0.004
			(0.015)	(0.015)
Crime rate			-0.251***	-0.224***
			(0.079)	(0.080)
Connectivity			-0.002***	-0.003***
			(0.001)	(0.001)
Value added			0.296***	0.269***
			(0.098)	(0.100)
Commute time				-0.016*
				(0.009)
Observations	451	451	446	446
R2	0.02	0.11	0.18	0.19
F-test weak ident. (H0: instruments jointly insignificant)	549.90	578.52	457.65	196.43
P-value LM test (H0: model underidentified)	0.00	0.00	0.00	0.00
P-value endog. test (H0: exogeneity of instrumented var.)	0.40	0.93	0.81	0.94
Panel B: First stage estimates				
Dependent variable	Log city size	Log city size	Log city size	Log city size
Log city size 1921	1.040***	0.882***	0.832***	0.708***
	(0.044)	(0.037)	(0.039)	(0.050)
House prices		0.825***	0.791***	0.740***
		(0.113)	(0.132)	(0.127)
Degree days			-0.647***	-0.633***
			(0.161)	(0.145)
Altitude			0.014	0.005
			(0.028)	(0.027)
Crime rate			0.395**	0.215
			(0.158)	(0.156)
Connectivity			-0.000	0.002
			(0.002)	(0.002)
Value added			0.106	0.210
			(0.246)	(0.227)
Commute time				0.073***
				(0.017)
Observations	451	451	446	446
R2	0.89	0.91	0.93	0.93

Notes: All regressions include a constant term. In Panel B are reported the first-stage regressions of log city size on historical population instrument (1921). In panel A are reported second-stage regressions of city premia on instrumented log city size. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10% levels. The F-statistic (or Kleibergen-Paap rk Wald statistic) reported on the weak instruments identification test exceeds all thresholds proposed by Stock and Yogo (2005) for the maximal relative bias and maximal size.

Table 10: Different estimates of the bounds on the potential bias due to unobservables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Oster (2017)	González and	Reliability ratio		Most conservative case
	Uncontrolled	Controlled	approach	Miguel (2015)	McKenzie (2012)	Baird et al. (2008)	
Log city size	-0.024***	-0.040***	[-0.045, -0.040]	[-0.055, -0.040]	[-0.076, -0.040]	[-0.110, -0.040]	[-0.132, -0.040]
	(0.006)	(0.015)					
R2	0.028	0.168					
Rmax			0.218	0.307	0.500	0.800	1.000
Controls	No	Yes					
Area and Year FE	Yes	Yes					
N. of observations	35,828	34,797					

Note: Set intervals estimation using an equal proportional selection assumption. González and Miguel's approach uses Rmax=2R*-R; Oster's approach uses Rmax=1.3R*, where R and R* are the R2 from column (1) and (2) respectively. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Controlling for spatial sorting

	(1)	(2)	(3)	(4)
Dependent variable	Happiness	City size premium	Happiness	
	OPROBIT	OLS	Heckman selection	
Subsample	Only Stayers	Only Stayers	Stage Two	Stage One
Log city size	-0.051***	-0.059***	-0.083***	-0.056***
	(0.008)	(0.018)	(0.012)	(0.009)
Sex	0.088***		0.151***	0.042*
	(0.022)		(0.033)	(0.021)
Age	-0.044***		-0.065***	0.009**
	(0.005)		(0.007)	(0.004)
Age squared	0.000***		0.000***	-0.000**
	(0.000)		(0.000)	(0.000)
Elementary school	-0.184***		-0.288***	0.093***
	(0.032)		(0.054)	(0.035)
Middle school	-0.051*		-0.093**	-0.028
	(0.024)		(0.037)	(0.027)
University	0.166***		0.174***	-0.222***
	(0.030)		(0.043)	(0.035)
Self-employed	-0.104**		-0.140***	0.213***
	(0.034)		(0.053)	(0.034)
Unemployed	-0.257***		-0.417***	0.008
	(0.064)		(0.106)	(0.064)
Retired	0.007		0.009	0.030
	(0.033)		(0.054)	(0.034)
Household size	0.024		0.041**	0.032**
	(0.010)		(0.016)	(0.013)
Married	0.469***		0.688***	-0.171***
	(0.027)		(0.041)	(0.031)
Income	0.106***		0.190***	0.022**
	(0.011)		(0.019)	(0.009)
Wealth	0.041***		0.091***	0.080***
	(0.005)		(0.008)	(0.005)
House prices	0.173***	0.195**	0.263***	0.118***
	(0.034)	(0.090)	(0.054)	(0.038)
Degree days	-0.078	-0.095	-0.168*	-0.262***
	(0.058)	(0.148)	(0.094)	(0.072)
Altitude	-0.012	0.012	0.025	0.049***
	(0.010)	(0.021)	(0.015)	(0.011)
Crime rate	-0.240***	-0.331***	-0.357***	0.012
	(0.041)	(0.078)	(0.064)	(0.042)
Connectivity	-0.002***	-0.002*	-0.003***	0.001***
	(0.000)	(0.001)	(0.001)	(0.001)
Value added	0.125**	0.265**	0.148**	-0.179***
	(0.044)	(0.109)	(0.072)	(0.058)
Second home inherited			-0.154**	-0.154***
			(0.067)	(0.037)
Home inherited			*excluded*	0.400***
				(0.028)
Additional controls	YES	YES	YES	YES
N	25125	429	34797	34797
athrho			0.264***	0.258***
			(0.029)	(0.029)
lnsigma			0.487***	0.486***
			(0.009)	(0.009)

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. Stayer= individual's current province of residence is the same of the one in which she was born. The exclusion restriction for the Heckman specification is inheritance of home of residence. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 12: Controlling for spatial sorting and commute time

	(1)	(2)	(3)	(4)
Dependent variable	Happiness	City size premium	Happiness	Happiness
	OPROBIT	OLS	Heckman selection	
Subsample	Only Stayers	Only Stayers	Stage Two	Stage One
Log city size	-0.022	-0.027	-0.047**	-0.069***
	(0.012)	(0.022)	(0.019)	(0.011)
Sex	0.088***		0.152***	0.041*
	(0.022)		(0.033)	(0.021)
Age	-0.044***		-0.064***	0.009**
	(0.005)		(0.007)	(0.004)
Age squared	0.000***		0.000***	-0.000**
	(0.000)		(0.000)	(0.000)
Elementary school	-0.187***		-0.291***	0.094***
	(0.032)		(0.054)	(0.035)
Middle school	-0.054*		-0.097***	-0.026
	(0.024)		(0.037)	(0.027)
University	0.164***		0.173***	-0.223***
	(0.030)		(0.043)	(0.035)
Self-employed	-0.105**		-0.142***	0.213***
	(0.034)		(0.053)	(0.034)
Unemployed	-0.256***		-0.416***	0.006
	(0.064)		(0.106)	(0.064)
Retired	0.005		0.007	0.030
	(0.033)		(0.053)	(0.034)
Household size	0.024*		0.041**	0.032**
	(0.010)		(0.016)	(0.013)
Married	0.469***		0.688***	-0.170***
	(0.027)		(0.041)	(0.031)
Income	0.107***		0.191***	0.022**
	(0.011)		(0.019)	(0.009)
Wealth	0.040***		0.090***	0.080***
	(0.005)		(0.008)	(0.005)
House prices	0.158***	0.176*	0.243***	0.116***
	(0.035)	(0.090)	(0.055)	(0.038)
Degree days	-0.030	-0.040	-0.107	-0.279***
	(0.057)	(0.141)	(0.093)	(0.071)
Altitude	0.009	0.009	0.021	0.050***
	(0.010)	(0.021)	(0.016)	(0.011)
Crime rate	-0.214***	-0.296***	-0.324***	0.005
	(0.041)	(0.080)	(0.065)	(0.045)
Connectivity	-0.002***	-0.003**	-0.003***	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)
Value added	0.102*	0.228**	0.120*	-0.169***
	(0.044)	(0.114)	(0.072)	(0.058)
Commute time	-0.015***	-0.016*	-0.019***	0.008*
	(0.004)	(0.009)	(0.007)	(0.004)
Second home inherited			-0.149**	-0.155***
			(0.067)	(0.037)
Home inherited			*excluded*	0.400***
				(0.028)
Additional controls	YES	YES	YES	YES
N	25125	429	34797	34797
athrho			0.264***	0.258***
			(0.029)	(0.029)
lnsigma			0.487***	0.486***
			(0.009)	(0.009)

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. Stayer= individual's current province of residence is the same of the one in which she was born. The exclusion restriction for the Heckman specification is inheritance of home of residence. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 13: Effects of urbanization on happiness - alternative clustering schemes

	(1)	(2)	(3)	(4)	(5)	(6)
	OPROBIT	OPROBIT	OPROBIT	OPROBIT	OPROBIT	OPROBIT
	St. err. clustered by individual	St. err. clustered by individual	St. err. clustered by city	St. err. clustered by city	Two-way clusters by city and indiv.	Two-way clusters by city and indiv.
Log city size	-0.050***	-0.024**	-0.050***	-0.024	-0.050***	-0.024**
	(0.007)	(0.010)	(0.012)	(0.019)	(0.007)	(0.010)
Commute time		-0.015***		-0.015*		-0.015***
		(0.004)		(0.008)		(0.004)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes
N	34797	34797	34797	34797	34797	34797
Pseudo R2	0.047	0.047	0.047	0.047	0.047	0.047
Log likelihood	-63133.858	-63114.495	-63133.858	-63114.495	-63133.858	-63114.495
AIC	126363.717	126326.990	126363.717	126326.990	126363.717	126326.990
BIC	126769.666	126741.397	126769.666	126741.397	126769.666	126741.397

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators and are estimated using sampling weights. Coefficients are reported with robust standard errors in parenthesis, which are clustered at individual level in columns (1) and (2); at city level in columns (3) and (4); and adopting a two-way clustered standard errors by both individual and city in columns (5) and (6). ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 14: Effects of urbanization on happiness - controlling for non linearities and alternative definitions of city size

	(1) OPROBIT LLM population	(2) OPROBIT LLM population	(3) OPROBIT City size dummies	(4) OPROBIT City size dummies	(5) OPROBIT Density	(6) OPROBIT Density
Log city size (pop)					-0.056***	-0.034***
					(0.010)	(0.011)
Log city area (ha)					0.009	0.023*
					(0.013)	(0.013)
Log LLM size (pop)	-0.026**	-0.013				
	(0.010)	(0.011)				
Medium city			-0.160***	-0.147***		
			(0.030)	(0.030)		
Large City			-0.245***	-0.186***		
			(0.028)	(0.033)		
Very large city			-0.350***	-0.238***		
			(0.058)	(0.065)		
Commute time		-0.020***		-0.013***		-0.016***
		(0.003)		(0.003)		(0.004)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes
N	34797	34797	27572	27572	34797	34797

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. In columns (3) and (4) City size: Small city (reference category) is up to 20,000 inhabitants; Medium city population is over 20,000 and up to 40,000 inhabitants; Large city is over 40,000 and up to 500,000 inhabitants; Very large city is over 500,000 inhabitants. In column (4) the biggest city (Rome) is excluded. In column (5) the two biggest cities (Rome and Milan) are excluded. In column (46) the three biggest cities (Rome, Milan and Naples) are excluded. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 15: Effects of urbanization on happiness - controlling for outliers

	(1) OPROBIT Without biggest city	(2) OPROBIT Without biggest city	(3) OPROBIT Without two biggest cities	(4) OPROBIT Without two biggest cities	(5) OPROBIT Without three biggest cities	(6) OPROBIT Without three biggest cities
Log city size	-0.054***	-0.029***	-0.054***	-0.029***	-0.054***	-0.028***
	(0.006)	(0.010)	(0.006)	(0.010)	(0.006)	(0.010)
Commute time		-0.014***		-0.014***		-0.014***
		(0.004)		(0.004)		(0.004)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes
N	34278	34278	33761	33761	33277	33277

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. In columns (1) and (2) the biggest city (Rome) is excluded. In columns (3) and (4) the two biggest cities (Rome and Milan) are excluded. In columns (5) and (6) the three biggest cities (Rome, Milan and Naples) are excluded. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 16: Effects of urbanization on happiness - controlling for value of amenities and education

	(1) OPROBIT Whole sample	(2) OPROBIT College	(3) OPROBIT College	(4) OPROBIT Non-College	(5) OPROBIT Non-College	(6) OPROBIT Whole sample	(7) OPROBIT Whole sample	(8) OPROBIT Whole sample	(9) OPROBIT Whole sample
Log city size	-0.048***	-0.044**	-0.042*	-0.049***	-0.023**				
	(0.005)	(0.022)	(0.024)	(0.007)	(0.011)				
Commute time			-0.001		-0.015***		-0.014***		-0.013***
			(0.010)		(0.004)		(0.004)		(0.003)
Value of Amenities	0.202***								
	(0.032)								
Elementary school X Log city size						-0.064***	-0.038***		
						(0.007)	(0.010)		
Middle school X Log city size						-0.051***	-0.026***		
						(0.006)	(0.010)		
High school X Log city size						-0.044***	-0.018*		
						(0.007)	(0.010)		
College grad. X Log city size						-0.035***	-0.009		
						(0.007)	(0.010)		
College grad. X Small city								Reference category	Reference category
College grad. X Medium city								-0.231***	-0.219**
								(0.089)	(0.088)
College grad. X Large city								-0.238***	-0.182***
								(0.069)	(0.069)
College grad. X Very large city								-0.308***	-0.200**
								(0.080)	(0.082)
Non-College X Small city								-0.164**	-0.167***
								(0.063)	(0.063)
Non-College X Medium city								-0.312***	-0.301***
								(0.063)	(0.062)
Non-College X Large city								-0.400***	-0.346***
								(0.063)	(0.063)
Non-College X Very large city								-0.510***	-0.404***
								(0.083)	(0.085)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34812	3854	3854	30943	30943	34797	34797	27572	27572

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. In columns (2) and (3) the sample is restricted to individuals who are college graduates or hold a postgraduate degree. In column (4) and (5) the sample is restricted to individuals who are not collage graduates. In columns (8) and (9) the reference category is college graduates who live in small cities and City size is defined in the following way: Small city is up to 20,000 inhabitants; Medium city population is over 20,000 and up to 40,000 inhabitants; Large city is over 40,000 and up to 500,000 inhabitants; Very large city is over 500,000 inhabitants. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 17: Effects of urbanization on happiness - controlling for relative income hypothesis

	(1) OPROBIT	(2) OPROBIT	(3) OPROBIT	(4) OPROBIT	(5) OPROBIT	(6) OPROBIT	(7) OPROBIT	(8) OPROBIT	(9) OPROBIT	(10) OPROBIT
Log city size	-0.051***	-0.024**	-0.052***	-0.028***	-0.052***	-0.027***	-0.051***	-0.034***	-0.051***	-0.027**
	(0.007)	(0.010)	(0.007)	(0.010)	(0.006)	(0.010)	(0.006)	(0.009)	(0.007)	(0.009)
Income	0.091***	0.091***	0.023**	0.024**	0.067***	0.068***			0.094***	0.093***
	(0.009)	(0.009)	(0.011)	(0.011)	(0.009)	(0.009)			(0.009)	(0.009)
Wealth	0.054***	0.054***	0.047***	0.047***	0.050***	0.050***			0.054***	0.054***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)			(0.004)	(0.004)
Reference income	0.160*	0.172**								
	(0.083)	(0.083)								
Commute time		-0.015***		-0.013***		-0.014***		-0.010***		-0.014***
		(0.004)		(0.004)		(0.004)		(0.003)		(0.003)
Relative income			0.472***	0.466***						
			(0.057)	(0.057)						
Richer					0.146***	0.145***				
					(0.019)	(0.019)				
2nd Wealth Quartile							0.094***	0.097***		
							(0.024)	(0.024)		
3rd Wealth Quartile							0.195***	0.194***		
							(0.024)	(0.024)		
4th Wealth Quartile							0.296***	0.293***		
							(0.027)	(0.027)		
2nd Income Quartile							0.244***	0.243***		
							(0.028)	(0.028)		
3rd Income Quartile							0.343***	0.342***		
							(0.029)	(0.029)		
4th Income Quartile					0.431***	0.431***				
							(0.031)	(0.031)		
Gini									0.126	0.245
									(0.263)	(0.273)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34724	34724	34724	34724	34724	34724	35737	35737	34724	34724

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. In columns (7) and (8) Income and Wealth are not included among individual controls and reference categories are: 1st Income and Wealth quartile. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 18: Effects of urbanization on happiness - controlling for income shocks

	(1) OPROBIT	(2) OPROBIT	(3) OPROBIT	(4) OPROBIT	(5) OPROBIT	(6) OPROBIT	(7) OPROBIT	(8) OPROBIT
Log city size	-0.063***	-0.033***	-0.064***	-0.016	-0.058***	-0.036***	-0.053***	-0.026***
	(0.007)	(0.011)	(0.013)	(0.018)	(0.007)	(0.011)	(0.007)	(0.010)
Commute time		-0.016***		-0.027***		-0.012***		-0.014***
		(0.004)		(0.007)		(0.004)		(0.004)
Past income shock (positive)	-0.055	-0.059						
	(0.081)	(0.081)						
Past income shock (negative)	-0.270***	-0.271***						
	(0.032)	(0.032)						
Expected income (increasing)			0.085	0.091				
			(0.094)	(0.095)				
Expected income (decreasing)			-0.398***	-0.402***				
			(0.061)	(0.061)				
Expected real income (increasing)					0.008	0.008		
					(0.038)	(0.038)		
Expected real income (decreasing)					-0.206***	-0.201***		
					(0.020)	(0.020)		
City income growth							-1.003	-0.844
							(0.986)	(0.984)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22795	22795	7589	7589	21956	21956	34714	34714

Notes: All specifications include geo (5 Macroareas: NW, NE, Center, South, Islands), year and month of interview indicators. Weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. Reference categories: Past income shock = last year income was normal with respect to the yearly ordinary household income; Expected income = income in the current year is expected the same compared with the previous year; Expected real income = current year individual's income is expected to rise about the same as prices. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Appendix A Definitions of variables and summary statistics

Here I provide a detailed description of the variables used in the paper whose definitions are not obvious.

- *Happy* Indicator obtained from the following question: "Considering all the aspects of your life, how happy would you say you are?" Coded between 0 and 10, with a higher number indicating more happiness. (source: SHIW)

- *Income* Log of equivalised household (monetary disposable) income. Equivalised household income is normally considered the most appropriate indicator of the standard of living of a family and is obtained by applying to total household income the modified OECD equivalence scale which assigns a coefficient of 1 to the head of household, 0.5 to other household members aged 14 or more, and 0.3 to those younger than 14. For each household the number of "equivalent adults" is calculated by summing the coefficients assigned to the various members. Household income is then divided by that coefficient and allocated to each household member. For more details see (Canberra Group, 2011, pp. 68-72). Finally, monetary disposable income refers to disposable household income net of imputed rents and gross of negative interest. (source: SHIW)

- *Wealth* Log of net equivalised household net wealth. Equavalised wealth is obtained by applying the modified OECD equivalence scale to total household net wealth (for more details on the OECD equivalence scale see *Income* above). (source: SHIW)

- *Education* Indicator variable expressing the individual's highest level of education and coded in the following way: 1 = Pre-primary and primary education; 2 = Middle school; 3 = High school degree; 4 = University degree or postgraduate degree. (source: SHIW)

- *House prices* Log of city-level house prices per square meter. Data on house prices are obtained from the Observatory of the real estate market managed by Italian Revenue Agency (AdE - Agenzia delle Entrate) and aggregated at city level according to the methodology of Cannari and Faiella (2008). Data are one-year lagged.

- *Crime rate* Log of the number of crimes (per 1,000 inhabitants) reported by the police forces to the judicial authority at provincial level. Data are one-year lagged. (source: ISTAT)

- *Value added* Log of the value added at provincial level. Data are one-year lagged. (source: ISTAT)

- *Degree days* Log of degree days. Heating degree days are typical indicators of household energy consumption for space heating. The sum of the degree days over periods such as entire heating seasons is used to calculate the amount of heating required for a building. The degree days of a city is computed as the sum, extended to all days of a conventional heating season, of the daily difference (if positive) between the base temperature (conventionally fixed for Italian cities by the European regulation UNI EN ISO 15927-6:2008) and the mean air temperature outside. A zero degree day in energy monitoring and targeting is when heating consumption is at a minimum, which is useful for power utility companies in predicting seasonal low points in energy demand. (source: ENEA)

- *Altitude* Log of altitude defined as the height (expressed in meters) above sea level of a city. (source: ISTAT)

- *Commute time* The time taken to reach the usual place of work or study for those who commute daily (mean value per city). The variable is originally coded by minute intervals in the following way: 1 = up to 15 minutes; 2 = between 16 and 30 minutes; 3 = between 31 and 60 minutes; 4 = over 60 minutes. To take into account that intervals do not have a constant time length, the variable is first recoded in minutes by replacing each of its values with the mean value of the relevant interval and then collapsed (mean) at city level. (source: ISTAT)

- *Connectivity* Connectivity refers to the number of connections in the commuting matrix ($flows \neq 0$) over the total number of possible connections, n(n-1), where n is the number of cities of the LLM. The index expresses the degree of flows intensity among cities. The higher the index, the higher is the intensity of inter-city flows; the lower the index, the higher is the proportion of worker flows within the same city of residence.

- *Stayer* A dummy equal to 1 if an individual's current province of residence is the same as the one in which she was born. Provinces are administrative units comparable in size to a US county. (source: SHIW)

- *Willingness-to-pay (WTP)* To obtain the city average WTP, the average income after local and state taxes is subtracted from imputed rents. Imputed rents are converted from housing values using a discount rate of 4.08 percent (equal to the average rent-to-price ratio in Italy, see Banca d'Italia, 2017 Annual Reports, Regional Economies series): this makes imputed rents comparable to the gross rents available for rental units. Net average income is obtained by applying both the relevant tax rate to the total income reported in each tax bracket, and regional and council tax rates on total income. This enable us to take into account the progressive effect of the tax system and the differentiated effect of local taxes.

- *Reference group income* Income of a reference group is calculated as a yearly average income of individuals living in the same area (with data aggregated into three macro-regions: North, Center and South), similar age (with data aggregated into three age groups: 18-44, 45-54 and more than 55 years) and similar education level (with data aggregated into four categories: Pre-primary and primary education, Middle school, High school, University or postgraduate degree). Thus there were 36 arbitrarily assigned reference groups. To some extent this procedure is justified by the fact that both work colleagues and friends are likely to belong to a similar age groups and to complete a similar level of education.

- *Past income shock* Indicator obtained from the following question: "Considering the total income of your household in year (t-1), would you say that it was unusually high, unusually low, or normal with respect to the yearly income your household generally makes in a normal year?" Coded: 1 = Unusually high; 2 = Normal; 3 = Unusually low. The question was not asked before 2010. (source: SHIW)

- *Expected income* Indicator obtained from the following question: "Consider your household's overall income in the current year. Compared with the previous year, do you think that it will be higher, the same or lower?" Coded: 1= higher; 2 = the same; 3 = lower; 4 = Don't know/No answer. The question was asked only in 2014. (source: SHIW)

- *Expected real income* Indicator obtained from the following question: "This year do you expect your household's total income to rise more than prices, less than prices, or about the same as prices?" Coded: 1 = Less than prices; 2 = About the same as prices; 3 = More than prices; 4 = Don't know; 5 No answer. The question was not asked before 2010. (source: SHIW)

Table A1: Summary statistics

Variable	Mean	St Dev	Percentiles				
			10	25	50	75	90
			Panel A: *Survey of Household Income and Wealth*				
Happiness	6.918	1.827	5	6	7	8	9
Sex	.616	.486	0	0	1	1	1
Age	55.048	16.448	35	41	55	69	77
Education	2.0858	.948	1	1	2	3	3
Self-employed	.115	.319	0	0	0	0	1
Unemployed	.026	.160	0	0	0	0	0
Retired	.401	.490	0	0	0	1	1
Household size	2.551	1.243	1	1	2	4	4
Married	.616	.486	0	0	1	1	1
Equiv. Income	14,503.82	15,822.26	5,971.112	8,051.732	12,218.67	16,941.54	23,390.95
Equiv. Wealth	124,848	194,314.9	1,885.148	15,340.4	76,000	155,434.8	276,250
Stayer	.743	.437	0	0	1	1	1
Inherited home	.204	.402	0	0	0	0	1
			Panel B: *Location Controls*				
City population	264,553	627,017.7	1,743	5,961	24,536	110,025	867,857
House prices (1)	1,275.038	708.9714	513.7321	723.7202	1,091.131	1,615.59	2,401.044
Degree days	1,985.782	651.5855	1,078	1,415	2,193	2,468	2,689
Altitude	199.9286	218.3668	10	20	122	307	476
Crime rate (2)	43.72	12.84	29.67	34.03	40.86	50.59	63.58
Value added (3)	24,430.48	10,411.97	14,102.49	16,425.59	23,497.23	27,761.43	30,504.29
Unempl. rate	9.701	4.871	4.871	6.155	7.781	14.015	17.399
Connectivity	71.344	23.640	31.463	52.269	78.080	94.152	100

Notes: (1) Euro per square meter (2) per 1,000 inhabitants (3) per capita. The statistics refer to the sample used in estimations and, in Panel A, are calculated using sampling weights. Although the continuous variables are generally expressed in natural logs in estimations, the table shows means and standard deviations of the levels to be more informative. The number of observations in Panel A is 35,828 from the waves 2004, 2006, 2008, 2010, 2012, 2014, 2016 of SHIW.

Appendix B Review of the Coefficients

This appendix offers a review of the other determinants of SWB.[28] According to estimates reported in Column 2 of Table 5, all the main determinants of happiness highlighted by the literature are confirmed. Reported happiness is high among those who are married, men, the well-educated and the employees, and it increases with household size. In line with previous empirical evidence on different countries, happiness is U-shaped in age (minimizing around the individual's middle-aged period).[29] According to the estimates, being unemployed has a sizable negative effect on happiness.

In a spatial equilibrium framework, local income and wealth are jointly determined with the local cost of living and amenities and so they partially depend on the extent of urbanization. Because of this, some studies that cannot reliably account for a full set of amenities do not include them among individual controls. However, since in the analysis I can rely on several city-level data correlated with the local cost of living and most relevant amenities, I choose to include income and wealth among individual controls. Column 3 of Table 5 shows the results of the inclusion of these controls: as widely predicted by the theory and previous empirical studies, both individual income and wealth have a sizable effect on SWB. Furthermore, the effect of urbanization on happiness is unchanged in terms of sign and statistical significance, albeit slightly lower in magnitude.

In urban economics, the higher house prices of big cities are a revealed signal of higher quality of life, other things being constant, because individuals will move toward the areas they find attractive, which, in turn, drives up housing prices (Gabriel *et al.* (2003)). On the other hand, a higher cost of living in big cities may have an adverse effect on SWB. To take into account the overall effect, I therefore include city-level house prices per square meter. In line with urban literature findings, higher housing values have a significant and positive effect on individual well-being, suggesting that they are associated with better local amenities which, in turn, increase individual well-being. Consistently, conditioning on house prices significantly lowers the coefficient on city size (from -0.022 to -0.055) since it allows us to partial out the effect of better local amenities in bigger cities.

Many researchers have hypothesized that individual well-being may be considerably affected by the physical, social, and economic environment in which the individuals are situated. To account for this, in Column 5 of Table 5 I add to the previous specification a full set of location-specific controls. I first condition on a vector of clearly exogenous observable amenities, such as weather conditions

[28]Indeed, it is particularly instruction to study the determinants of SWB in Italy since, in an international comparison, it consistently performs poorly in terms of SWB: for example, according to Eurostat Italy ranks below the average of European countries and last among countries at a comparable stage of economic devel-opment: `http://ec.europa.eu/eurostat/statistics-explained/index.php/Quality_of_life_indicators_-_overall_experience_of_life`.

[29]One tentative explanation of the latter result put forward in the literature is that the decline and then rise in well-being through the years may reflect a process of adaptation to circumstances; by the middle of their lives, people frequently experience a gap between their early adulthood aspirations and their real accomplishments. During old age they adapt some of their aspirations to circumstances and thereby come to enjoy life more (see, e.g., Blanchflower and Oswald (2004)).

and natural amenities, that, according to social psychology literature, may affect mood and, in turn, subjective well-being. I try to control for such factors by including a measure of heating degree days that are typical indicators of household energy consumption for space heating, and so also express how cold winters are in each specific city. More mountainous topography may provide greater consumption amenities, even though it may make production more difficult and reduce employment opportunities. I then control, too, for city altitude (height above sea level of a city). The effect of both of these natural amenities measures is found to be not statistically different from zero. Most probably, this is due to the fact that the positive effect of a natural amenity is offset by the negative effect of higher levels of congestion associated with their attractiveness.

By living in a safe city residents feel less vulnerable and scared, which could have an indirect impact on their SWB. I then add the county crime rate to the location-specific controls and, as expected, I find a statistically significant negative effect on SWB.

Finally, I include the county-level per capita value added because living in a stronger local economy is expected to increase well-being. In fact, empirical evidence regularly finds that high individual income increases individual well-being, but there is also evidence that the local per capita income of an area has a positive effect on the well-being of its residents, even among those who are richer (Helliwell and Huang (2014)). This latter effect could be because of decreased (perceived) risk of becoming unemployed in an area with a strong local economy. In addition to this, areas with high per capita income are supposed to have a greater offer of amenities that may make life more enjoyable. In line with these assumptions, per capita value added is found to have a strong and positive effect on SWB as shown in Column 5 of Table 5. In an unreported estimation, I replace value added with an alternative and more direct proxy of labour market risk, such as the unemployment rate, while the effect on the city size coefficient remains unchanged (see also Column 7 of Table 6.

Overall, even after the inclusion of a full set of location-specific controls, the negative effect of urbanization on SWB is still strongly significant. As already underlined, only the inclusion of commute time (Column 6) significantly decreases the city size coefficient both in magnitude and statistical significance.

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