

Big-city life (dis)satisfaction? The effect of urban living on subjective well-being*

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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 classifications: D60, I31, R23, R41, H54, J61

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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 interest-

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

²A 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)).

³Rome 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)).

⁴A 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

ing 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 cost-effective transport networks, 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.

Results of the analysis show that urbanization negatively affects individuals' well-being, even after taking into account heterogeneity of living conditions within cities. Estimations yield a happiness (negative) premium with respect to city size of -0.059 (Section 5). Commute time accounts for most of the differences in SWB among cities of different size. An IV strategy and a coefficient stability analysis *à la Altonji* tackle unobserved heterogeneity concerns (Section 6.1); a Heckman selection model (Section 6.2) shows that results are not driven by spatial sorting of citizens.

Congestion may negatively impact the economic growth of metropolitan areas through three channels: i) the monetary costs of congestion-induced travel delays; ii) when it slows metropolitan growth and limits agglomeration economies; and iii) the fiscal burdens stemming from public-sector congestion mitigation policies. This work highlights another potential channel, which reinforces 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 (Section 4). 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.

explained by negative congestion effects overruling positive agglomeration advantages.

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, had a striking negative impact on aggregate growth 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 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. 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/his happiness than whatever benefits she/he may derive from a longer commute. 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. 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 primary source of data 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. Each wave of the survey includes approximately 8,000 households, distributed over about 350 Italian municipalities. The sampling is in two stages: first municipalities are chosen from different strata from throughout Italy and then households are randomly chosen from registry office 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 reports individuals' city of residence (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). House prices are from The Italian Revenue Agency (AdE). Data on environmental variables are from the *Italian National Agency for New Technologies, Energy and Sustainable Economic Development* (ENEA). 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 limitation on the city of residence of respondents.

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 men, younger, highly educated and employed report themselves as happier. 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; 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 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 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.⁵ 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,⁶ 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.

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 acquaintance-ship". Characteristically, big-city dwellers are exposed to unceasing external con-

⁵The 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.

⁶A recent work by Helliwell *et al.* (2018) finds very similar differences in happiness and commute time between Canadian urban and rural communities.

tacts with numbers of persons that are nevertheless impersonal and transitory.⁷

In addition to this, big-city dwellers are exposed to a more competitive environment, where there is a lower willingness among people to cooperate and support each other, that may reduce happiness. 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.

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 health.

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" control⁸ 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 1.6 to 2.8 times the effect 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

⁷It 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)).

⁸In 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.

SWB stems from the former, whose effect on SWB accounts, in terms of standardized coefficients, for as much as 2.6 to 6.7 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).⁹ 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, in the next sections 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.

5 Big-city negative premium

A first hypothesis to test is whether there are systematic differences in happiness levels across Italian cities of different size, after controlling for individual and location characteristics. Empirical studies on SWB typically perform a single stage estimation with all the explanatory variables used at once, i.e. including micro-data and 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,¹⁰ 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 , $\hat{\sigma}_c$, is obtained from the following first-stage regression:

$$h_{ict} = \sigma_c + \mathbf{x}_{it}'\beta + d_t + d_m + \epsilon_{ict}, \quad (1)$$

⁹However, the well-being measures may be quite strongly correlated with each other as shown by previous studies (see Clark (2016)) and, as it stands also clear, by the results reported in Table 3.

¹⁰Clustering standard errors at the city level is not sufficient to avoid this pitfall since individuals can move between areas.

where $\mathbf{x}'_{it}$ is a vector of time-varying individual characteristics expected to have a significant explanatory power according to the related literature,¹¹ d_t and d_m are respectively year and month of interview dummies, and σ_c is a set of city 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 5.

In the second stage, the estimated city fixed effects $\hat{\sigma}_c$ are used as dependent variable and are regressed on a measure of urbanization (as expressed by the log of its population), controlling for city characteristics¹² $\mathbf{z}'_c$ and macro-area fixed effects m_a :

$$\hat{\sigma}_c = \log(pop_c) + \mathbf{z}'_c \gamma + m_a + \eta_{ic}, \quad (2)$$

All the regressions are weighted by the number of observations per city to account for differences in the precision of the first stage estimates. Results reported in Table 5 (Columns 2 to 4) show that this weighted two-stage procedure gives rise to estimates of the city-size effect on pooled-OLS happiness premia which are negative and statistically significant. The city-size coefficient estimates do vary somewhat across specifications, suggesting that studies not controlling for a bevy set of city features may produce inaccurate results. In particular, the biggest variation in coefficient magnitude occurs when housing values are included among controls (Column 3). 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 -0.026 to -0.065) since it partials out the effect of better local amenities in bigger cities. 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 (Column 4).

The negative effect of city-size on SWB is not only significant but also sizable since it has, in absolute terms, the largest standardized beta coefficient of all the

¹¹More 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.

¹² $\mathbf{z}'_c$ is a vector of location-specific features that may affect individual well-being. They include city's house prices; natural amenities such as degree days (heating degree days express how cold winters are in each specific city) and altitude; commute time; inter-city connectivity (the index expresses the intensity of worker flows among cities, the greater the index the higher the intensity of inter-city flows); county crime rate; unemployment rate and value added. For a more in-depth explanation see the variable's definition in Appendix A, see also Appendix B for coefficient discussion).

location-specific controls. More specifically, a one standard deviation increase in $\log(pop_c)$ reduces the pooled-OLS happiness premia by around 35 per cent of a standard deviation.¹³ City size is also confirmed a good predictor of differences in SWB as it can explain in isolation about one-eighth of the variation that is left after controlling for observable individual characteristics (R^2 of 0.13 in Column 2) while all the other location controls together explain about one-sixth of the variation (R^2 of 0.16 in an unreported regression including all the location controls and excluding city-size); in terms of adjusted- R^2 , the increase in explanatory power from the uncontrolled regression in Column 2 (adjusted- R^2 of 0.119) and the one with full controls reported in Column 4 (adjusted- R^2 of 0.187) is rather small.¹⁴

The existence of differences in well-being across areas is somehow puzzling for spatial equilibrium models (e.g, Roback (1982)) according to which a city's unhappiness must be offset by some other benefit, such as higher real income. Such implications go beyond the aim of this work. Nevertheless, it is worth mentioning that Glaeser *et al.* (2016) propose a model where people have life goals other than being satisfied, and they may wittingly make choices that reduce happiness in order to achieve other aims.¹⁵

In addition to this, when commute time is added to the city level variables, the city-size negative effect greatly decreases in magnitude and is not statistically

¹³For the sake of comparison, the effect of city-size, in terms of standardized coefficients, is 1.75 times the one of crime rate and it is slightly larger than house prices.

¹⁴In the working paper version of this article Loschiavo (2019), I have also estimated the effect of city size on SWB in a single stage ordered probit regression by including all the explanatory variables used at once. In this case, the estimated coefficient is almost unchanged, falling slightly from -0.059 to -0.050. In addition, I have carried out alternative estimations for the pooled OLS two-stage estimation to check if result holds true regardless the clustering scheme adopted in equation 1: namely, when clustering standard errors i) by individual; ii) by city; iii) by adopting two-way clustered standard errors by both individual and city (instead of clustering just by either of the two); and iv) when variance is estimated using Jackknife Repeated Replications (JRR) replicated weights in order to account for the complex sampling design in the SHIW. These alternative clustering schemes do not change the level of statistical significance of any coefficient in the Table.

¹⁵Glaeser *et al.* (2016) model incorporate spatial differences in happiness into the spatial equilibrium framework. Their rationale is that SWB may not be equivalent to the economists' concept of utility. Under this view, agents make decisions in order to jointly maximize expected future happiness and other objectives. Compensating differences in other dimensions offset persistent spatial differences in happiness. An alternative view in explaining spatial differences in well-being is provided by a vast amount of literature from behavioral economics which has found that people are often susceptible to bias, make inconsistent choices, base their own satisfaction on the comparison with their peers and depart from the standard model of the rational economic agent in other ways (e.g, Kahneman and Krueger (2006)).

significant (see Table 5 Column 5), suggesting that actually a good 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 2 with each of the variables measuring socioeconomic conditions of municipalities where the individual resides.

The augmented specification of Table 5 Column 5 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 R^2 and the lowest ones for AIC and BIC, confirming the superior performance of the full specification in terms of goodness of fit.¹⁶

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. This result is 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 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 (Harari (2017)). 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.¹⁷ 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

¹⁶It 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. 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.

¹⁷Consistently, 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.

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 to 3 of Table 7 show that including these indicators among individual controls in the first step does not affect previous results of the second step estimations. 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 4 to 6 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 they 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 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 is taken into account. The influence on the results of the reference income hypothesis and aggregate and individuals' income shocks are presented in the online Appendix B.

6.1 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 1921.¹⁸ 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 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 8 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

¹⁸The 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.

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 this coefficient stability analysis can be misleading if it ignores the fact that coefficient movements must be scaled by R^2 movements.¹⁹ For this reason, a correction that takes into account the R^2 is proposed. This correction delivers a bound for the 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 $R_{max} = 1$.²⁰ In order not to underestimate the selection on observables, I also perform the exercise running a single stage ordered probit instead of the two-step procedure of Section 5 (results hold also true performing the latter procedure).

Accordingly, the adjusted coefficients for the specification with full controls presented in Column 5 of Table 5 are reported in the last five columns of Table 9. The bounds confirm that the true effect of city size is negative, and possibly even

¹⁹Oster (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):

$$\hat{\hat{\alpha}} = \hat{\alpha}^* - (\hat{\alpha} - \hat{\alpha}^*) \times \frac{R_{max} - R^*}{R^* - R}, \quad (3)$$

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.

²⁰More 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 ($R_{max}=1$).

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 $R_{max}=1$.²¹ 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 IV and the *à la Altonji* approach, it is possible to provide robust results with respect to endogeneity concerns.

6.2 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 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 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 cent level (Table 10). 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 sample of the population, I adopt a Heckman selection model. As exclusion restriction, I use an indicator variable that is equal to 1 if the individual has inherited the house where she/he lives and 0 otherwise. This exclusion restriction implies that, conditional on

²¹ $R_{max}=1$ implicitly assumes that there is exactly zero measurement error in the reported outcome variable. A case which seems implausible in most real-world applications.

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 associated with relatively large search and sunk costs. Thus, homeowners face higher switching costs than do others, which, in turn, may negatively affect their propensity 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 10), suggesting that much of the difference in happiness between cities of different size reflects more than the selection of unhappy people into unhappy places.²²

Comparison between relevant Columns of Table 10 and Table 11 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.²³

²²An 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.

²³Were 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.

6.3 Additional robustness checks

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

Table 12 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 12, I have replaced for each individual the population size of the municipality of residence with the population size of the LLM in which she/he 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. In Columns 3 and 4, 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.

To check if findings are driven by the unhappiness of one or some of the largest cities, in the working paper version of this article Loschiavo (2019) I have also explored removing them from the sample. In particular, when sequentially excluding the three biggest Italian cities (Rome, Milan and Naples) I find that such sample restrictions do not affect results.

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, Due-senberry (1949); Easterlin (1974); Ferrer-i Carbonell (2005); Luttmer (2005)). Since income distribution in big cities is usually highly skewed, I have tested if previous findings may be driven by the omission of income comparisons in the model (such as the effect of the reference and relative income on SWB) or by inequality aversion (see e.g. Fehr and Schmidt (1999)). According to social psychology literature, individuals' memories are imperfect and susceptible to bias (Kahneman *et al.* (2003)). 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 have exploited 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. Furthermore, I have also taken into account the effect of income shocks at city level. Overall, results on the negative effects of city size on SWB, as well as the attenuating effect of commute time, hold also when both income comparisons are included in the model and shocks to individual and aggregate income are taken into account. For the sake of brevity, such estimations are not reported here but they are available in the working paper version of this article Loschiavo (2019).

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 thereby 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.²⁴ Adjusted amenity-value estimates reported in Columns 1 and 2 of Table 13 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

²⁴For a more in-depth explanation see the definition of the variable in Appendix A.

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 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 two different specifications. As a first exercise, the log of city population is interacted with an indicator variable expressing individuals' highest educational attainment. I then take it a step further and 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: 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. Both specifications require interacting city-size variables with individual education so that a single stage ordered probit regression is adopted.

Estimates of the first specification show that the negative effect of urbanization for college graduates is weaker and statistically less significant than for non-college graduates (Columns 3 and 4 of Table 13). 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.²⁵

Nevertheless, when comparing the effect of living in cities of different sizes for individuals within the same educational group (Columns 5 and 6), 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 proba-

²⁵In the working paper version of this article Loschiavo (2019), I have also split the sample by education level, distinguishing college graduates from those who did not graduate from college. I have then run separate regressions on the two sub-samples and found that the negative effect of urbanization for college graduates is weaker and statistically less significant than for non-college graduates.

bly not important enough to completely offset the negative effects of living in bigger cities for both skill groups.²⁶ 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.

7 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 big-city negative well-being premium 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

²⁶For 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).

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 (0.000)	5.871 (0.000)	2.043 (0.000)
Mean Commute (minutes)	33.982 (0.000)	36.623 (0.001)	-2.640 (0.000)
Log Population	9.504 (0.000)	10.289 (0.000)	-0.785 (0.000)
Log house prices	7.244 (0.000)	7.033 (0.000)	0.212 (0.001)
Difference between Urban and Non-Urban Means			
Variable	Urban	Non-Urban	Difference
Happiness	6.734 (0.000)	7.007 (0.000)	-0.274 (0.000)
Mean Commute (minutes)	39.844 (0.000)	34.108 (0.001)	5.736 (0.000)
Log Population	11.448 (0.000)	9.410 (0.000)	2.038 (0.000)
Log house prices	7.374 (0.000)	7.093 (0.000)	0.281 (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) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS
Commuting (sat.)	0.155*** (0.006)	0.109*** (0.006)	0.062*** (0.006)	0.214*** (0.012)	0.135*** (0.012)	0.082*** (0.012)	0.232*** (0.012)	0.137*** (0.012)	0.111*** (0.012)
Relationsh. (sat.)		0.207*** (0.010)	0.161*** (0.010)		0.333*** (0.020)	0.278*** (0.020)		0.400*** (0.019)	0.373*** (0.020)
Time use (sat.)			0.172*** (0.007)			0.197*** (0.014)			0.097*** (0.014)
Income	0.071*** (0.023)	0.058*** (0.023)	0.056*** (0.022)	0.135*** (0.048)	0.114*** (0.043)	0.107*** (0.038)	0.084*** (0.038)	0.059*** (0.032)	0.056*** (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) OLS	(2) OLS	
Commuting (satisf.)	0.239*** (0.012)	0.143*** (0.012)	0.339*** (0.015)
Time use (satisf.)		0.286*** (0.013)	
Income	0.060*** (0.038)	0.050*** (0.035)	0.021 (0.043)
Individual controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
<i>N</i>	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: City size well-being premium - two stage estimations

Dependent variable	(1)	(2)	(3)	(4)	(5)
	Happiness	City Indicators coefficients of column (1)			
	OPROBIT	OLS			
Log city size		-0.026** (0.010)	-0.065*** (0.018)	-0.059*** (0.016)	-0.031 (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*** (0.075)	0.226*** (0.082)	0.221*** (0.083)
Degree days				-0.027 (0.138)	0.024 (0.132)
Altitude				0.006 (0.019)	0.003 (0.019)
Crime rate				-0.233*** (0.079)	-0.202** (0.082)
Connectivity				-0.003*** (0.001)	-0.003*** (0.001)
Value added				0.156* (0.092)	0.127 (0.095)
Commute time					-0.015* (0.008)
<i>N</i>	34812	452	452	447	447
<i>R</i> ²		0.13	0.16	0.21	0.22
AIC		300.39	287.70	252.65	248.58
BIC		325.07	316.49	301.88	301.92

Notes: Column (1) include year and month of interview indicators and is estimated using sampling weights. Reference categories: education = high school; marital status = single; employment status = employee. Columns (2) to (5) include a constant term, geo (5 Macroareas: NW, NE, Center, South, Islands) indicators and are weighted by the number of observations per city. Coefficients are reported with robust standard errors in parenthesis, which are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: City size well-being premium - sequential controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	City size premium	City size premium	City size premium	City size premium	City size premium	City size premium	City size premium	City size premium	City size premium
Log city size	-0.065*** (0.018)	-0.021*** (0.004)	-0.019*** (0.004)	-0.015*** (0.004)	-0.025*** (0.004)	-0.019*** (0.004)	-0.025*** (0.004)	-0.003 (0.007)	
Commute time								-0.011*** (0.003)	-0.012*** (0.002)
House prices	0.215*** (0.075)								
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)		
N	452	447	447	452	452	452	451	452	452
R^2	0.16	0.13	0.13	0.14	0.15	0.14	0.14	0.14	0.13

Notes: see Table 5.

Table 7: City size well-being premium - controlling for heterogeneity in location and housing quality

	(1) OPROBIT Whole sample	(2) City Indicators coefficients of column (1)	(3) OLS City Indicators coefficients of column (1)	(4) OPROBIT Only living in center	(5) City Indicators coefficients of column (4)	(6) OLS City Indicators coefficients of column (4)
Log city size		-0.055*** (0.016)	-0.028 (0.021)		0.029 (0.033)	0.096 (0.062)
Commute time			-0.015* (0.008)			-0.031 (0.021)
City indicators	Yes			Yes		
Center	0.021 (0.026)					
Outskirt	0.007 (0.029)					
Luxury neighborhood	0.026 (0.034)			0.060 (0.053)		
Deteriorate neighb.	-0.215*** (0.052)			-0.236*** (0.087)		
Luxury house	0.101*** (0.036)			0.018 (0.063)		
Deteriorated house	-0.072 (0.046)			-0.220** (0.086)		
Individual controls	Yes			Yes		
Location controls		Yes	Yes		Yes	Yes
N	34812	447	447	4957	283	283
R^2		0.20	0.21		0.14	0.15

Notes: in columns (4) to (6) the sample is restricted to individuals living in city center; see also Table 5.

Table 8: IV estimation of the city size well-being premium

Panel A: Second stage estimates				
Dependent variable	(1)	(2)	(3)	(4)
	City size premium	City size premium	City size premium	City size premium
Instrumented log city size	-0.023* (0.012)	-0.079*** (0.017)	-0.062*** (0.016)	-0.029 (0.024)
House prices		0.306*** (0.061)	0.213*** (0.075)	0.198*** (0.075)
Degree days			-0.020 (0.080)	-0.002 (0.080)
Altitude			-0.006 (0.015)	-0.004 (0.015)
Crime rate			-0.251*** (0.079)	-0.224*** (0.080)
Connectivity			-0.002*** (0.001)	-0.003*** (0.001)
Value added			0.296*** (0.098)	0.269*** (0.100)
Commute time				-0.016* (0.009)
Observations	451	451	446	446
R^2	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*** (0.044)	0.882*** (0.037)	0.832*** (0.039)	0.708*** (0.050)
House prices		0.825*** (0.113)	0.791*** (0.132)	0.740*** (0.127)
Degree days			-0.647*** (0.161)	-0.633*** (0.145)
Altitude			0.014 (0.028)	0.005 (0.027)
Crime rate			0.395** (0.158)	0.215 (0.156)
Connectivity			-0.000 (0.002)	0.002 (0.002)
Value added			0.106 (0.246)	0.210 (0.227)
Commute time				0.073*** (0.017)
Observations	451	451	446	446
R^2	0.89	0.91	0.93	0.93

Notes: see also Table 5. 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. 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 9: Different estimates of the bounds on the potential bias due to unobservables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Uncontrolled	Controlled	Oster (2017) approach	González and Miguel (2015)	McKenzie (2012)	Baird et al. (2008)	Most conservative case
Log city size	-0.024*** (0.006)	-0.040*** (0.015)	[-0.045, -0.040]	[-0.055, -0.040]	[-0.076, -0.040]	[-0.110, -0.040]	[-0.132, -0.040]
R^2	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 R^2 from column (1) and (2) respectively. Columns (1)-(2) weighted estimates; variance estimated using Jackknife Repeated Replications (JRR) replicated weights. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Controlling for spatial sorting

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

Notes: columns (1), (3) and (4) 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. Column (2) see Table 5. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Controlling for spatial sorting and commute time

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

Notes: see Table 10.

Table 12: City size well-being premium - controlling for alternative definitions of city size

	(1) OLS LLM population	(2) OLS LLM population	(3) OLS Density	(4) OLS Density
Log city size (pop)			-0.064*** (0.020)	-0.041* (0.023)
Log city area (ha)			0.010 (0.021)	0.024 (0.021)
Log LLM size (pop)	-0.033* (0.019)	-0.019 (0.020)		
Commute time		-0.022*** (0.007)		-0.018** (0.009)
Location controls	Yes	Yes	Yes	Yes
N	254	254	447	447
R^2	0.18	0.21	0.21	0.22

Notes: Robust standard errors in parenthesis, which are clustered at LLM level in Columns (1)-(2) and at city level in Columns (3)-(4); see also Table 5.

Table 13: Effects of urbanization on happiness - controlling for value of amenities and education

	(1)	(2)	(3)	(4)	(5)	(6)
	City size premium		Happiness OPROBIT	Happiness OPROBIT	Happiness OPROBIT	Happiness OPROBIT
Log city size	-0.050*** (0.013)	-0.023 (0.019)				
Commute time		-0.015* (0.008)		-0.014*** (0.004)		-0.013*** (0.003)
Value of Amenities	0.266*** (0.089)	0.256*** (0.089)				
Elementary school X Log city size			-0.064*** (0.007)	-0.038*** (0.010)		
Middle school X Log city size			-0.051*** (0.006)	-0.026*** (0.010)		
High school X Log city size			-0.044*** (0.007)	-0.018* (0.010)		
College grad. X Log city size			-0.035*** (0.007)	-0.009 (0.010)		
College grad. X Small city					Reference category	Reference category
College grad. X Medium city					-0.231*** (0.089)	-0.219** (0.088)
College grad. X Large city					-0.238*** (0.069)	-0.182*** (0.069)
College grad. X Very large city					-0.308*** (0.080)	-0.200** (0.082)
Non-College X Small city					-0.164** (0.063)	-0.167*** (0.063)
Non-College X Medium city					-0.312*** (0.063)	-0.301*** (0.062)
Non-College X Large city					-0.400*** (0.063)	-0.346*** (0.063)
Non-College X Very large city					-0.510*** (0.083)	-0.404*** (0.085)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes
N	447	447	34797	34797	27572	27572
R ²	0.21	0.22				

Notes: columns (1)-(2) see Table 5. Columns (3) to (6) 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 (5)-(6) 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. *** p<0.01, ** p<0.05, * p<0.1.

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.

- *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.
- *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)
- *Degree days* Log of degree days. This measure is preferred to annual average temperatures because it better reflects how much the temperature varied within a year. 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)

- *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)
- *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)
- *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 and aggregated at city level according to the methodology of Cannari and Faiella (2008). Data are one-year lagged.
- *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)
- *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)
- *Value added* Log of the value added at provincial level. Data are one-year lagged. (source: ISTAT)
- *Wealth* Log of net equivalised household net wealth. Equivalised 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)

- *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.

Table A1: Summary statistics

Variable	Mean	St Dev	Percentiles				
			10	25	50	75	90
Panel A: <i>Survey of Household Income and Wealth</i>							
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	2.086	.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	276,25
Stayer	.743	.437	0	0	1	1	1
Inherited home	.204	.402	0	0	0	0	1
Panel B: <i>Location Controls</i>							
City population	264,553	627,017.7	1,743	5,961	24,536	110,025	867,857
House prices (1)	1,275.038	708.971	513.732	723.720	1,091.131	1,615.59	2,401.044
Degree days	1,985.782	651.586	1,078	1,415	2,193	2,468	2,689
Altitude	199.929	218.367	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 ONLINE NOT FOR PUBLICATION

Review of the Coefficients This appendix offers a review of the other determinants of SWB.²⁷ According to estimates reported in Column 1 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).²⁸ 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. As widely predicted by the theory and previous empirical studies, both individual income and wealth have a sizable effect on SWB.

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 (see Column 3 of Table 5). 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 -0.026 to -0.065) 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 consid-

²⁷Indeed, it is particularly instructive 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 development: http://ec.europa.eu/eurostat/statistics-explained/index.php/Quality_of_life_indicators_-_overall_experience_of_life.

²⁸One 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)).

erably affected by the physical, social, and economic environment in which the individuals are situated. To account for this, in Column 4 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 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. Consistently, the county crime rate has 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 positive effect on SWB. 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 6 of Table 6).

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