Living on my own: The impact of the Covid-19 pandemic on housing demand*

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Abstract

We quantify the impact of Covid-19 on housing demand and identify its drivers by exploiting a unique dataset of online housing sales advertisements containing high-frequency and dwelling-specific measures of perspective buyers' search activity. We show that the pandemic generated an increase in housing search activity, in particular for less congested areas, mainly due to rising interest in larger, single-family properties, with outdoor spaces. These patterns are mostly explained by the surge in work from home rather than by epidemiological conditions and government restrictions, suggesting that the new housing trends could be long-lasting legacies of the Covid-19 crisis.

Keywords: Covid-19, housing market, work from home, online housing ads.

JEL Classification: D13, E24, I18, O18, R21, R31.

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1 Introduction

The literary masterpiece *Decameron* by the 14th-century writer Giovanni Boccaccio took inspiration from the spread of the Black Death in Florence in 1348. In the story, a group of young men and women shelter in a secluded villa outside the city to escape the epidemic, benefiting from the natural beauty and isolation of the countryside.

The Covid-19 outbreak pandemic in early 2020 unexpectedly thrust the modern world into a situation that was not dissimilar to that of the medieval plague-ridden Florence. Nowadays, too, the fear of contagion may have driven households away from congested city centers. Unlike back then, however, additional factors have influenced housing choices: many people experienced working-from-home arrangements for the first time and for a prolonged period, as well as new ways of spending their income remotely (e.g. e-commerce, pay-TV and so on). Moreover, in a number of countries government mandated lockdowns reduced the attraction of city life even more. As a result, housing demand in Italy shifted towards small towns and rural areas (Figure 1), and a similar pattern has been documented for the United States and for the United Kingdom.[1] It is an open question as to whether these factors have caused a permanent change in real estate demand, implying a large and heterogeneous impact on prices and liquidity across the different segments of the market that could persist beyond the pandemic.

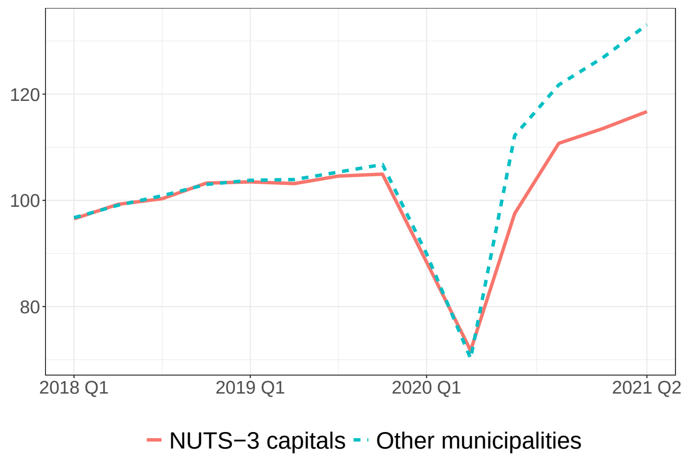
The aim of this paper is to measure the impact of the epidemic on housing demand, with respect to both the physical characteristics of the dwellings and to their location, as well as to identify and quantitatively assess the drivers of the shifts in demand. We focus on Italy, whose particular experience of the pandemic together with the availability of detailed data allow such identification.

Coronavirus hit Italy very early on, in the opening months of 2020, and a strict countrywide lockdown was enacted from March until May; after a summertime lull, in autumn the second wave of infection was addressed with differentiated restrictions across the country. Meanwhile, according to consumer surveys, the fear of infection was widespread and working-from-home arrangements surged.[2]

[1] See, in particular, Liu and Su (2021), Gupta et al. (2021), Bloom and Ramani (2021) for the United States and Bricongne et al. (2021) for the United Kingdom.

[2] Depalo and Giorgi (2021) estimate that the percentage of employees in the private sector working from home rose ten-fold, to 14.4 per cent in the second quarter of 2020. The expansion was more marked in the public sector, rising to 33 per cent from 2.4 per cent over the same period (Giuzio and Rizzica, 2021). Basso and Formai (2021) report that more than 80 per cent of private firms resorted to remote working, compared with less than 30 per cent the year before.

Figure 1: House sales in Italy



Source: OMI (branch of the Italian Tax Revenue Agency). *Notes:* Data are seasonally adjusted and represented as an index equal to 100 in 2018. According to the European nomenclature of territorial units for statistics (NUTS), level 3 regions are equivalent to the US counties. The average population in the NUTS-3 capitals is about 165 thousand inhabitants, while in the other municipalities is about 5,000 inhabitants.

Over this period, we exploit a unique dataset, collecting the universe of housing sales advertisements (ads) on the most popular online portal for real estate services in Italy. For each ad, weekly detailed information is provided about the physical characteristics, the location and the asking price of the dwelling. Direct evidence of the interest of potential buyers in each house is made available by the record of the weekly number of views (*clicks*) and of contacts received by the seller from potential buyers through the website (*contacts*). These data allow us to: (i) carry out a timely analysis of shifts in households' search activity in the housing market in connection with changing local health conditions and government restrictions; (ii) exploit information on potential buyers interest in both sold and unsold homes; (iii) investigate housing demand at a very detailed level, given that in each period listings far exceed transactions.[3] To our knowledge, this is the first paper employing this type of very granular data to analyze house search activity.

Our empirical analysis shows a sudden significant shift in housing demand immediately after the outbreak of the pandemic, regarding both the physical charac-

[3]Previous research (Pangallo and Loberto, 2018; Loberto et al., 2021) has shown that housing search activity is a strong predictor of final demand and we find that this relationship has not changed significantly during the pandemic.

teristics and the location of houses.[4] Total housing search activity rose on average by about one third, an outcome at odds with previous evidence on negative impacts of epidemics or natural disasters on the residential real estate market.

Although demand increased almost everywhere and in all market segments, its intensity has been heterogeneous: searches in rural areas rose by 11 percentage points more than in cities. Greater demand for dwellings in less congested places – that we also observe in home transactions data (Figure 1) – is connected to changes in demand for housing characteristics. Indeed, search activity rose mostly for bigger homes, single-family properties, and dwellings with outdoor spaces. Thus, the desire to move out of large cities was mainly due to increased interest in housing properties that are less commonplace in congested urban areas. Effects on housing prices and the composition of housing supply were evident as early as the second semester of 2020.

Delving into the relative importance of the drivers of these developments, we investigate the role of three possible transmission channels from the pandemic to housing demand: the fear of contagion (just as in the *Decameron)*, the government mandated restrictions and the increase in remote work. In order to disentangle the contribution of each of these factors, which are highly interrelated and affected housing demand simultaneously, we employ detailed data on epidemiological conditions at the commuting-zone level and exploit a very specific institutional setting that was in place in Italy in the last quarter of 2020, when restrictions were differentiated across regions. As the same mandatory restrictions applied to commuting zones with very different health conditions, within-region heterogeneity across zones at a weekly frequency allow us to identify the impact of both local epidemiological conditions and containment measures.

We find that the impact of epidemiological conditions is negligible. An increase in Covid-19-related hospitalizations has a negative but very small impact on housing search activity; the heterogeneity of the effects across different dwelling types is limited. Containment measures have a negative and much larger impact on overall housing searches, and cannot therefore explain either the surge in residential real estate demand or its re-composition. It is likely that households perceive health conditions and containment measures as transitory factors. On the other hand, using data from the European Labour Force Survey to estimate the share of remote workers, we find that remote working explains both the surge and the

[4] In this paper, we use the expressions *housing search activity* and *housing demand* interchangeably when it is clear that we do not refer to actual housing transactions.

re-composition in housing search activity very well, with the strongest impact on demand for outdoor spaces and for larger houses.

Overall, our results suggest that the Covid-19 pandemic has created mismatches between a share of households and their current homes, probably because they have re-defined their priorities in terms of housing amenities and commuting distance to the workplace. The analysis suggests that the housing market trends observed since the outbreak of the pandemic should persist beyond the end of the health emergency, as long as the share of employees working from home remains substantially higher than before.[5]

Our work is closely linked to the papers estimating the heterogeneous impact of Covid-19 on housing markets. Liu and Su (2021), Gupta et al. (2021) and Bloom and Ramani (2021) all use Zillow estimates of average housing prices at the zip code level in the United States. As already mentioned, they find a substantial reallocation of housing demand away from city centers towards residential areas in the outskirts related to the possibility of teleworking, as do Bricongne et al. (2021) for the United Kingdom. Our results are in line with this stream of literature; however, as we have a timely and direct measure of the interest of potential buyers in each dwelling we can also disentangle the role of house location from that of their characteristics, and provide evidence in favour of a stronger relevance for the latter. Other recent papers analyze the informational content of online housing search activity (van Dijk and Francke, 2018; Zhao, 2020; Piazzesi et al., 2020; Gargano et al., 2021) but none has similarly detailed information at the listing level or equivalent geographical coverage.

Our paper also contributes to the literature on the consequences of the surge in teleworking and its likely persistence over time (Bartik et al., 2020; Barrero et al., 2020; Juhász et al., 2020; Bick et al., 2020). Our findings are consistent with those of Stanton and Tiwari (2021): using pre-pandemic data, they show that the share of expenditure on housing was 7 per cent higher for households with remote workers, reflecting the need for larger and better-quality dwellings, usually within the same urban area. Our findings are also in line with Haslag and Weagley (2021), who highlight how the broad shift to remote work arrangements has given individuals more flexibility on where they can work, decreasing the shadow costs associated with work location proximity and increasing the importance of quality-of-life motivations. Looking ahead, several papers argue that work from home will

[5]For example, Bick et al. (2020) find that in the United States more than one third of employed workers expect to continue working from home in the future, at least on a part-time basis.

have a significant impact on the organization of cities (Ouazad, 2020; Brueckner et al., 2021; Davis et al., 2021; Delventhal et al., 2021).

Finally, our paper follows up on previous literature that has examined the trade-offs between housing prices and unexpected shocks on households' preferences connected to health issues and climate risk (Davis, 2004; Smith et al., 2006; Hallstrom and Smith, 2005; Wong, 2008; Francke and Korevaar, 2021).

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents descriptive evidence on the impact of Covid-19 on the Italian housing market, using both survey and online data. Section 4 quantifies the impact of the pandemic on housing demand and Section 5 identifies the key drivers. Section 6 concludes.

2 The data

Our primary data source is a dataset of home listings published since January 2018 on Immobiliare.it, the largest online portal for real estate services in Italy. Immobiliare.it provides us with weekly snapshots of all ads visible on the website every Monday. The sample includes about 3 millions of listings, covering the full country (see Tables G.1 and G.2). Detailed information about the physical characteristics, the location and the asking price of a dwelling are available. We also know the date when the seller created and removed the ad while, given the purposes of the portal, information on whether the dwelling has been sold and on actual transaction prices are missing.

The company further provides us with key information to measure the interest of potential buyers in each dwelling. First, we observe the number of weekly views of each ad's web page (*clicks*). Second, we know how many times in a week the seller has been contacted by a potential buyer through the specific form on the ad's web page or through the smartphone application (*contacts*).[6] *Clicks* allow us to measure potential buyers' search activity across different geographic areas and market segments. *Contacts* imply that potential buyers take an additional action, by sending a message to the seller, and are thus meant to measure more accurately the interest in a particular home and signal a concrete interest in buying. For this reason, *contacts* will be our preferred measure of housing search activity, but all

[6]See Figure G.1 in the Internet Appendix.

the results would hold using *clicks*.[7] All our measures are collected at the dwelling level as we do not have information on potential buyers' characteristics.

Compared to standard definitions of housing demand – based on actual prices and transactions – our approach has some advantages. First, we have timely and high-frequency information on housing search activity. Actual transactions, instead, are lagged. The property deed is usually closed and registered several weeks after the buyer and the seller find an agreement, and possibly many months after the buyer started searching for a home. Second, we exploit information on both sold and unsold homes. Third, in each period there listings far exceed transactions, and this allows us to investigate housing search activity at a very granular level. All these features of our data are crucial to: *(i)* assess the key changes in housing demand, and *(ii)* identify the drivers of the changes in housing demand.

There is some caveat too. One could be concerned that *clicks* and *contacts*, which in normal times proved to be reliable proxies of housing demand[8], may provide a too noisy signal in times of epidemic, as people spent more time at home and had more time for wandering around the website without a concrete intention of purchasing a home. However, in Section 4.3 we will show that the pattern of our measures of search activity remained very similar to that of house sales also during the large swings occurred in 2020 (Figure C.1). Moreover, while the dynamic of *clicks* and *contacts* was nearly identical before the pandemic, in 2020Q3 the latter rebounded more markedly, probably in connection to mobility restrictions that made in-person visits to real estate agencies more difficult.[9]

This leads us to the second caveat. Sending an e-mail through the online form is not the only way of contacting the seller. Indeed, certain categories of individuals (e.g., older people) do not use at all the Immobiliare.it platform (and, more generally, digital tools) to search for a home, preferring more traditional channels (e.g., real estate agents). Should these potential buyers have different housing preferences from those using the platform, we would be introducing a bias by focusing on this measure of search activity and our results would not easily extend to the overall population. However, previous research shows that overall listing data available

[7] When investigating *clicks* and *contacts* within narrow categories, their pattern could be partly different as they reflect different steps of households' search activity (see Appendix A). First, buyers look to many ads that are broadly consistent with their preferences. Then, they contact only the sellers of the preferred listings.

[8] Pangallo and Loberto (2018) and Loberto et al. (2021).

[9] Figure G.2 in the Internet Appendix reports the distributions of average daily *clicks* and *contacts*. The ratio between *contacts* and *clicks* spiked in May and June 2020 but it then came back to levels similar to those prevailing in 2019.

on the Immobiliare.it platform were instead representative of the Italian housing market before the Covid-19 pandemic (Loberto et al., 2021). Besides, this information should have become even more representative of the actual housing demand in Covid times, due to the sudden difficulty in visiting the houses for sale in person and the larger propensity of real estate agents to use digital tools.[10]

We cross-check all the evidence based on online listings with those from the Italian Housing Market Survey (IHMS). The IHMS is conducted at quarterly frequency since 2009 by Banca d'Italia on a panel of about 1,400 real estate agents. The survey is unique in Europe in collecting at high frequency agents' opinions regarding the course of house sales, price trends compared with the previous quarter and the short- and medium-term outlook of real estate markets at the local and the national level. Since the outbreak of the epidemic, specific questions aimed at investigating its impact, both in the short and in the longer-run, were included.

In our analysis we will focus primarily on two levels of spatial aggregation: commuting zones and local housing markets. The latter are identified by OMI, a branch of the Italian Tax Revenue Agency, as contiguous neighborhoods that satisfy strict requirements in terms of homogeneity of housing prices, urban and socioeconomic characteristics, and endowment of services and urban infrastructures. Table G.3 in the Internet Appendix reports a set of descriptive statistics on local markets. We also exploit information about population density at the census tract level.[11] When we lack data at the commuting zones level, we will focus of provinces (NUTS-3 regions), that are equivalent to the US counties.[12]

To identify the drivers of the changes in housing demand, we also exploit several other data sources. We use detailed data on local epidemiological conditions provided by *Istituto Superiore di Sanità* (ISS, the National Institute of Health). Information about employment, wages and remote working is drawn from the Labour Force Survey (LFS) conducted by Istat. We also exploit data from other data sources to account for income and wealth status at the province level: tax returns data (diffused by the Ministry of Economy and Finance), bank loans and deposits (Bank of Italy) and car purchases (Ministry of Infrastructures). Additional details

[10]Notice that we also miss the information on potential buyers who use Immobiliare.it and contact the seller by making a phone call instead of by sending an email. However, buyers preferring to make phone calls should have in any case seen the web pages of the listings, and therefore enter in this analysis through the *clicks* they made.

[11]Local housing markets are larger than census tracts. In Italy, there are 27,426 local markets and 402,678 census tracts.

[12]Italy is divided into 20 regions (NUTS-2 regions), 107 provinces (NUTS-3 regions), 660 commuting zones, and about 7,900 municipalities.

about the data are reported in Appendix A.

3 The Covid-19 pandemic and the housing market

Italy was the first European country severely hit by the pandemic. The first Covid-19 case was officially identified on the 21st of February and since then the epidemic gained momentum at a fast pace (Figure C.2a). The government reacted by enacting a strict nationwide lockdown starting from March 10th, as reflected in the sharp rise of the Oxford Stringency Index (Figure C.2b). The containment measures allowed to bend the infection curve within a couple of months: from the 4th of May, economic activities gradually re-opened. During the summer the spread of the virus slowed down and restrictions were eased but a new surge of infections started from mid-October onward. To face the second wave of contagion, from the 6th of November the government implemented restrictions targeted at the regional level to limit the negative impact on economic activity in those territories characterized by lower infections and hospitalization rates.

Against this background, the housing market was deeply affected by the evolution of the health conditions and the consequent mandatory restrictions.[13] Real estate activities halted almost completely in March and April, during the first national lockdown. However, following the re-opening in May, both housing prices and transactions started to rise strongly. The recovery was sharper in smaller municipalities, differently from the pre-Covid trend of increasing demand for urban areas.

These patterns suggest that the outbreak of the pandemic had strong and immediate consequences on the housing choices of Italian households. Thanks to specific questions introduced since the wave referred to the first quarter of 2020, the IHMS provides us with real-time information on agents' perceptions about the impact of the pandemic on the real estate market, both in the short and in the longer-run.[14]

According to the agents, in spring 2020 on average 42 per cent of potential buyers had delayed their purchases due to the pandemic, 22 per cent of them canceled it altogether. The health crisis made real estate agents perceive a change in

[13] Appendix B provides a description of the main institutional details of the Italian housing market – including mortgage origination – and medium-term trends.

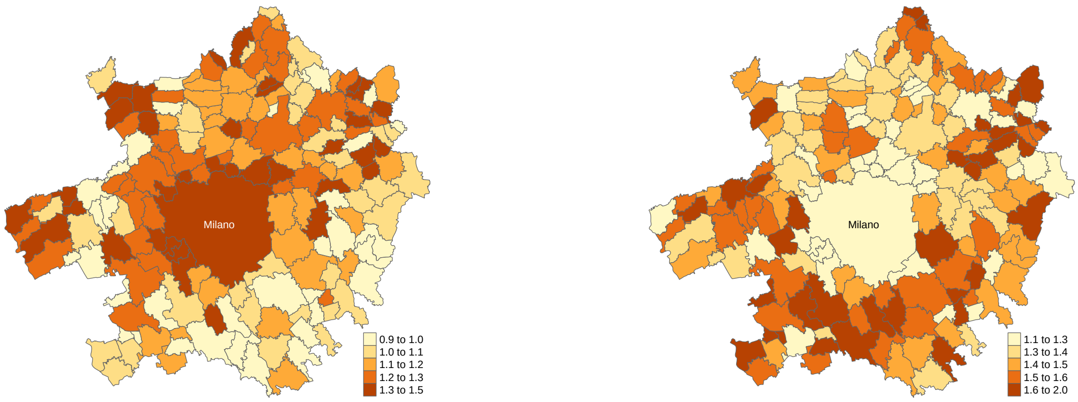
[14] Additional evidence is presented in Internet Appendix F. The Covid-19 related questions in the IHMS are summarized in Section F.2 of the Internet Appendix.

housing demand: both potential buyers' preferences in 2020Q2 and the transactions that were actually intermediated in Q2 and Q3 pointed towards an increase in the interest in single-family homes with outdoor spaces. These changes were perceived to be persistent (Figure C.3a). The houses sold in that period were somewhat larger than those intermediated in the past by the same agencies, and with a lower average price per square meter. Considering the conformation of the Italian cities, these houses would largely be located in the semi-peripheral areas. Agents signaled also a modification in the composition of buyers and their motivation, towards a change in the primary home and away from buying second homes, suggesting some uneasiness with their current housing arrangements (Figure C.3b).

Agents were also requested to provide their expectations about the sign of the impact of the pandemic and its expected duration with reference to homes posted on the market, number of potential buyers and selling prices. At the onset of the pandemic, agents were evenly divided on the outlook for supply, with shares of about 40 per cent thinking that the effects were going to be either positive or negative; demand and prices were instead seen as negatively affected. Agents' opinions, however, rapidly evolved as they realized that the pandemic had not triggered a disruption of the market: in 2021 the balance between those reporting a positive impact on potential buyers and those seeing a negative effect turned positive (Figure C.4a).[15] An econometric analysis reveals that the real estate agents' optimism or pessimism about the evolution of housing demand in the early stages of the pandemic was tightly linked to the shift in households' preferences. Such changes were detected mainly by the agencies which were active in the *winning* market segments, thus explaining their favorable prospects in connection to the newly popular locations and dwelling features. The agents perceived these effects as persistent and increasingly so as the situation evolved: in 2021Q2 the share of agents expecting that the impact of Covid-19 would last beyond 2021 rose to above 60 per cent.

[15]The Covid-19 shock prompted also changes in how agencies practically dealt with potential buyers. At the end of 2020 agents were explicitly asked if the difficulties in organizing visits to homes due to the restrictive measures connected to the pandemic or the fear of contagion have had a significant impact on brokerage activities, or if their agencies managed to substitute in-person visit with camera-assisted on-line views or other digital tools. Almost 60 per cent of the respondents reported that the overall pandemic effect was low or moderate thanks to such instruments, against about 25 per cent pointing to a severe impact on their activity.

Figure 2: Change in housing search activity in the commuting area of Milan



(a) *Ratio of the number of daily average clicks in 2019 and 2018*

(b) *Ratio of the number of daily average clicks in 2020 and 2019*

Notes: ratio of the number of daily average *clicks* during the period May-December of 2020 and 2019. Darker polygons are the municipalities with the larger increase in search activity. The scales of the charts are different as they represent the quintiles of the distribution in each year.

3.1 Evidence from online listings

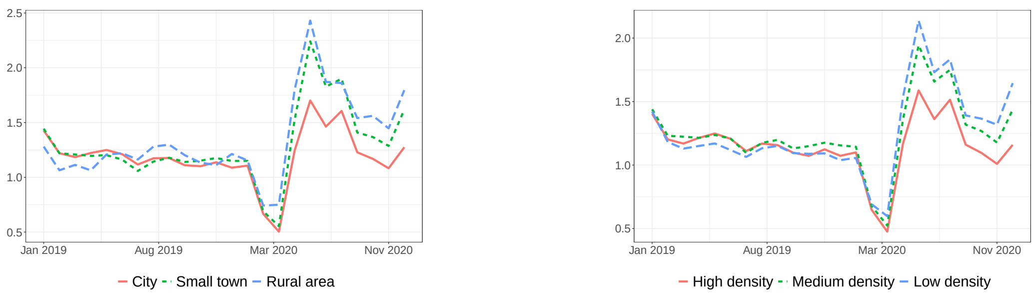
The granular data taken from Immobiliare.it allow us to investigate more thoroughly the dynamics of the Italian housing market depicted by real estate agents. Here we present a few stylized facts about housing search activity over the years 2019-2020. We focus on a sub-sample of ads referring to homes located in the most populous 100 commuting zones, since these are representative of the national housing market.[16]

Figure 2 reports the year-on-year change in average daily *clicks* in the commuting zone of Milan during the period May-December in 2019 and 2020. Milan is the second largest Italian city, and the capital of the region most affected by the epidemic. Since the end of the national lockdown the growth of housing search activity in the city center has been much lower than in close, but less densely populated, areas. That is a reversal of the pre-epidemic trend, characterised by search activity increasing mostly inside the urban area of Milan. We find a similar evidence for

[16]Figure G.3 in the Internet Appendix represents the selected commuting zones, which cover 2,877 municipalities (out of 7,903) and 74 per cent of listings in our sample. Results hold when the analysis is conducted on the full sample.

Rome and Turin, the two other largest Italian housing markets (Figures G.4 and G.5 in the Internet Appendix).

Figure 3: Daily *contacts* per ad: ratio with respect to the previous year



(a) *Degree of urbanization* (b) *Population density*

Notes: in panel (a) the degree of urbanization is based on Eurostat classification. In panel (b) 'low density' refers to houses located in areas characterized by a population density in the first quartile of its distribution among the ads posted on the portal; 'medium density' corresponds to the second and third quartiles of the population density distribution and 'high density' to the fourth quartile.

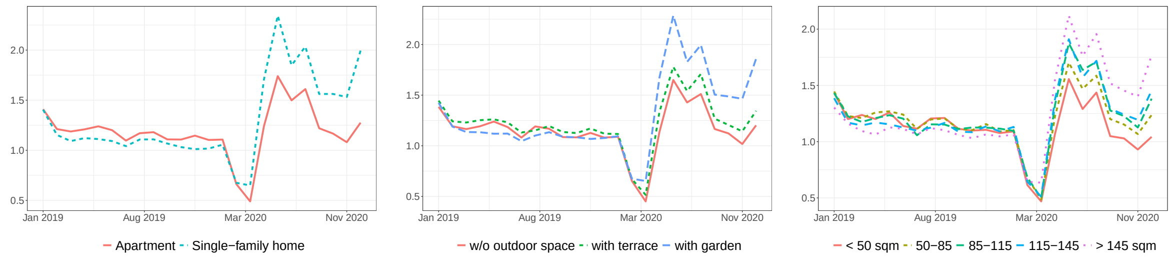
This pattern has been broad-based. Figures 3 and 4 represent the evolution of average daily *contacts* per ad compared to the same month of the previous year to control for seasonal effects.[17] In Figure 3 we distinguish ads according to the neighbourhood congestion, considering either the degree of urbanization (panel a) or population density at the census track level (panel b). Both charts provide evidence of parallel trends up to February 2020. Then, immediately after the outbreak of the pandemic search activity in less congested area rebounded much strongly than that in more populous location.

Figure 4 differentiates dwellings according to the physical characteristics emerged as relevant in the IHMS. Our data allows us to distinguish apartments from single-family homes and to classify them according to availability of outdoor spaces (terrace or private garden) and to their size (floor area). The pandemic clearly signed a structural break in housing demand, leading to a rise in interest towards single-family homes and dwellings endowed with outdoor spaces, especially private gardens. Moreover, since May 2020 users are also more likely to contact agencies for larger houses (panel c), as it is visible from the number of *contacts* monotonically increasing in the floor area. Overall, both figures 3 and 4 show that online search

[17]Regarding the supply of homes on the market, the number of ads posted on Immobiliare.it declined at the outbreak of the pandemic but resumed pre-Covid levels in the summer of 2020.

activity has increased in almost all locations and market segments, although with different intensities not justified by pre-pandemic trends.[18] In the next Section we quantify these differentiated effects through an econometric analysis.

Figure 4: Daily *contacts* per ad: ratio with respect to the previous year



(a) *Property type* (b) *Outdoor space* (c) *Floor area*

4 How the pandemic has shaped housing demand: quantitative evidence

To quantify the impact of the Covid-19 outbreak on housing demand through the information coming from listings, we run the following pooled OLS regression:

$$y_{i,k,t} = \alpha_{k,t} + \left(\beta_1 C_{1,t} + \beta_2 C_{2,t}\right) \mathbf{X}_i + \gamma \mathbf{X}_i + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,k,t} \tag{1}$$

We consider monthly-frequency observations, therefore t is a month-year tuple. The dependent variable, y, is the logarithm of the number of *clicks* for ad i in location k during period t, or a Bernoulli variable equal to one if the seller of the ad i is contacted by a potential buyer at least once during period t.[19] We use *clicks* to investigate demand for congestion, otherwise we prefer to use *contacts*. However, all results are very similar regardless of which dependent variable we use.

[18]Figure G.2c in the Internet Appendix further shows that the *contacts* to *clicks* ratio, after having fallen during the national lockdown in March-April 2020, since May 2020 overshot its pre-pandemic levels. This is consistent with the view that the spike in online search activity in the second half of 2020 signals a genuine interest in house purchase, rather than a mere curiosity by people forced to stay at home and indulging into scrolling the most desirable houses

[19]The choice to model *contacts* as a binary variable is motivated by the significant number of zeros, and because the number of *contacts* in a month is greater than one only for a small fraction of observations (see Figure G.2 in the Internet Appendix).

The variables $C_{1,t}$ and $C_{2,t}$ are two dummies. $C_{1,t}$ is equal to one for the two-month period March-April 2020, that is immediately after the outbreak on Covid-19 in Italy. $C_{2,t}$ is equal to one from May 2020 onward. We split the post-outbreak period into two sub-periods because during March and April the Italian government issued a national stay-at-home order, that implied a mandatory closure of real estate agencies and an almost complete shutdown of the housing market (Figure C.1).

The variables in $\mathbf{X}$ represent physical characteristics (e.g. size) or those related to the location of the dwelling (e.g. population density) of our interest. $\mathbf{Z}$ includes a list of physical characteristics of the dwelling (property type, floor area, elevator, garage, terrace, garden), the distance from the centroid of the commuting zone (in km), and a set of time varying controls, such as the asking price per square meter, the occurrence of a price revision during the month, and the number of days the ad has been listed on the website during month t. *Ceteris paribus*, relatively overpriced listings get less online interest, and price revisions can trigger a temporary increase in *clicks* or *contacts*. We control also for time on market, because listings get more attention in the early weeks they are online.

Finally, $\alpha_{k,t}$ is a set of time-varying fixed effects where, depending on the specification adopted, k would be the commuting zone or the local housing market, to control for any source of unobserved heterogeneity at the local level. The impact of the epidemic has been very heterogeneous both among different geographic locations and over time. Therefore, the time-varying fixed effects allow us to identify the shift in demand for the different types of houses, while controlling for local idiosyncratic shocks and for potential shifts in the composition of the supply of houses on sale in a given market. Standard errors are clustered at the commuting zone level. Since the epidemic circulates with people's movements, commuting zones are ideal geographic areas for studying the impact of an epidemic. Moreover, as households are still uncertain about the future organization of work, they may prefer to move in a relatively nearby area, from which it is possible to reach their place of work at least periodically.

Our parameters of interest are β_1 and β_2, which measure the shift in housing demand for the dwellings' characteristics (or the location variables) being examined. Our identification assumption is that there would have been no major change in housing demand had the Covid-19 pandemic not occurred. To show that this assumption is plausible, we report also the estimates of the following generalization of (1):

$$y_{i,k,t} = \alpha_{k,t} + \sum_{j=1}^{N} \beta_j^M M_{j,t} X_i + \gamma \mathbf{X}_i + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,k,t} \tag{2}$$

where $M_{j,t}$ is a set of monthly dummy variables (one for each period t) and N equals the total number of periods in our dataset (36 months). Our identification assumption implies that the estimates for the β_j^M parameters would be broadly constant up to February 2020, and any major jump should be detected from March 2020 onward. To better clean up for seasonality in housing search activity, we will report $\beta_j^M - \beta_{j-12}^M$.[20]

4.1 Results

From May 2020 onward, after the end of the national lockdown that began in March, online search activity surged. Once controlling for homes characteristics and location, the number of *clicks* increased by almost 40 per cent compared to the pre-epidemic levels (Table D.1, columns 1-2).[21] The probability that a seller is contacted by a potential buyer rose by between 6 and 8 percentage points, a very relevant growth compared to a pre-epidemic probability of 22.5 per cent (Figure 5 and Table D.1, columns 3-5). As already shown in Section 3, the rise in online search activity has been broad-based across locations and market segments. This large increase is consistent with the assessments of the real estate agents discussed in Section 3, with the path of home sales (Figure 1) and with the results of the annual household survey run by Nomisma, an independent research institute specialized in housing market analyses. According to that survey, after the outbreak of the epidemic the share of Italian households who wanted to purchase a home in the following 12 months rose from 9.5 to 12.8 per cent.[22] Although our data do not allow to disentangle the intensive and extensive margin, given the the large increase in housing transactions it is plausible that most of the increase in search activity is explained by an expansion of the pool of potential buyers. In the following, we focus on the relative change in housing demand across locations and for different dwellings' characteristics.

Changing demand for location. After the outbreak of Covid-19, the search activity of potential buyers went up mainly in less congested places. *Clicks* increased mostly in municipalities classified as rural areas (11 per cent more than in urban

[20]Seasonal effects arise, for instance, because the interest in houses with a private garden generally increases in spring and summer.

[21]To measure the average change in aggregate housing search we substitute $\alpha_{k,t}$ fixed effects with monthly location-specific seasonal dummies.

[22]A summary (in Italian) of the study is available at `https://www.nomisma.it/come-abiteremo-insieme-lndagine-sulle-famiglie-italiane-2021/`.

areas) and in less densely populated census tracts (Table D.2, columns 1-2). Overall, *clicks* are still higher for listings of houses localized inside cities, but the positive wedge compared to homes in rural municipalities diminished. The elasticity of *clicks* to population density decreased also when controlling for time-varying fixed effects for the local housing market (column 3).This means that potential buyers started searching for less congested areas also inside a local housing market, while we do not detect any statistically significant impact of local population density before the epidemic.

The evidence is even more striking when considering the impact on the probability that a seller is contacted by a potential buyer (columns 4-6). After May 2020, this probability has become negatively correlated with population density. Compared to *clicks*, *contacts* point to a stronger increase of housing demand both in suburbs and rural areas than in cities. Since *contacts* are a sharpest indicator of potential buyers' interest, these results are consistent with the better performance of house sales in small cities than in larger ones. However, these results should not be interpreted as a definitive debacle of large cities. Considering the coefficients for variables *suburbs* and *rural area* in columns 1 and 4, research activity is still stronger in cities, although the gap with less congested areas has narrowed by about one third.

Changing demand for dwelling characteristics. Given the insights gained from the IHMS regarding the changing demand for dwelling characteristics, we want to provide a quantification of this shift through online search activity. Moreover, we want to assess to what extent the demand for less congested locations can be explained by a shift toward housing typologies with specific characteristics.

We estimate equation (1) interacting $C_{1,t}$ and $C_{2,t}$ with the following dwelling characteristics: single-family home (binary), availability of a terrace (binary), availability of a private garden (binary), and size (categorical). To limit the impact of the location, we allow for time-varying fixed effects at the local housing market level. We estimate a linear probability model where the variable of interest is the probability of observing at least one *contact* for a given ad in month t.

Our results confirm that since May 2020 households are more interested in single-family, larger dwellings, with an outdoor space (Table D.3, columns 1-4). Considering the likelihood to contact the sellers of houses with outdoor spaces compared to those without, this wedge increased already during the national lockdown. As the characteristics that we consider are positively correlated[23], we focus on the results of the joint estimation (column 5). We observe that coefficients associated with the availability of a private garden or a terrace remain relatively unchanged compared to the case where each characteristic is analysed separately. After May 2020 the probability to contact the seller increased by 2.9 percentage points for houses with a private garden, and by 0.9 points for those with a terrace. The magnitude of the impact is sizeable, as before the epidemic the unconditional probability for a seller to be contacted was 22.5 per cent. Moreover, before the epidemic, homes with a private garden were by 5.3 percentage points more likely to receive a contact compared to those without it (2.9 points in the case of a terrace). Hence the "premium"(in terms of contact probability) for a garden increased by more than 50 per cent and that related to the presence of a terrace by about one third. Also the coefficients for the different dwelling sizes remain broadly unchanged across specifications; the effect of size on search activity is generally negative but we find a relatively stronger interest in larger dwellings after the pandemic. When interacting all dwelling features with the Covid-19 dummies, the coefficient associated with single-family homes post-May shrinks from 0.031 to 0.012 (columns 3 and 5). The presence of ground floor apartments with a private garden in a multi-family property is not unusual in Italy.[24] Therefore, we gauge that housing demand moved mostly toward the presence of a private garden.

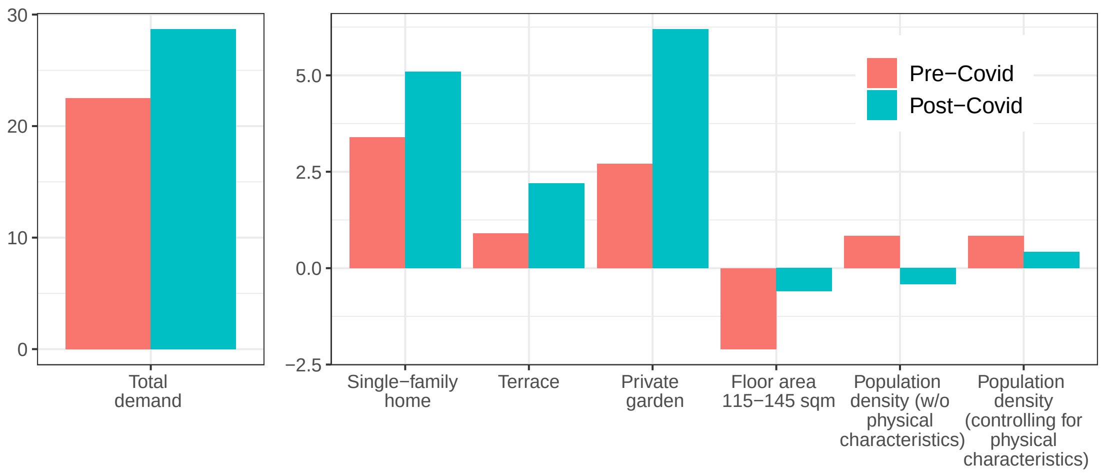
The role of location and dwellings' characteristics. Finally, we consider the joint impact of the epidemic on the demand for housing characteristics and location (Figure 5 and Table D.4), including time-varying fixed effects for the commuting zones. Accounting for the change in search activity for dwellings' characteristics downsizes the role of location. There is evidence of a relatively greater search activity for houses in suburban and rural municipalities only in March-April 2020, when a strict stay-at-home order was in place and households may have been scared of living into large cities, but not from May onward (column 1). The strongest growth in housing demand outside the urban areas in the second half of 2020, that we observe in the descriptive statistics and in Table D.2, is entirely explained by the different housing needs of potential buyers. However, a municipality may be a too large area to assess the impact of the pandemic on location choices. Even within

[23]Single-family homes usually have a private garden and are larger than apartments (their median floor area is 180 square meters against 90 for apartments).

[24]In the baseline sample of the 100 most populous commuting zones, 62% of dwellings with a private garden are single-family homes, while the rest belong to multi-family properties.

a small town, most of the dwellings could be concentrated in a small area, while households may prefer living in places where homes are more spread out. For this reason we also conduct the analysis by exploiting the heterogeneity in population density at the census tract level (column 2). Compared to the results in Table D.2, the coefficient associated with population density post-May 2020 is still negative and statistically significant. Then, households do not necessarily want to move from big cities to small towns, but they just search for houses in less congested places. However, the estimated coefficient shrinks from -0.006 to -0.002, meaning that the changing interest in housing physical characteristics accounts for two thirds of the increase in the demand for lower congestion.

Figure 5: Estimated probability of a *contact*



Notes: The left panel reports the estimates of Table D.1, column (3). The red bar is the probability of a *contact* before March 2020 and the blue one is the probability of a *contact* from May 2020 onward. The right panel reports the estimates of Table D.4, column (2). The bars correspond to the additional probability of receiving a *contact* for dwellings with a specific characteristic either before the outbreak of the pandemic or from May 2020 onward. For population density, we report the effect of an increase of population density by 1 standard deviation (coefficients are multiplied by 2.1). The effect of population density without controlling for physical characteristics is taken from Table D.2, column (5).

4.2 Robustness checks

As already mentioned, our identification assumption is that there would have been no major change in housing demand had the Covid-19 pandemic not occurred. To assess how plausible this assumption is, Figure D.1 reports the results of model (2), which captures how the demand for the characteristics of interest has changed over time by interacting them with monthly dummies. All charts clearly show a structural break in March 2020. If any, before the epidemic search activity was more intense for smaller apartments, without a private garden, and in more densely populated locations. After the epidemic, past trends have reversed. Results are robust to conducting the analysis over the full sample (Tables G.4-G.7 in the Internet Appendix) and to the exclusion of the main commuting zones and considering *clicks* instead of *contacts*.[25]

Results are confirmed when we implement a regression discontinuity design (RDD) around the day of the Covid-19 outbreak (February, 21). We estimate model (1) using weekly data since February 3rd, and considering as dependent variable the occurrence of a *contact* during the week. First, we include in the sample data up to February 24th. Then, we recursively increase the sample by adding the data of the next week to detect changes in β_1 (see Figure G.6 in the Internet Appendix). We find that the estimates for β_1 become statistically significant since mid-March, a week after the national lockdown was issued.

A potential concern is that our estimates could be biased by supply effects. Our econometric strategy and some robustness exercises ease these concerns. In all regressions we control for the duration of the ad (because online interest is decreasing in the duration) and for the occurrence of a price revision (because this usually triggers an increase in online interest). More generally, in our model supply factors are controlled for by the local housing market*time dummies . Results are even reinforced once we remove such dummies and explicitly control for the number of ads posted on the website and their composition in terms of location and dwelling characteristics. Moreover, we estimated model (1) using weekly data since February 3rd, considering only those listings that were online both before and after February 21th and including listings fixed effects. As for the RDD exercise, the dependent variable is the occurrence of a *contact* during the week. We find that the results are the same of the RDD, ruling out significant distortions from the supply side of the market (see Figure G.7 in the Internet Appendix).

As an additional robustness check we also conduct the analysis by introducing

[25]When excluding the main commuting zones the interaction of the Covid dummies with the size of the dwelling is not significant, possibly because in the less populated commuting zones the average house size was already bigger before the outbreak of the pandemic. The main patterns are confirmed also when considering the log of *clicks* instead of the probability of receiving a *contact*, although the shift in demand towards some dwelling features may be downsized or amplified compared to our benchmark regressions. For instance *clicks* signal a stronger interest in very large dwellings, but this could possibly be related to looking at "dream houses"rather than to a concrete intention of buying those dwellings. Results are reported in the Internet Appendix (Tables G.8-G.9).

an interaction term between the Covid dummies and the average housing prices in the local housing market before the pandemic (Tables G.10-G.11 in the Internet Appendix). Although our main regressions already exploit the variation within narrowly defined local housing markets, this additional control allows checking whether the results are driven by more affluent households remaining in the sample and buying houses in more expensive areas. Results remain mostly unchanged and the additional interaction term takes a negative and significant coefficient, indicating that after the pandemic, if anything, demand has been redirected to less expensive markets.

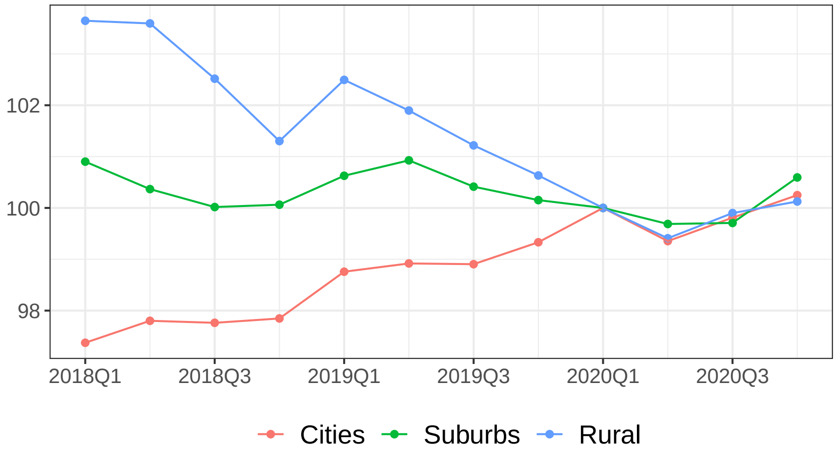
4.3 From housing search to housing demand

So far we have investigated the reaction of the housing market to the outbreak of the pandemic through our measures of housing search activity, namely *clicks* and *contacts*. These indicators represent an original feature of our dataset that we deem particularly interesting for our research questions, as they allow detecting swifts in potential buyers' interests almost in real time. Alternative approaches would involve the use of microdata on actual transactions and prices, but unfortunately they are not available for the Italian market. However we can still verify whether the effects we have found on search activity are consistent with the patterns of aggregate data and measures of housing supply and asking prices available in our dataset.

Regarding the relationship between search activity and actual transactions, in Section 2 we have already discussed how *clicks* and *contacts* can be considered reliable proxies of actual housing demand on the basis of previous studies and of the visual inspection of their joint dynamics in the post-Covid period (Figure C.1). Here we corroborate that evidence in a slightly more formal way. By regressing actual quarterly transactions in a given province on the average number of *contacts* per listing for homes located in the same province, we confirm a significant correlation between sales and search activity in the previous quarter (Table G.12 in the Internet Appendix). By introducing a dummy equal to one for observations referred to 2020, we find that, if anything, this relationship has even reinforced after the outbreak of the pandemic. Figure C.5 further describes a strong correlation between housing transactions and the lag of total *contacts* received by dwellings located in the same province, without any major change between 2019 and 2020.

Our data further allows us to analyse the evolution and the composition of housing supply through the number of new ads posted on the website each month. Housing supply, after a sharp drop in March and April 2020 in connection to the halt

Figure 6: Hedonic prices by degree of urbanization



Source: Our computation on data from Immobiliare.it. *Notes*: For dwellings located in areas classified with different degrees of urbanization, we separately estimate the hedonic regression $\log(P_{i,k,t}) = \alpha_k + \delta_t + \gamma \mathbf{Z_{i,t}} + \varepsilon_{i,k,t}$, where: $P_{i,k,t}$ is the first asking price of listing i; α_k and δ_t are local market and year-quarter fixed effects. We plot coefficients $\exp(\delta_t) * 100$ normalized to 100 in 2020Q1. Each listing appears only in the quarter in which enters the market.

of real estate agents' activity, rebounded to levels similar to those of the previous year (Figure D.2a). In terms of composition, we observe a decline in the share of single-family and larger homes and of those with a private garden and located in less congested areas (Figure D.2, panels b-f). This lends support to the view that people owning this kind of houses preferred not to put them on sale, as they probably valued more these features of their current home.

Lastly, we may ask whether our findings are reflected in the dynamic of housing prices. Since 2020 the growth in housing prices has been stronger than in the recent past, suggesting that demand exerted upward pressures, overall. An alternative approach to test whether certain locations or dwellings' characteristics have become more valuable since the Covid-19 outbreak would entail estimating hedonic regressions, in which the evolution of prices depends on a time component and the value (shadow price) assigned to the physical characteristics of the dwellings on sale. Since we do not have transaction prices, we must rely on asking prices. By distinguishing different types of location, we observe that the dynamics of hedonic prices was markedly different before 2020: other things being equal, prices were increasing in cities, declining in rural areas and almost flat in suburban areas (Figure 6). At the beginning of 2020 the declining trend of prices in rural areas reversed, confirming the larger increase in demand for these locations. By including time-varying coefficients for different physical characteristics of the dwelling, we can also investigate how their shadow prices evolve over time. Although these prices tend to be sticky and lagging compared to our direct measure of housing demand, the estimates of the hedonic regression are consistent with our findings (Figure D.3). The pre-Covid downward trend in the shadow prices for single property homes, for the presence of a garden or a terrace and for the dwelling's size all halted or reversed in 2020.[26]

5 From the pandemic to shifts in housing demand: drivers

The surge and the re-composition in housing demand are robust findings of our analysis. In this Section we move one step further and explore the drivers of such developments. Identifying the channels of the transmission from the pandemic to the housing market is key to assess whether, and to what extent, these changes will be transitory or permanent.

We consider three possible channels, namely the fear of contagion, the government mandated restrictions and the structural changes in work arrangements, such as the extended possibility of remote working. Although the first two factors should in principle be temporary, a recent survey shows that the large majority of Italian households attributes a positive probability to a new pandemic occurring in the next ten years.[27] Hence the fear of infection and the mobility restrictions imposed during the Covid-19 health crisis not only could have had a direct (possibly negative) effect on the possibility of visiting dwellings on sale but could also have made salient the negative consequences of such an event and permanently changed consumers' habits, thus shifting households' demand for a long-term investment such as housing.

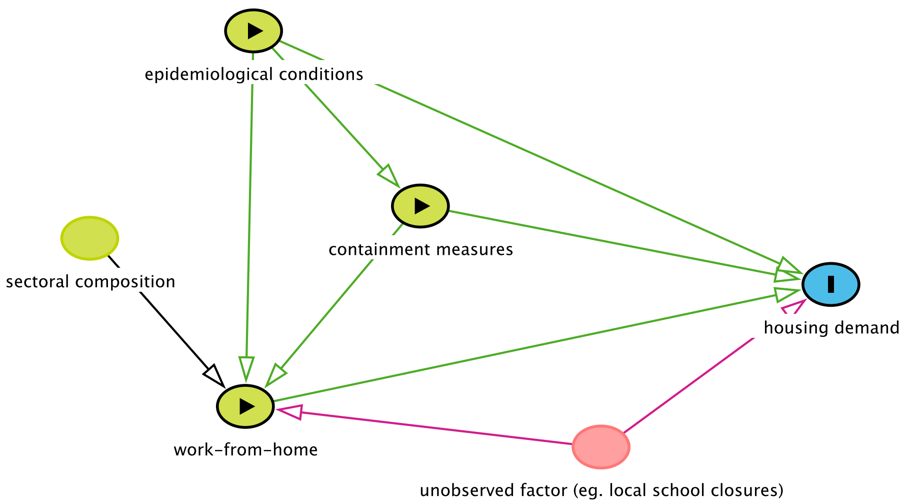
Disentangling the contribution of each of these factors is difficult, because they are highly interrelated and they affected housing demand simultaneously. Figure 7

[26]From the IHMS we can also compute the average discount on the initial asking price, that is a measure of market tightness. This discount has declined more in non-urban areas than in urban ones: considering the surveys conducted in October, in non-urban areas the average discount decreased from 13.6 per cent in 2019 to 11.7 per cent in 2020 and 10.1 per cent in 2021; in urban areas the average discount was 11.1 per cent in 2019, 9.7 per cent in 2020 and 9 per cent in 2021.

[27]According to the fourth wave of the Special Survey of Italian Households conducted by Banca d'Italia in March 2021, about 20 per cent of households think that a new pandemic will certainly occur in the next 10 years (see Bank of Italy, 2021).

provides the graphical representation of the causal dependencies that we investigate through a Directed Acyclical Graph (DAG). Here, we exploit the granularity and high-frequency nature of our data to identify the magnitude of these causal links. A key assumption is that any change in the exogenous determinants of housing transactions should trigger a close response in the observed pattern of buyers' search across market segments.

Figure 7: Directed Acyclical Graph (DAG) of the drivers of change in housing demand



We proceed in three steps. First, we estimate the impact of local epidemiological conditions by exploiting a very specific institutional setting in place in Italy in the last quarter of 2020. Second, by using a similar econometric strategy we jointly assess the role of epidemiological conditions and containment policies. Finally, we investigate the impact of work from home, using also an instrumental variable approach to take into account the possibility that some unobserved factor (e.g. local school closures) simultaneously affect both remote working and housing demand. We will instrument work from home through the pre-Covid sectoral differences across Italian provinces. In what follows we will measure search activity using only *contacts*, but we would obtain similar results using *clicks*.

5.1 Epidemiological conditions

The impact of epidemiological conditions is often hard to disentangle from that of government restrictions. In Italy, containment measures were generally adopted with a short lag with respect to the trend of epidemiological conditions. Since these measures are detrimental to economic activity, they have been proportional to the level of hospital congestion caused by the epidemic.

Only nationwide restrictions were introduced between August and October 2020, and these policies were milder than those implemented since November.[28] From early November, the national government imposed restrictions at the regional level depending on a dashboard of indicators about overall epidemiological conditions and hospital capacity in each region.[29] The algorithm that determined the degree of restrictions was established at the national level and evaluated every Friday. On the same day, based on the outcome of this algorithm, the Ministry of Health assigned to each region a risk level, either yellow, orange or red. Each risk level implied a set of containment measures, whose tightness increased with the level of risk.[30] We describe these policies in the next section. In this framework, containment measures were a deterministic function of average epidemiological conditions in each region.[31] Local governments could not overrule the national government policy. At most, local administrators could introduce additional containment measures, such as school closures.

This particular institutional setting, jointly with the localized nature of spikes in contagion, has two implications. First, many municipalities have been subject to strict containment measures, although epidemiological conditions were not worrying. This happened, for instance, to municipalities like Bergamo which had been hit severely by the pandemic during the first wave in March-April but whose hospitalization rates were low at the end of the year. Second, strict containment measures may not have been promptly imposed on the hardly hit municipalities because of favorable regional indicators. Overall, this institutional setting gave rise to a large within-region heterogeneity in epidemiological conditions for a given stance of containment measures, and the local population was aware of such differences daily thanks to the local press and TV news (Figure E.1).[32]

[28]There is an exception to this statement. In the last week of October, five regions adopted restrictions to mobility that were stricter than national containment measures.

[29]Italy is divided into 20 regions. However, one region (Trentino Alto Adige) is the union of two provinces (Bolzano and Trento) that have special administrative powers and are often considered as separate regions.

[30]When a region moved to a higher risk class, it could not move back to milder restrictions for at least two weeks.

[31]The input indicators did not include forecasts or simulations to improve transparency and avoid subjective assessments. See Borin et al. (2021) for more details about the algorithm determining the endogenous mitigation policies.

[32]For a comparison between hospitalisation rates across commuting zones and provinces in the early stage of the pandemic and the second half of the 2020, see Figures H.1 and H.2 in the Internet Appendix.

Since our data on housing search activity are weekly, we can exploit within-region heterogeneity to identify the impact of epidemiological conditions by including region-by-week fixed effects to control for regional restrictions. Here, we measure epidemiological conditions through the weekly number of hospitalizations per 1,000 inhabitants in the commuting zone. In principle, both the epidemiological situation of the location of the house on sale and that of the potential buyer's residence can matter. Since we do not have information on the latter, we conduct the analysis at the commuting zone level, which provides us with sufficient within-region variability and likely captures the epidemiological conditions of both the house and the potential buyers' locations.

More formally, we estimate the following linear probability model using weekly data from September to December 2020:[33]

$$y_{i,j,k,t} = \alpha_i + \gamma_{k,t} + \beta_0 Hosp_{j,t} + \beta_1 Hosp_{j,t}\mathbf{X}_i + \delta\mathbf{X}_i + \zeta\mathbf{Z}_{i,t} + \varepsilon_{i,j,k,t} \tag{3}$$

where $y_{i,j,k,t}$ is a dummy variable equal to 1 if ads i, in commuting zone j and region k, gets a contact during week t; α_i are listing fixed effects; $\gamma_{k,t}$ are region-by-week fixed effects that control for government restrictions, and $\mathbf{Z}_{i,t}$ are time-varying controls (like the listing price and time-on-market). β_0 and β_1 measure the differential impact across dwelling characteristics. Standard errors are clustered at the commuting zone level.

It must be emphasized that the impact of epidemiological conditions would have been difficult to identify using data on actual transactions. Indeed, it is hard to believe that an increase in the circulation of the virus had a detectable impact on actual transactions in the same or closely subsequent weeks. In contrast, our exercise is based on a much milder assumption. In particular, if the fear of contagion is a determinant of the increase or the re-composition in final housing demand, we expect online search activity to react promptly to epidemiological conditions. A potential concern is that a week is a too short period to investigate the impact of epidemiological conditions on housing search. However, in Section 5.3 we will consider the impact of hospitalisations at monthly frequency and the heterogeneity

[33] We exclude commuting areas encompassing more than one region and those in Valle d'Aosta and Trentino Alto Adige, because of limited within-region heterogeneity or because containment measures were not homogeneous inside the region.

in cumulative hospitalisations across locations during 2020.[34]

First, we find that the direct impact of local epidemiological conditions on housing search activity (β_0) is negative and statistically significant (Table E.1, column 1). However, the magnitude is very small. A unit increase in $Hosp$ is about six times the 75^{th} percentile of its empirical distribution (0.15 hospitalisations per 1,000 population). Therefore, an increase in hospitalisations equivalent to the 75^{th} percentile of the empirical distribution would decrease the probability that a buyer contacts a seller by $0.011 \times 0.15 \approx 0.16$ percentage points, that is a negligible effect considering that the unconditional weekly probability that a seller is contacted is equal to 9.5 percent.[35] Considering Covid-19 contagions or deaths does not alter this conclusion (Table E.1, column 2). Therefore, we exclude that the fear of contagion is a driver of the surge in housing demand that we observe in the data.

Considering the estimates of β_1, we find that changing epidemic conditions have a differential effect on search activity depending on dwellings characteristics, consistent with the trends identified in Section 4, except for the variable private garden (Table E.1). However, by jointly considering β_0 and β_1, we gauge that the impact of an increase in hospitalisations is negative for almost all types of properties. Moreover, the magnitude of the differential, as measured by β_1 and taking into account the empirical distribution for $Hosp$, is always very small, except for home size.[36]

5.2 Containment measures

The identification of the impact of containment measures is more challenging. Although some measures were implemented nationwide in October 2020 (like the requirement of wearing face masks or the suspension of public activities), we focus on the regulatory framework introduced by the DPCM of November 3rd (see Figure E.2).[37] As explained above, regions were classified either as yellow, orange or

[34]One could argue that a worsening of the local epidemiological conditions, though being a relevant driver of final housing demand, does not affect online research activity because the latter does not require face-to-face contacts. However, this argument would be relevant in case a decrease in search activity had to be explained, while in our case is the opposite.

[35]Considering lagged values of hospitalisations (the first or the second lags), we found that β_0 almost doubles. Then, the magnitude would still be small.

[36]An increase in hospitalisations has a tiny positive effect only on the online interest in big houses.

[37]During October we can identify four different containment measures ranked by the stringency of restrictions. Policies 1 to 3 were nationwide. Policy 1 made wearing face masks mandatory in all public places - outdoors and indoors - (decree-law 7 October 2020). Policy 2 (October 13) introduced limits to public gatherings. Policy 3 (24 October 2020) *inter alia* suspended the activities of gyms, swimming pools, cinema, etc. Policy 4 (22 November) introduced curfews in five regions.

red zones, corresponding to increasing degrees of risk and therefore to increasing stringency of containment measures. In yellow regions mobility was limited during the night and high schools and universities could run only online courses. In orange regions people could not move outside their municipality of residence except for work-related reasons and exceptional needs; moreover, bars and restaurants could operate only take-away. In red regions other activities (such as hairdressers, shops) and middle-schools were also shutdown. We remark that the evaluation of the regional epidemiological indicators was conducted at the national level on a weekly basis, and the local government cannot overrule these national government decisions.

Therefore, we restrict our attention to the period between November 3 and December 21 and estimate the following regression:

$$\begin{aligned} y_{i,j,k,t} = \alpha_i + \gamma_t + \beta_0 Hosp_{j,t} + \beta_1 Orange_{k,t} + \beta_2 Orange_{k,t}\mathbf{X}_i + \\ \beta_3 Red_{k,t} + \beta_4 Red_{k,t}\mathbf{X}_i + \delta\mathbf{X}_i + \zeta\mathbf{Z}_{i,t} + \xi\mathbf{W}_{k,t} + \varepsilon_{i,j,k,t} \end{aligned} \tag{4}$$

where $Orange_{k,t}$ and $Red_{k,t}$ are dummy variables for the policy regime that was in place in region k in week t. $\mathbf{W}_{k,t}$ is a vector of regional variables, including weekly contagions and hospitalisation per 1,000 population in region k up to lag 2. The baseline policy is the yellow zone; therefore, we identify the differential impact on housing search of being in a orange or red zone compared to a yellow one. This is not a big issue because the restrictions associated with the yellow zone were very similar to those prevailing since October 24.[38]

We find that stricter containment measures (red zone) have a negative and statistically significant effect on housing search. Being in a red zone, the weekly probability that that a buyer contacts a seller is lower by 1.3 percentage points compared to a yellow zone (Table E.2, column 1). Being in an orange zone has a milder impact (-0.4 percentage points). We do not find evidence of heterogeneity across different dwelling characteristics. β_4 is not statistically significant in most cases, except when the policy is interacted with population density (columns 2-6).[39]

[38]Indeed, if we consider only the regions classified as yellow zones between November 3 and November 16 and implement a regression discontinuity design around November 3, we find that being in a yellow zone entails no significant effect on housing search compared to previous measures.

[39]In this case, β_4 is positive. Then, the drop in search activity is stronger in the less congested areas, apparently at odds with the evidence of Section 4. However, this might be due to the fact that less densely populated areas are usually those located in municipalities outside the main urban areas; since in orange and red zones mobility across municipalities was forbidden, contacting a seller to plan a visit to a house located in the above areas was for many potential buyers probably pointless.

Summing up, epidemiological conditions and government restrictions to mobility cannot explain the surge and re-composition in housing search activity that we have identified in Section 4. Both factors actually point to a decrease in search activity, consistently with the vast literature on the impact of natural disasters and epidemics on housing demand. A possible caveat to our interpretation is that households do not respond immediately, but with some weeks or months delay. In the next Section this hypothesis is tested with respect to epidemiological conditions, and rejected empirically.

5.3 Work from home

The most stringent measures entailed significant restrictions to mobility and school closures, inducing firms and workers, whenever possible, to opt for working from home. Hence households may have tilted their preferences towards larger houses with more facilities because they spent at home not only more leisure time in lack of better alternatives (as cinema, theatres, gyms and the like were all closed) but also more working time.

The Labour Force Survey conducted by Istat allows us to trace at quarterly frequency the share of workers employed who worked remotely in each province.[40] The diffusion of remote working was quite low before the pandemic and increased dramatically in 2020: on average, the share of private sector workers who worked from home was 2.4 per cent in 2019, with a standard deviation of 1.3, and it reached 7 per cent in 2020Q2, with significant heterogeneity across provinces (Figure E.3). In our benchmark regression we focus on the private sector because only a relatively small subset of the public administration employees which was forced to work remotely in 2020 could expect to continue also after the end of the health emergency.[41] As we will discuss later, many private sector workers may have instead perceived that the pandemic was to change their working arrangement in a permanent way. In any case, the overall picture and the econometric results look very similar when considering the change in work from home in the total economy.[42]

In order to better discern the relative role played by the different channels we estimate the regression (5) where the impact of the epidemiological situation, that of

[40]Unfortunately, we do not have information on remote-working in the commuting zones. Therefore, compared to the previous sections our analysis on work from home will exploit provincial level data.

[41]In Italy about one third of public sector workers are teachers (more than 1 million over about 3 millions in 2019), who experienced remote working during the national lockdown and possibly also during the second wave of the pandemic but clearly expected this situation to be temporary.

[42]See also Figure H.3 and Table I.1 in the Internet Appendix.

containment measures (via the region-by-month fixed effects) and that from remote working are jointly evaluated.

$$\begin{aligned} y_{i,m,j,k,t} =& \alpha_m + \gamma_{k,t} + \beta_0 Hosp_{j,t} + \beta_1 Hosp_{j,t} * \mathbf{X}_i + \beta_2 WFH_{j,t} + \\ & \beta_3 WFH_{j,t} * \mathbf{X}_i + \delta \mathbf{X}_i + \zeta \mathbf{Z}_{i,t} + \varepsilon_{i,m,j,k,t} \end{aligned} \tag{5}$$

where $y_{i,m,j,k,t}$ is a dummy variable equal to 1 if ad i, in local market m, province j and region k, gets a contact during month t; α_m are local housing market fixed effects, $\gamma_{k,t}$ are region-by-month fixed effects, which capture the impact of containment measures, $Hosp_{j,t}$ are hospitalisations per 1,000 inhabitants in province j during month t, $WFH_{j,t}$ is the share of workers of the private sector experiencing work from home in province j during month t. Because working from home is a slow-moving variable and is available only at quarterly frequency, it would be redundant to estimate equation (5) at weekly frequency. We thus use monthly data between January 2018 and December 2020, which represent a good compromise between the low frequency variable $WFH_{j,t}$ and the need for controlling for epidemiological conditions and policy measures that evolve more rapidly.[43] Notice also that we include local housing market fixed effects instead of individual ads fixed effects because the sample period is longer and implies a lot of turnover in the ads posted on the website. Standard errors are clustered at the province level.

We find that working from home has a significant and economically relevant impact on housing demand, while the coefficient for hospitalisations is not significant (Table E.3, column 1). A one percentage point increase in the share of remote workers is associated with an increase in the probability of a contact by 0.2 points, signalling that remote working boosted overall housing demand. This effect is large, because the post-pandemic growth in the share of private-sector remote workers across provinces ranges from 0.1 to 12.3 percentage points (average is 3.1). Moreover, β_2 is almost always positive and statistically significant, indicating that remote working can explain the re-composition in search activity. The strongest impact is estimated for the demand of private gardens and larger houses: in both cases, a one percentage point rise in the share of employees experiencing work from home would increase the probability of a contact by 0.3 points (Table E.3, columns 2 and 5). Overall, work from home is the only factor that can jointly explain the surge and the re-composition in housing demand quantified in Section 4, rationalizing the unprecedented trends that we observe in the housing market.

[43] Estimates of model (5) at quarterly frequency are similar to our main specification.

These results square well with survey evidence gathered from real estate agents in the April 2021 wave of IHMS, confirming that our findings represent broad national trends and do not refer only to the share of population more inclined to use digital tools.[44] First, real estate agents expected that, in a three-year horizon, characteristics searched by potential buyers would be very different from those prevailing before the epidemic: demand would rise especially for single-family homes and outdoor spaces, and to a smaller extent for larger houses and those in less congested locations. Second, as for the underlying reasons for this change in preferences, two out of three real estate agents interviewed held that work from home was a key driver.

5.3.1 Instrumental variable approach

Finally, we address potential concerns for the interpretation of the impact of remote working. Indeed, estimates of equation (5) may be biased because both work from home and housing demand could be affected by containment measures imposed by local governments. While the main decisions to contain the epidemic were taken by the national government, local administrators could for example implement school closures because of localized infection clusters, and school closures were plausibly one of the main determinants of parents' choice to work from home, therefore introducing an omitted variable bias in the OLS estimates.

Keeping that in mind, we adopt an instrumental variable approach (2SLS) that exploits structural differences in occupation across provinces. Our goal is to estimate the impact of the change in the share of employees working from home on the change in the relative demand for specific housing characteristics following the pandemic outbreak.[45] To instrument the change in work from home we use two variables: *(i)* the share of employees in the information and communication technology (ICT) and financial sectors and *(ii)* the share of employees with a bachelor degree, both taken before the pandemic (average of 2018-2019). Jobs in these sectors and high-skill jobs are potentially more amenable to working from home. Indeed, both instruments are strongly correlated with the change in work from home after the pandemic outbreak (Figure H.4 in the Internet Appendix). Since these variables are uncorrelated with local epidemiological conditions (Table I.2 in the Internet

[44] In principle remote workers may be more likely to use online home selling platforms than the rest of the population. If this were true, our results could suffer from sample selection bias.

[45] We used the same 2SLS approach to estimate the impact of work from home on total housing search. We found that the magnitude is similar to the OLS estimate in Table I.1.

Appendix), we are confident that they are not correlated with the occurrence of local restrictions (such as school closures) that may cause an increase in the diffusion of work from home (exclusion restriction).

Our first stage involves the estimation of the following regression:

$$\Delta WFH_j = \delta + \beta_1 ICT\_FIN_j + \beta_2 BACHELOR_j + \gamma \mathbf{\Omega}_j + \eta_j \tag{6}$$

where ICT_FIN_j and $BACHELOR_j$ are, respectively, the average shares of employees in the ICT or financial sectors and holding a bachelor degree in province j before the pandemic (2018-2019). $\mathbf{\Omega}_j$ is a set of control variables at the province level, that we include also in the second stage. Among the latter, we include several controls for the level of income and its variation during the pandemic. Indeed, our instruments may be positively correlated with households' financial situation and job stability, so that omitting to control for these effects could determine an upward bias in the estimated impact of work from home on housing demand. We control for pre-pandemic socioeconomic conditions in the province through the average level of income, housing asking prices and the share of permanent employees in 2019. We proxy the change in financial conditions during the pandemic through several variables: the change in private sector employment, in total employment, in the share of permanent employees, in hours worked, in the use of short-term work schemes, in bank deposits and loans, in car purchases and in labour income.[46] Additional control variables that we include in $\mathbf{\Omega}$ are the population in 2019, the size of the province in km^2, the cumulative number of Covid-19-related hospitalizations per 1,000 inhabitants and the percentage change in average housing asking prices and listings. Despite the large number of control variables, the two instruments turn out to explain well the change in work from home (Table E.4). In the second stage, our goal is to estimate the causal impact of work from home on the shift in housing demand for specific dwelling and location characteristics. As a first step, for each province we estimate a slightly revised version of equation (1):

$$y_{i,k,t} = \alpha_{k,t} + \Delta_X * COVID * \mathbf{X}_i + \gamma \mathbf{X}_i + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,k,t} \tag{7}$$

where $y_{i,k,t}$ is a dummy variable equal to 1 if ad i in local market k receives a contact in month t, $\alpha_{k,t}$ are local market fixed effects, Δ_X measures the relative

[46]The data on income published by the Ministry of Economy and Finance at the province level based on tax returns for 2020 are not yet available. However, in pre-pandemic years this variable is correlated at the 80 per cent with labour income from the Labour Force Survey, which we include in the regression (Figure H.5 in the Internet Appendix).

change in search activity for the characteristic X_i due to the pandemic (dummy $COVID = 1$ from March 2020 onward) and $\mathbf{Z}_{i,t}$ are homes' characteristics and time-varying controls (e.g. price, time-on-market). We estimate equation (7) for each province and house characteristic X (single-family home, private garden, terrace, size, population density). In the second step, for each house characteristic we regress Δ_X on the instrumented change in work from home and other controls, including the cumulative hospitalisation experienced by the province from March until December 2020 and all the above mentioned variables capturing the income level and the change in financial conditions occurred in 2020:

$$\Delta_{X,j} = \alpha_k + \beta \Delta WFH_j + \gamma \mathbf{\Omega}_j + \epsilon_j \tag{8}$$

The IV estimates confirm the relevance of work from home and the irrelevance of epidemiological conditions in explaining the change in housing preferences after the outbreak of the pandemic (Table E.5). The coefficients of work from home are statistically and economically significant for all characteristics except population density. In this case, however, standard diagnostic tests reject the hypothesis of endogeneity for ΔWFH_j, and therefore they do not support the IV strategy[47]: in an OLS regression the impact of work from home turns out to be significant also for the preference towards less congested locations (Table I.4 in the Internet Appendix). Therefore, the diffusion of work from home is the key determinant of the re-composition in housing demand. The large set of control variables in $\mathbf{\Omega}_j$ eases the concerns that this result is driven by the relation between the instruments and average income.[48] These results are robust to the exclusion of the three main urban centres (Rome, Milan and Turin), where the increase in work from home has been stronger. Our findings are also broadly confirmed when only the share of workers in the ICT and financial sectors is used as instrument (Table I.5 in the Internet Appendix), and when regional dummies are included.

The strong rise in work from home potentially explains the full impact of the pandemic on the changes in housing demand. Indeed, by multiplying the average change in work from home (3.1 percentage points) by the associated coefficients in Table E.5, we obtain almost exactly the average Δ_X across provinces estimated in equation (7). Specifically, the average Δ_X for single-property houses is 0.016,

[47]See Table I.3 in the Internet Appendix for diagnostic tests of the IV approach.

[48]In any case, a higher average income does not imply a larger demand for houses in the suburbs or in rural areas. Indeed, the empirical evidence for the pre-pandemic period rules out a positive relationship between our instruments and the demand for homes in less congested areas or larger houses (Table I.6 in the Internet Appendix).

which is approximately equal to 3.1×0.00541; for private garden we have that the average Δ_X is 0.019, only slightly higher than 3.1×0.00455. The same proximity holds for population density (by considering the OLS estimate) and slightly less for terrace.[49]

5.4 The changing preferences of Italian households

Overall, our results suggest that the Covid-19 pandemic created mismatches between some households and their current homes, likely because they have re-defined their priorities regarding housing arrangements and commuting distance to the workplace. This conclusion is inferred from our analyses and does not stem from direct observation as we have only the records on what types of homes potential buyers are looking for, but not potential buyers' characteristics and their motivation for searching a house. Here we discuss why this hypothesis is more plausible than other competing explanations, and we argue that re-composition in housing demand is possibly long-lasting.

Housing search activity has grown in virtually all locations, including in large cities and most market segments. This evidence is supported by other sources. As already mentioned in Sections 3 and 4.1, surveys on households and real estate agents point to a large increase in home buyers following the outbreak of the pandemic. This pattern is difficult to reconcile with well-known drivers of housing demand. Even real estate agents, who know their reference market very well, were surprised by these trends (see Figure C.4). According to the Regional Bank Lending Survey (RBLS), the credit supply conditions for residential mortgages, as well as the characteristics of the mortgage loans granted in 2020, remained broadly unchanged compared to 2019. Moreover, also trends in current and expected income – or in population – cannot explain the surge in housing demand. Therefore, the most plausible explanation is that the housing needs of many households changed after the pandemic.

It is more challenging to argue that the changing composition in housing demand is due to a change in housing preferences for the primary residence. For example, households' preferences over the primary residence may have remained unchanged, but many households might have begun looking for a second/holiday home. This

[49] The calculation regarding the size is less informative, because the effect of this variable is typically non-linear, but our procedure for estimating the causal impact of work from home requires estimating a single coefficient Δ_X using a linear specification with a continuous variable (instead of different size categories as in the OLS specification).

would imply a decrease of purchases of primary homes as a share of total transactions, but this is at odds with the evidence coming from several sources. If any, the share of transactions of houses to be used as a primary residence increased.[50] Besides, our benchmark estimates are based on a sample including the largest 100 local commuting zones only, which leaves out most of the Italian touristic locations.

Moreover, what we observe can hardly be explained by a change in the composition of buyers due to income effects.[51] While there might have been such a re-composition, several arguments support that this is not the driving force of the changes in housing demand. First, should most of the less wealthy home buyers have exited the market as a result of the recession, this would be more consistent with a decreasing housing demand, while we find the opposite. And even if the surge in demand were due only to households that did not suffer income losses from the pandemic, it is unclear why all of them decided to start looking for a new home immediately after the outbreak of the pandemic. Second, we exploit the heterogeneity within very local housing markets, controlling for all potential unobserved factors with monthly fixed effects. By construction, local housing markets are homogeneous regarding households' socioeconomic characteristics, primarily because of the housing prices. Therefore, the potential distortion induced by a possible recomposition of the pool of potential buyers has to be minor in our analyses, being already largely controlled for by the fixed effects. Finally, we are aware that our findings on the important role of remote working in explaining the shifts in housing demand could be possibly connected to the higher income and job stability associated with those occupations that can be done from home. However, our results are robust to including a large battery of province-level variables that control for income and wealth effects. Moreover, before the pandemic, a higher average provincial income was not associated with a stronger search activity for larger houses in

[50] According to real estate agents, since the beginning of the pandemic the share of potential buyers looking for a second home has declined while the share of families willing to change their home of residence has increased. This is also confirmed by official data on home transactions: based on OMI data, in the second quarter of 2020 the share of transactions regarding the purchase of a primary residence was 77.5 per cent, higher than in the corresponding period of the previous year and its average value in 2018 (about 74 and 73 per cent, respectively). According to the RBLS, in 2020 more than 90 per cent of residential mortgages was directed to owner-occupied housing rather than investment purposes, a higher share than the previous year.

[51] The current and expected household disposable income (and the tightly linked access to credit) are relevant in housing choices. Being so many those affected by the pandemic, one could suspect that the pool of searching households was re-balanced towards the most affluent ones.

less congested locations but quite the opposite.[52] Hence, we view as more plausible that the larger possibility to work from home changed the housing needs, and this is the key driver of the re-composition of housing demand. Preliminary evidence on search activity in 2021 shows similar trends to 2020, although the vaccination campaign has greatly reduced the fear of contagion and risks of further restrictions, while work from home is still at much higher levels than in 2019.

Moreover, the prominent role of work from home sheds light on a key question, namely whether such changes in housing demand will be transitory or persistent. The evidence collected so far lends support to the latter conclusion. Although the use of remote working has declined compared to the peak levels reached during the national lockdown in March-April 2020, the reversal has been only partial and there are widespread expectations that remote working will be much more pervasive in the future than in pre-pandemic times. According to the latest Survey of Industrial and Service Firms, conducted by the Bank of Italy in the first months of 2021, at the end of the pandemic emergency the average daily percentage of employees working from home would be about 6 per cent (according to the same firms, it was 1.3 in 2019 and 15 per cent on average during 2020). These considerations are shared by real estate agents, who were recently asked about their expectations of longer-term (3 years ahead) changes in the demand for some dwelling characteristics: the large majority of them expect the shifts in housing preferences to persist and attribute a very significant role to the diffusion of remote working.[53]

6 Conclusions

By using a unique dataset of online housing ads representative of the Italian housing market, we find that the Covid-19 pandemic has led to an overall increase in housing demand and a shift toward dwellings with specific physical characteristics, such as the availability of outdoor spaces, larger surface areas and their being single-family properties. Our analyses indicate that the tale of the housing market in the wake of the recent pandemic reads quite differently from that of 14th-century

[52]Following the methodology in Section 4, we estimate for each province the relative online interest in congestion and physical characteristics in 2018 and 2019. The correlation between average provincial income and the search activity is positive only for houses with a private garden, and negative or nil for the other characteristics.

[53]In the second quarter of 2021, real estate agents were asked what role the possibility of remote working has on the expectations about the changes in demand. The possible answers were: 'no role', 'small role', 'somewhat significant role', 'very significant role', 'don't know'. About 67 per cent of the agents reported a 'somewhat significant' or 'very significant' role of remote working.

plague-ridden Florence. The worsening of health conditions, which induced the *Decameron*'s main characters to abandon the city, did not play a significant role in current home purchasing choices, while work from home stands as the main driver of the changes in housing demand.

This suggests that these changes could be long lasting and, looking ahead, have significant repercussions on the distribution of the wealth, which is largely composed of residential properties; on financial stability, due to the variation in the values of collateral; and on the agglomeration forces that usually make cities a hub for growth and innovation.

References

Bank of Italy, "Italian Housing Market Survey. Short-term Outlook - Methods and Sources," `https://www.bancaditalia.it/pubblicazioni/metodi-e-fonti-note/metodi-note-2019/metodologia.pdf`, 2019.

_ , "Box: Italian households during the epidemic: the Bank of Italy's Survey," Economic Bulletin 2 2021.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis, "Why Working From Home Will Stick," Working Paper, Becker Friedman Institute December 2020.

Bartik, Alexander W., Zoe B. Cullen, Edward L. Glaeser, Michael Luca, and Christopher T. Stanton, "What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys," NBER Working Papers 27422, National Bureau of Economic Research, Inc June 2020.

Basso, Gaetano and Sara Formai, " Il lavoro da remoto in Italia durante la pandemia," Covid-19 Note, Bank of Italy January 2021.

Bick, Alexander, Adam Blandin, and Karel Mertens, "Work from Home After the COVID-19 Outbreak," CEPR Discussion Papers 15000, C.E.P.R. Discussion Papers July 2020.

Bloom, Nicholas and Arjun Ramani, "The doughnut effect of COVID-19 on cities," VoxEU column January 2021.

Borin, Alessandro, Sabina Marchetti, Francesco P. Conteduca, Giuseppe Ilardi, and Andrea Brandolini, "An epidemic model for Covid-19 with endogenous mitigation policies," 2021.

Bricongne, Jean-Charles, Baptiste Meunier, and Sylvain Pouget, "Web Scraping Housing Prices in Real-time: the Covid-19 Crisis in the UK," Working Papers 827, Banque de France 2021.

Brueckner, Jan, Matthew E Kahn, and Gary C Lin, "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?," Technical Report, National Bureau of Economic Research 2021.

Cesaroni, Tatiana, "Average time to sell a property and credit conditions: evidence from the Italian Housing Market Survey," Working Papers LuissLab 18136, Dipartimento di Economia e Finanza, LUISS Guido Carli 2018.

Davis, Lucas W., "The Effect of Health Risk on Housing Values: Evidence from a Cancer Cluster," *American Economic Review*, December 2004, *94* (5), 1693–1704.

Davis, Morris A, Andra C Ghent, and Jesse M Gregory, "The Work-at-Home Technology Boon and its Consequences," Working Paper, National Bureau of Economic Research 2021.

Delventhal, Matthew J., Eunjee Kwon, and Andrii Parkhomenko, "How do cities change when we work from home?," *Journal of Urban Economics*, 2021, p. 103331.

Depalo, Domenico and Federico Giorgi, "Il lavoro da remoto in Italia durante la pandemia: i lavoratori del settore privato," Covid-19 Note, Bank of Italy January 2021.

Francke, Marc and Matthijs Korevaar, "Housing Markets in a Pandemic: Evidence from Historical Outbreaks," *Journal of Urban Economics*, 2021, *forthcoming.*

Gargano, Antonio, Marco Giacoletti, and Elvis Jarnecic, "Local Experiences, Search and Spillovers in the Housing Market," Technical Report 2021.

Giuzio, Walter and Lucia Rizzica, "Il lavoro da remoto in Italia durante la pandemia: le Amministrazioni Pubbliche," Covid-19 Note, Bank of Italy January 2021.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh, "Flattening the curve: Pandemic-Induced revaluation of urban real estate," *Journal of Financial Economics*, 2021.

Hallstrom, Daniel G. and V. Kerry Smith, "Market responses to hurricanes," *Journal of Environmental Economics and Management*, November 2005, *50* (3), 541–561.

Haslag, Peter and Daniel Weagley, "From L.A. to Boise: How Migration Has Changed During the COVID-19 Pandemic," 2021.

Juhász, Réka, Mara P Squicciarini, and Nico Voigtländer, "Away from Home and Back: Coordinating (Remote) Workers in 1800 and 2020," Working Paper 28251, National Bureau of Economic Research December 2020.

Liu, Sitian and Yichen Su, "The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market," *Economics Letters*, 2021, *207*, 110010.

Loberto, Michele, Andrea Luciani, and Marco Pangallo, "What do online listings tell us about the housing market?," *International Journal of Central Banking*, 2021, *forthcoming.*

Ouazad, Amine, "Resilient Urban Housing Markets: Shocks vs. Fundamentals," CIRANO Working Papers 2020s-53, CIRANO October 2020.

Pangallo, Marco and Michele Loberto, "Home is where the ad is: online interest proxies housing demand," *EPJ Data Science*, 2018, *7* (47).

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel, "Segmented housing search," *American Economic Review*, 2020, *110* (3), 720–59.

Riccardo, Flavia, Marco Ajelli, Xanthi D Andrianou, Antonino Bella, Martina Del Manso, Massimo Fabiani, Stefania Bellino, Stefano Boros, Alberto Mateo Urdiales, Valentina Marziano, Maria Cristina Rota, Antonietta Filia, Fortunato Dapos;Ancona, Andrea Siddu, Ornella Punzo, Filippo Trentini, Giorgio Guzzetta, Piero Poletti, Paola Stefanelli, Maria Rita Castrucci, Alessandra Ciervo, Corrado Di Benedetto, Marco Tallon, Andrea Piccioli, Silvio Brusaferro, Giovanni Rezza, Stefano Merler, Patrizio Pezzotti, and the COVID-19 working group, "Epidemiological characteristics of COVID-19 cases and estimates of the reproductive numbers 1 month into the epidemic, Italy, 28 January to 31 March 2020," *Eurosurveillance*, 2020, *25* (49).

Smith, V. Kerry, Jared C. Carbone, Jaren C. Pope, Daniel G. Hallstrom, and Michael E. Darden, "Adjusting to natural disasters," *Journal of Risk and Uncertainty*, 2006, *33* (1/2), 37–54.

Stanton, Christopher T and Pratyush Tiwari, "Housing Consumption and the Cost of Remote Work," Working Paper 28483, National Bureau of Economic Research February 2021.

van Dijk, Dorinth W and Marc K Francke, "Internet search behavior, liquidity and prices in the housing market," *Real Estate Economics*, 2018, *46* (2), 368–403.

Wong, Grace, "Has SARS infected the property market Evidence from Hong Kong," *Journal of Urban Economics*, January 2008, *63* (1), 74–95.

Zhao, Yunhui, "US Housing Market during COVID-19: Aggregate and Distributional Evidence," Working Paper WP/20/212, International Monetary Fund September 2020.

Data and additional Figures and Tables

A Data

Immobiliare.it. We obtained from Immobiliare.it weekly files of all listings that are online on Monday. Starting from these snapshots, we construct four datasets. The main dataset is the one with unique ads. Three datasets track the weekly change of asking prices, visits and contacts. The information available for each ad is reported in Table A.1.

When investigating *clicks* and *contacts* within narrow categories, their pattern could be partly different as they reflect different steps of households' search activity. When starting to look for a house on the portal, potential buyers first need to select the location of interest. Then, the website proposes only homes within the chosen location, that can be clicked upon to explore the details. Users can impose other filters as well but that can result in a low number of available homes, so that it is generally convenient to click upon most of the ads within the chosen location and then contact the agency only for those that look most interesting based on the description. This suggests that *clicks* could be more informative about location preferences while *contacts* could capture better the interest in some dwelling features (such as outdoor spaces) within a given location.

Table A.1: Information contained in the database provided by Immobiliare.it.

Type of data	**Variables**
Numerical	Price, floor area, rooms, bathrooms
Categorical	Property type, furniture, kitchen type, heating type, maintenance status, balcony, terrace, floor, air conditioning, energy class, basement, utility room
Related to the building	Elevator, type of garden, garage, porter, building category
Contractual	Foreclosure auction, contract type
Related to the seller	Publisher type (private citizen or real estate agency), agency name and address
Visual	Hash codes of the pictures, pictures count
Geographical	Longitude, latitude, address
Related to the ad	Clicks, contacts
Temporal	Ad posted, ad removed, ad modified
Textual	Description

The Italian Housing Market Survey (IHMS). The Italian Housing Market Survey is conducted at quarterly frequency since 2009 by the Bank of Italy with the cooperation of Tecnoborsa and the Tax Revenue Agency on a panel of about

1,400 real estate agents, representative of the reference universe consisting of about 32,000 agencies who work on behalf of third parties. The 15 most-populated towns in Italy and their hinterland are all covered in the sample.

About two thirds of the interviews are computer-assisted telephone interviews, while the rest are computer-assisted web interviews with a questionnaire that could be filled out online. The full methodology of the survey is described in Bank of Italy (2019). A quarterly report describing the main results is made available on the Bank of Italy's website.

The survey is unique in Europe in collecting at high frequency the sentiment of the housing market directly from the intermediaries (Cesaroni, 2018). The standard questionnaire collects, mostly in a qualitative way, agents' opinions regarding the course of house sales, price trends compared with the previous quarter and the short- and medium-term outlook at the local and the national level.

Since the outbreak of the epidemic, specific questions aimed at investigating its impact, both in the short and in the longer-run, were included. Agents were also asked about changes in the potential buyers' motivations to look for a house and in the demand for specific dwellings' characteristics, also in connection with the diffusion of remote working.

Commuting zones. The Italian Statistical Institute (ISTAT) identifies 660 commuting areas (*Sistemi locali del lavoro*), based on census data on individual home-to-work daily commuting patterns. Since the epidemic circulates with people's movements, commuting zones are ideal geographic areas for studying the impact of an epidemic. Moreover, as households are still uncertain about the future organization of work, they may prefer to move in a relatively nearby area, from which it is possible to reach their place of work at least periodically. Finally, commuting zones cross administrative borders, and this feature is useful in identifying the impact of mobility restrictions imposed by local authorities.

Local housing markets. We identify local housing markets inside each city by adopting the partition developed by OMI, the Real Estate Observatory of the Italian Tax Revenue Agency. OMI identifies local housing markets ("OMI zones") as contiguous areas that satisfy strict requirements in terms of homogeneity of housing prices, urban and socio-economic characteristics, and endowment of services and urban infrastructures. This partition is periodically revised to satisfy these criteria, and the last major revision dates back to 2014. Generally, local housing markets are larger than census tracts. In Italy there are 27,426 "OMI zones"and 402,678 census tract. To provide an example, the capital city of Rome is composed by more than 200 "OMI zones".

Measures of population density. We complement the dataset of online listings with two measures of congestion for a given location. The first measure is the degree of urbanization proposed by Eurostat, which classifies municipalities into cities, towns and suburbs, and rural areas. About 67 per cent of municipalities are classified as rural areas, about 30 per cent as towns and suburbs and only 3 per cent as cities. However, cities account for 33 per cent of Italian population, while rural areas for 25 per cent only.

To measure congestion at a more granular level, we use census data and we compute the population density for each census tract (number of residents per square meter). Since census tracts are much smaller than local housing markets, we exploit this source of heterogeneity within local housing markets to better assess how much households value living in a less congested area.

Epidemiological conditions. The evolution of the epidemic at the local level is based on data collected by the *Istituto Superiore di Sanità* (ISS, the Italian National Institute of Health). See Riccardo et al. (2020) for a description of the data.

Labour Force Survey (LFS). The information about remote working is drawn from the Labour Force Survey (LFS) conducted by Istat in compliance with Eurostat guidelines. The survey involves about 150,000 individuals and is performed on a continuous basis, which implies that there are interviews every week. Specifically, the survey asks whether the respondent has worked from home in the reference period; we use this information to build the quarterly share of smart-workers employed in the private sector in each province. From the LFS we also derive other information, such as wages and the share of employees in the financial and ICT sectors, that we use either as controls or to instrument work from home.

Other data. In our econometric analysis we also exploit data from other data sources that capture income and wealth effects at the province level: tax returns data (diffused by the Ministry of Economy and Finance), bank loans and deposits (Bank of Italy) and car purchases (Ministry of Infrastructures).

B Institutional details of the Italian housing market

In this Section, we briefly describe the main trends and institutions of the Italian housing market.

The 2011 Sovereign debt crisis had a strong impact on the Italian housing market. From 2011 to 2013, housing transactions fell by one-third and only resumed growth in 2014. Housing prices experienced a more moderate but more persistent decline; they stabilized only in 2019, after having declined by more than 20 percent.

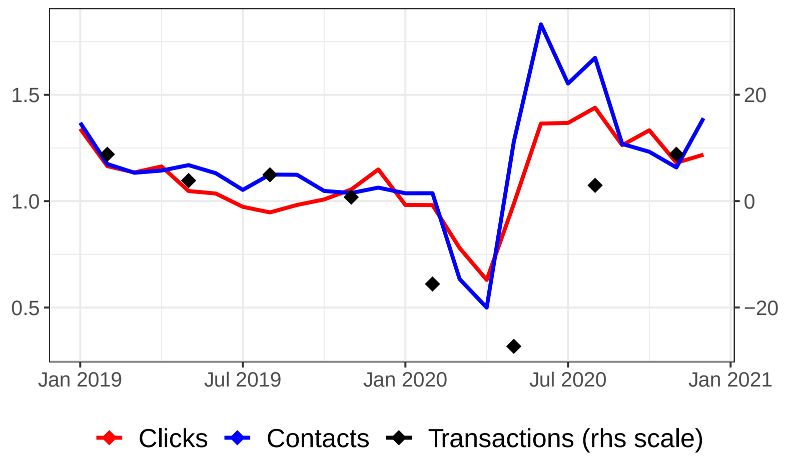
The share of homeowners is higher than 70 per cent. Housing is by far the largest asset held by households and absorbs most of their savings. Only half of all households' home purchases are financed through a mortgage loan, and the average loan-to-value is about 65 per cent.

Transaction costs associated with purchasing a home include transaction taxes, notary fees, brokerage fees, and mortgage-related costs. Real-estate brokers intermediate about 50 per cent of all housing transactions, but this share is higher in cities and larger commuting zones.

Listing prices are not legally binding, and the seller can always refuse to sell to a potential buyer. In general, the buyer and the seller negotiate the final price and other contractual arrangements. When a broker is involved in a sale, the seller cannot simultaneously negotiate with multiple buyers, which rules out bidding wars. Usually, the final price is below the listing price. According to the Italian Housing Market Survey, during 2018-2020 the average discount compared to the initial asking price was about 10 per cent, and the final price was lower than the initial asking price in about 95 per cent of transactions.

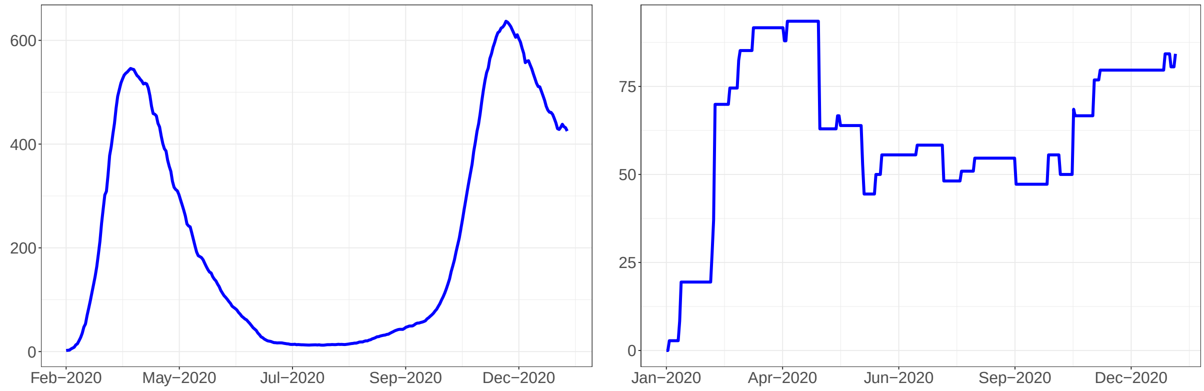
C Descriptive evidence

Figure C.1: Daily *clicks* and *contacts* per ad and housing sales



Source: clicks and *contacts* are based on data from Immobiliare.it and are computed as ratios with respect to the same period of the previous year. House sales are q-o-q growth rates based on OMI data.

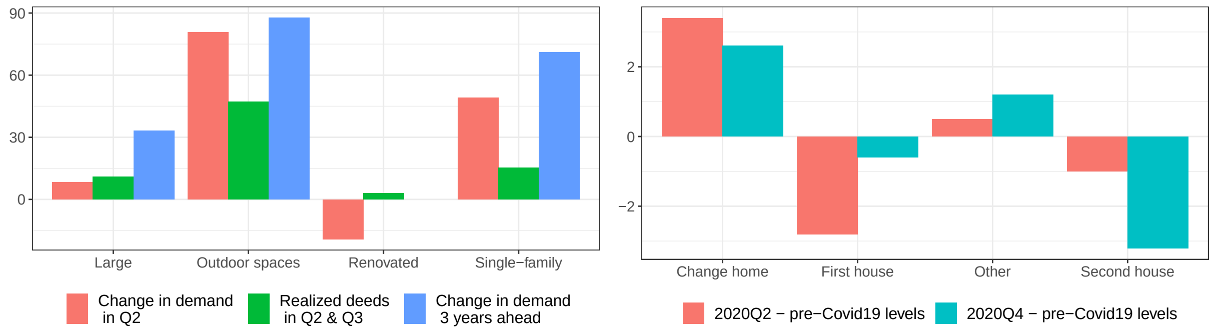
Figure C.2: The evolution of the Covid-19 pandemic in Italy



(a) *Hospitalizations per million* (b) *Oxford Stringency Index*

Source: Our World in Data.

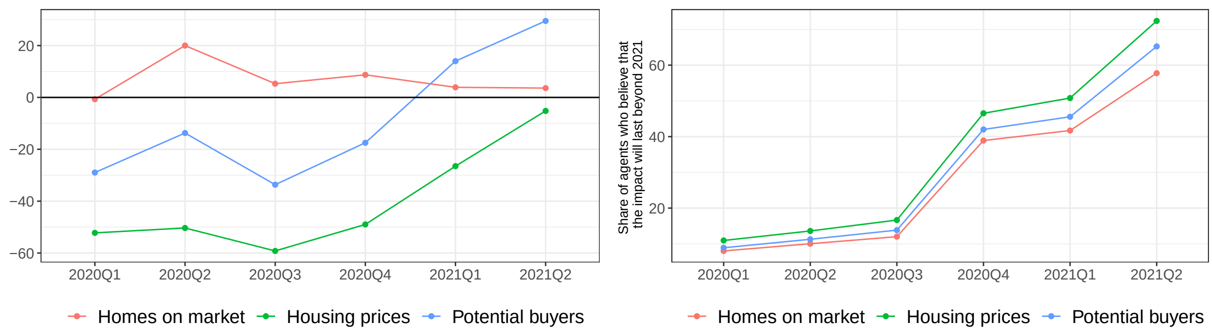
Figure C.3: Change in dwellings and buyers' characteristics after the pandemic



(a) *Characteristics of dwellings* (b) *Buyers' characteristics*

Source: our computations on IHMS data. *Notes:* the left panel represents the percentage points balances between respondents indicating "increasing" and "decreasing" in answering to the questions about changes in prevailing characteristics of the housing demanded by potential buyers (2020Q2) or intermediated (2020Q3). In 2021Q1 agents were also asked about their expectations of changes in demand 3 years ahead (grey bars). The right panel represents how the shares of potential buyers classified according to their motivation for buying a home has changed in 2020Q2 and 2020Q4 with respect to pre-pandemic levels. Survey questions are reported in Section F.2 of the Internet Appendix.

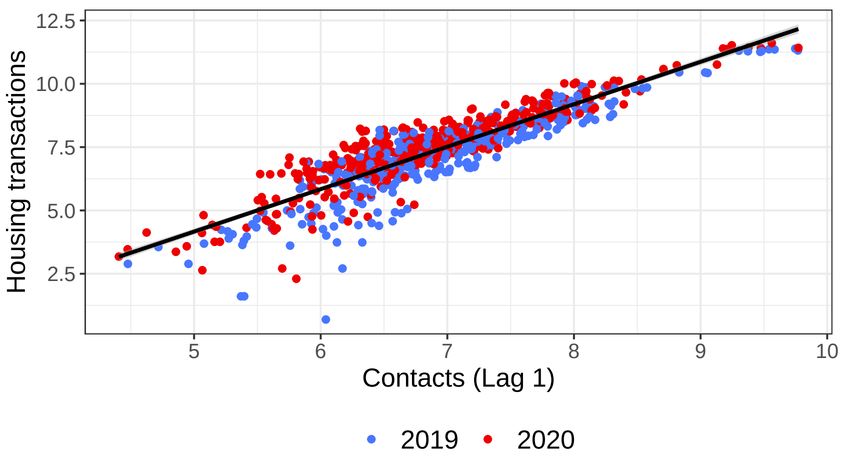
Figure C.4: Judgments about how the pandemic will influence the national housing market



(a) *Sign of the impact* (b) *Duration of the impact*

Notes: the left panel represents the percentage points balances between respondents indicating a positive or a negative impact of the pandemic on the variables of interest. The right panel represents the share of real estate agents reporting either a positive or a negative impact of Covid-19 on the variables of interest who believe that the effects will last beyond 2021.

Figure C.5: Housing search activity and actual transactions



Sources: Actual transactions are taken from OMI; *contacts* are based on data from Immobiliare.it. *Notes*: Each dot corresponds to an Italian NUTS-3 region (province) and a quarter. The y-axis represent the log of actual transactions, the x-axis the log of total *contacts* received in the previous quarter by dwellings located in the same province. We select the first lag of *contacts* on the basis of the estimates reported in Table G.12 of the Internet Appendix.

D How the Covid-19 pandemic has shaped housing demand

Table D.1: Effects of Covid-19 on housing demand

	Log(Clicks)		P(Contacts> 0)		
	(1)	(2)	(3)	(4)	(5)
(Intercept)			0.225***		
			(0.016)		
Mar-Apr 2020	-0.053*	-0.037	-0.037***	-0.032***	-0.027***
	(0.028)	(0.034)	(0.002)	(0.003)	(0.006)
Post May 2020	0.367***	0.379***	0.062***	0.075***	0.079***
	(0.022)	(0.025)	(0.004)	(0.004)	(0.006)
Observations	11,717,459	11,717,459	11,717,459	11,717,459	11,717,459
R^2	0.343	0.471	0.034	0.071	0.121
Within R^2	0.263	0.280		0.040	0.045
Commuting zone×Month fixed effects	✓			✓	
Local housing market×Month fixed effects		✓			✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month. We include month-of-the-year dummies to account for seasonality.

Table D.2: Effects of Covid-19 on housing demand by location

	Log(Clicks)			P(Contacts> 0)		
	(1)	(2)	(3)	(4)	(5)	(6)
Suburbs	-0.185***			-0.043***		
	(0.034)			(0.010)		
Rural areas	-0.302***			-0.056**		
	(0.068)			(0.022)		
Mar-Apr 2020*Suburbs	-0.053*			0.014***		
	(0.030)			(0.003)		
Post May 2020*Suburbs	0.016			0.015***		
	(0.023)			(0.005)		
Mar-Apr 2020*Rural areas	0.048*			0.028***		
	(0.026)			(0.004)		
Post May 2020*Rural areas	0.105***			0.016**		
	(0.021)			(0.006)		
Log of population per m^2		0.022***	0.0007		0.004***	-0.002***
		(0.003)	(0.001)		(0.0009)	(0.0004)
Mar-Apr 2020*Log of population per m^2		-0.002	-0.002**		-0.004***	-0.002***
		(0.002)	(0.001)		(0.0005)	(0.0005)
Post May 2020*Log of population per m^2		-0.012***	-0.003***		-0.006***	-0.001***
		(0.002)	(0.001)		(0.0008)	(0.0004)
Observations	11,717,459	11,591,151	11,591,151	11,717,459	11,591,151	11,591,151
R^2	0.374	0.369	0.518	0.075	0.075	0.143
Within R^2	0.246	0.240	0.256	0.036	0.036	0.040
Commuting zone×Time dummies fixed effects	✓	✓		✓	✓	
Local housing market×Time dummies fixed effects			✓			✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table D.3: Effects of Covid-19 on *contacts* by dwellings' characteristics

	P(Contacts>0)				
	(1)	(2)	(3)	(4)	(5)
Single-family home	0.056***	0.056***	0.049***	0.043***	0.041***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Terrace	0.035***	0.033***	0.035***	0.031***	0.029***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Private garden	0.055***	0.064***	0.064***	0.060***	0.053***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Size (m^2)	-0.0008***	-0.0008***	-0.0008***		
	(5.22×10^{-5})	(5.23×10^{-5})	(5.23×10^{-5})		
Size = 50-85				-0.012*	-0.012*
				(0.007)	(0.007)
Size = 85-115				-0.020	-0.020
				(0.013)	(0.013)
Size = 115-145				-0.047***	-0.045***
				(0.016)	(0.016)
Size > 145				-0.140***	-0.135***
				(0.015)	(0.015)
Mar-Apr 2020*Private garden	0.006***				0.005**
	(0.002)				(0.002)
Post May 2020*Private garden	0.034***				0.029***
	(0.002)				(0.002)
Mar-Apr 2020*Terrace		0.006***			0.004**
		(0.002)			(0.002)
Post May 2020*Terrace		0.011***			0.009***
		(0.002)			(0.001)
Mar-Apr 2020*Single-family home			0.003		-0.009***
			(0.002)		(0.002)
Post May 2020*Single-family home			0.031***		0.012***
			(0.003)		(0.002)
Mar-Apr 2020*Size = 50-85				0.002	0.002
				(0.004)	(0.004)
Post May 2020*Size = 50-85				0.011***	0.010***
				(0.003)	(0.003)
Mar-Apr 2020*Size = 85-115				-0.0009	-0.001
				(0.007)	(0.007)
Post May 2020*Size = 85-115				0.017***	0.014***
				(0.005)	(0.005)
Mar-Apr 2020*Size = 115-145				0.001	0.001
				(0.006)	(0.006)
Post May 2020*Size = 115-145				0.022***	0.014**
				(0.006)	(0.005)
Mar-Apr 2020*Size > 145				0.013*	0.014**
				(0.007)	(0.006)
Post May 2020*Size > 145				0.028***	0.007
				(0.007)	(0.007)
Observations	11,717,459	11,717,459	11,717,459	11,717,459	11,717,459
Local housing market×Time dummies fixed effects	✓	✓	✓	✓	✓

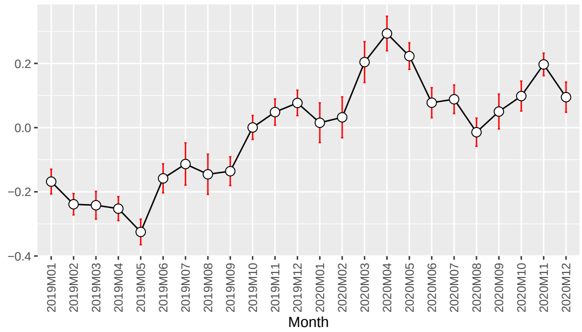
Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table D.4: Effects of Covid-19 on *contacts* by dwellings' characteristics and location

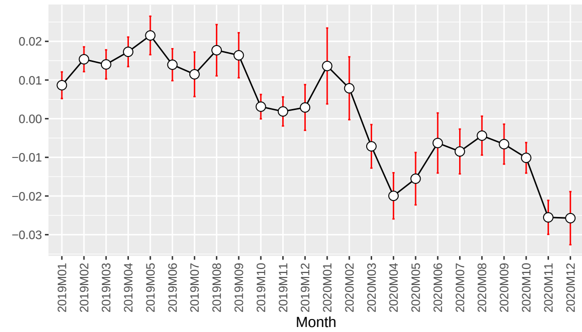
	P(Contacts>0)	
	(1)	(2)
Suburbs	-0.040***	
	(0.010)	
Rural areas	-0.050**	
	(0.022)	
Log of population per m^2		0.004***
		(0.0009)
Mar-Apr 2020*Single-family home	-0.005*	-0.004
	(0.003)	(0.003)
Post May 2020*Single-family home	0.018***	0.017***
	(0.002)	(0.002)
Mar-Apr 2020*Terrace	0.008***	0.008***
	(0.002)	(0.002)
Post May 2020*Terrace	0.013***	0.013***
	(0.002)	(0.002)
Mar-Apr 2020*Private garden	0.010***	0.010***
	(0.003)	(0.003)
Post May 2020*Private garden	0.036***	0.035***
	(0.003)	(0.003)
Mar-Apr 2020*Size = 50-85	0.005	0.004
	(0.004)	(0.004)
Post May 2020*Size = 50-85	0.015***	0.016***
	(0.004)	(0.004)
Mar-Apr 2020*Size = 85-115	0.0005	0.0007
	(0.006)	(0.006)
Post May 2020*Size = 85-115	0.018***	0.018***
	(0.004)	(0.004)
Mar-Apr 2020*Size = 115-145	-0.0002	-0.0005
	(0.006)	(0.006)
Post May 2020*Size = 115-145	0.015***	0.015***
	(0.005)	(0.005)
Mar-Apr 2020*Size $>$ 145	0.011*	0.010*
	(0.006)	(0.006)
Post May 2020*Size $>$ 145	0.005	0.006
	(0.008)	(0.008)
Mar-Apr 2020*Suburbs	0.011***	
	(0.003)	
Post May 2020*Suburbs	0.004	
	(0.005)	
Mar-Apr 2020*Rural areas	0.024***	
	(0.004)	
Post May 2020*Rural areas	-0.003	
	(0.007)	
Mar-Apr 2020*Log of population per m^2		-0.003***
		(0.0005)
Post May 2020*Log of population per m^2		-0.002**
		(0.0009)
Observations	11,717,459	11,591,151
Commuting zone×Time dummies fixed effects	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

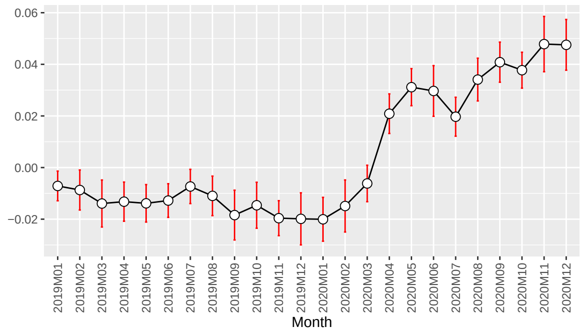
Figure D.1: Relative interest in dwelling characteristics and location by month



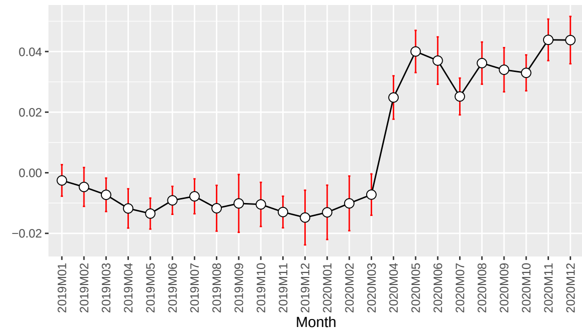
(a) *Rural area*



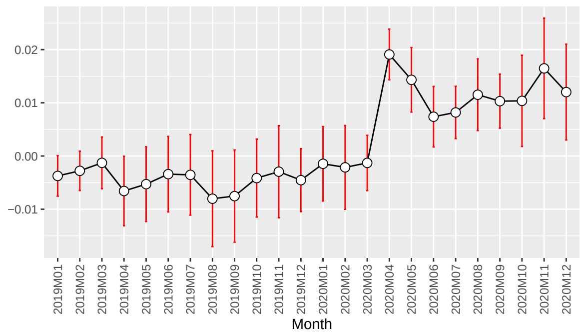
(b) *Population per* m^2



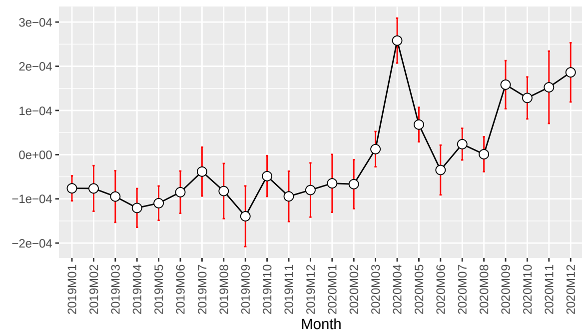
(c) *Property type*



(d) *Garden*



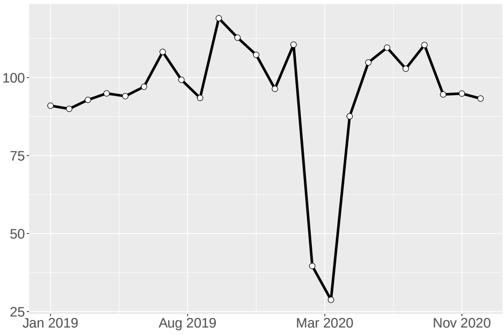
(e) *Terrace*



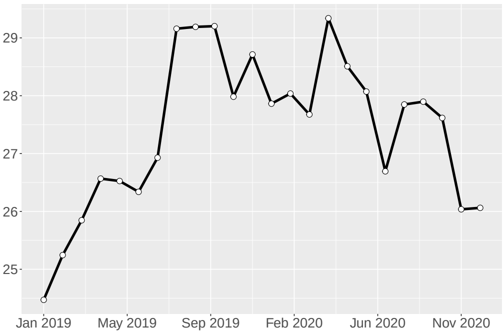
(f) *Floor area*

Notes: In these charts we reports for each variable of interest the estimates of $\beta_j^M - \beta_{j-12}^M$ from model (2). In charts *(a)* and *(b)* the dependent variable is the logarithm of clicks. In charts *(c)-(f)* the dependent variable is $P(Contacts > 0)$.

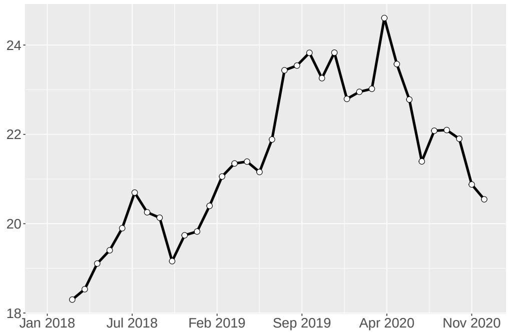
Figure D.2: Newly posted listings and their composition by location and characteristics



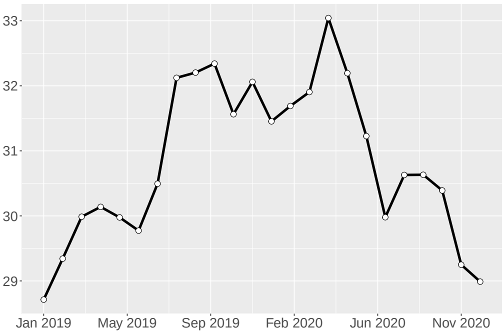
(a) *Total index*



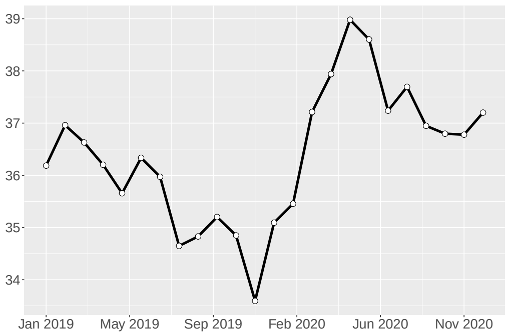
(b) *Population density*



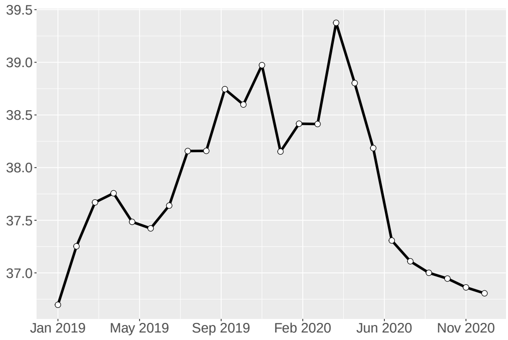
(c) *Property type*



(d) *Garden*



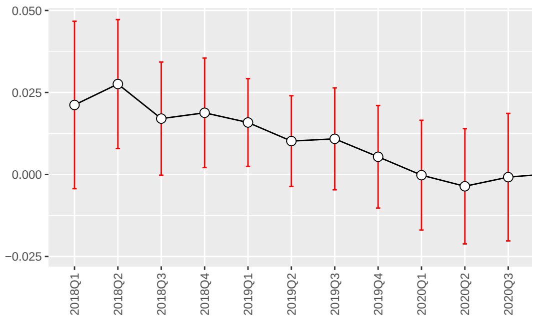
(e) *Terrace*



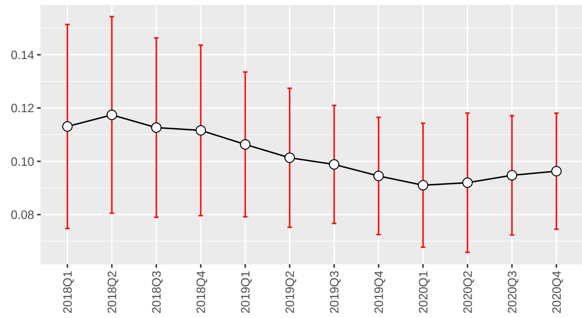
(f) *Floor area*

Notes: Monthly data: in panel (a) data are seasonally adjusted and represented as and index equal to 100 in 2019. For all the other panels, data are moving averages of three terms. In any month, new listings are those which receive the first *click* in that month. For population density, we consider the share of new listings in areas where the population density is below the first quartile of the distribution calculated in 2018. For size, we consider the share of listings whose surface area is greater than 115 square meters.

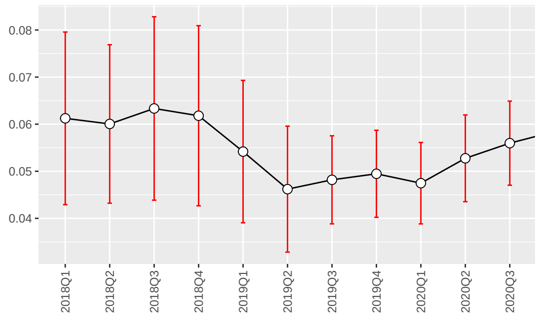
Figure D.3: Shadow prices of some dwelling characteristics by quarter



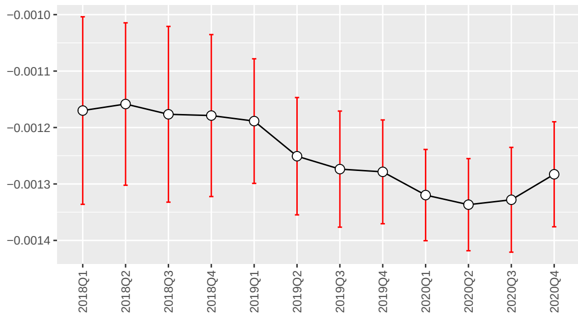
(a) *Property type*



(b) *Garden*



(c) *Terrace*

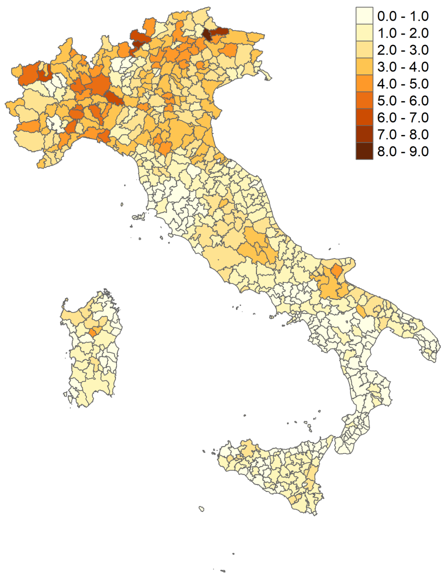


(d) *Floor area*

Notes: Time varying coefficients for property type, garden, terrace and size in the hedonic regression $\log(P_{i,k,t}) = \alpha_k + \delta_t + \sum_{j=1}^{N} \beta_j^Q Q_{j,t} X_i + \gamma \mathbf{Z_{i,t}} + \varepsilon_{i,k,t}$, where: $P_{i,k,t}$ is the first asking price of listing i; α_k and δ_t are local market and year-quarter fixed effects; $Q_{j,t}$ is a set of quarterly dummy variables (one per each year-quarter). Coefficients β_j^Q measure the average contribution of a single characteristic of the dwelling to the asking price, keeping fixed all other characteristics.Standard errors are clustered at the commuting area level. Each listing appears only in the quarter in which enters the market.

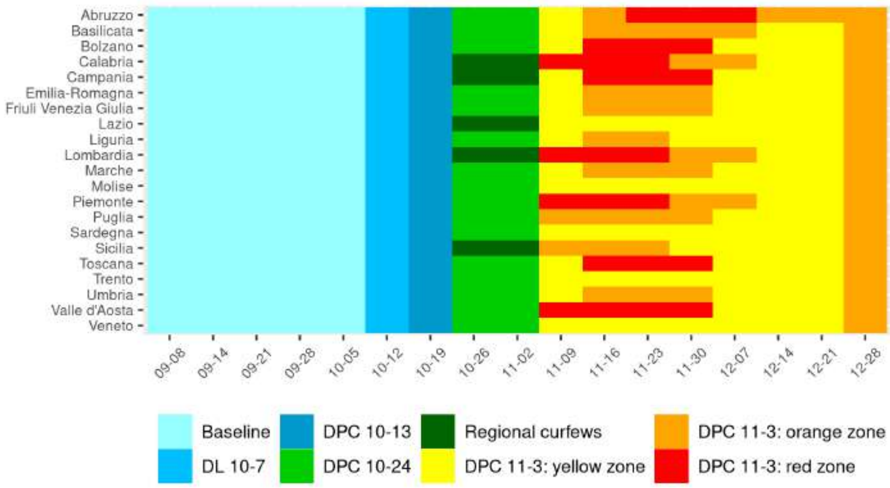
E Channels of transmission

Figure E.1: Covid-19 hospitalisations in the commuting areas. September-December 2020



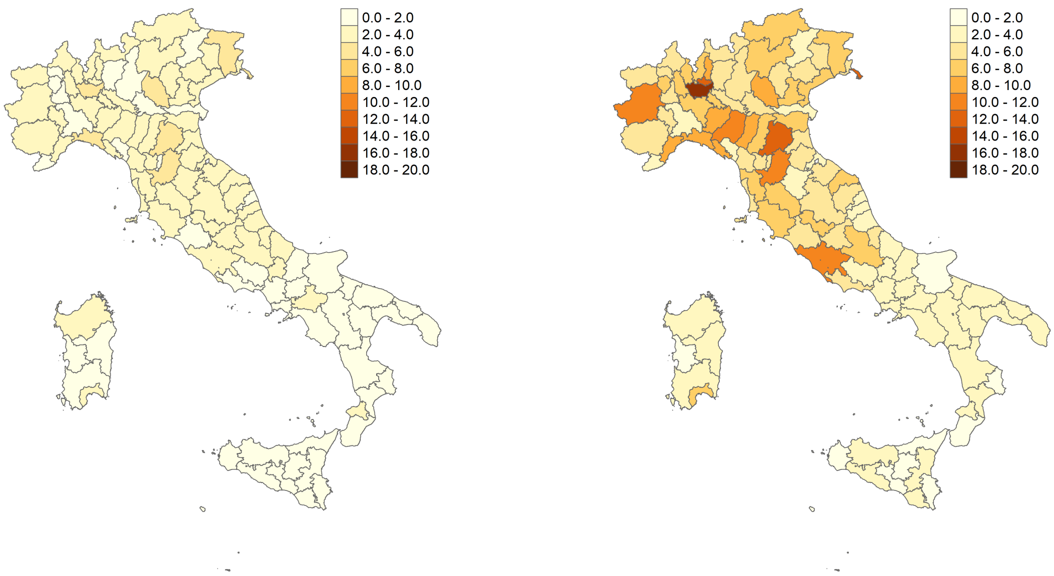
Source: Istituto Superiore di Sanità (ISS, Italian National Institute of Health). *Notes:* Number of Covid-19 hospitalisations per 1,000 persons across commuting areas.

Figure E.2: Covid-19 containment measures during September-December 2020



Notes: Containment policies 1 through 7 are incremental, i.e., Policy 4 adds additional restrictions to those imposed under Policy 3. Policies 1 to 3 were nationwide, while policies 4 to 7 were applied to specific regions based on regional epidemiological conditions. Policy 1 (October 7) makes mask mandatory indoors and outdoors. Policy 2 (October 13) introduces limits to public gatherings. Policy 3 (October 24) provides for additional limits on gatherings and the shutdown of some activities (i.e., theaters). Policy 4 (22 November) introduces curfews. The DPCM of November 3 introduces three sets of stricter measures (including school closures).

Figure E.3: Share of private sector workers experiencing work from home



(a) *2019*

(b) *2020*

Source: Labour Force Survey. *Notes*: Share of private sector workers (percentage points) experiencing work from home across provinces.

Table E.1: Impact of epidemiological conditions on housing demand

	P(Contacts> 0)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hospitalisations	-0.0113***	-0.0106*	-0.0124**	-0.0149***	-0.0135***	-0.0355***	-0.0406***
	(0.0041)	(0.0054)	(0.0049)	(0.0049)	(0.0044)	(0.0092)	(0.0099)
Contagions		-1.56×10^{-5}					
		(0.0004)					
Deaths		-0.0039					
		(0.0078)					
Hosp.*Private garden			0.0037				
			(0.0047)				
Hosp*Terrace				0.0098***			
				(0.0034)			
Hosp*Single-family home					0.0097**		
					(0.0045)		
Hosp*Size = 50-85						0.0188***	
						(0.0063)	
Hosp*Size = 85-115						0.0205***	
						(0.0060)	
Hosp*Size = 115-145						0.0237**	
						(0.0092)	
Hosp*Size > 145						0.0411***	
						(0.0086)	
Hosp*Log of population per m^2							-0.0051***
							(0.0014)
Observations	6,920,001	6,920,001	6,920,001	6,920,001	6,920,001	6,920,001	6,841,877
R^2	0.3196	0.3196	0.3196	0.3196	0.3196	0.3196	0.3198
Within R^2	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016
ID listing fixed effects	✓	✓	✓	✓	✓	✓	✓
Region×Week fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include price per m^2, price revision and time on market. Contagions, hospitalisations and deaths are defined as the weekly numbers to 1,000 population in the commuting zone.

Table E.2: Impact of containment measures on housing demand

	P(Contacts> 0)					
	(1)	(2)	(3)	(4)	(5)	(6)
Hospitalisations	0.0012	0.0010	0.0013	0.0014	0.0017	0.0008
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0048)	(0.0044)
Orange zone	-0.0036*	-0.0031	-0.0035*	-0.0032	-0.0010	0.0041
	(0.0018)	(0.0020)	(0.0020)	(0.0020)	(0.0036)	(0.0038)
Red zone	-0.0133***	-0.0126***	-0.0134***	-0.0138***	-0.0133***	-0.0038
	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0037)	(0.0041)
Orange zone*Single-family home		-0.0020				
		(0.0013)				
Red zone*Single-family home		-0.0029**				
		(0.0014)				
Orange zone*Private garden			-0.0003			
			(0.0012)			
Red zone*Private garden			0.0004			
			(0.0011)			
Orange zone*Terrace				-0.0010		

				(0.0012)		
Red zone*Terrace				0.0011		
				(0.0010)		
Orange zone*Size = 50-85					-0.0018	
					(0.0027)	
Red zone*Size = 50-85					-0.0009	
					(0.0031)	
Orange zone*Size = 85-115					-0.0017	
					(0.0031)	
Red zone*Size = 85-115					-0.0009	
					(0.0032)	
Orange zone*Size = 115-145					-0.0027	
					(0.0033)	
Red zone*Size = 115-145					0.0020	
					(0.0037)	
Orange zone*Size > 145					-0.0049	
					(0.0032)	
Red zone*Size > 145					0.0008	
					(0.0034)	
Orange zone*Log of population per m^2						0.0013***
						(0.0005)
Red zone*Log of population per m^2						0.0016***
						(0.0005)
Observations	2,858,032	2,858,032	2,858,032	2,858,032	2,858,032	2,825,866
R^2	0.3800	0.3800	0.3800	0.3800	0.3800	0.3801
Within R^2	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
ID listing fixed effects	✓	✓	✓	✓	✓	✓
Weekly time dummies	✓	✓	✓	✓	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include price per m^2, price revision and time on market. In column (2) to (7) we control for weekly contagions and hospitalisation per 1,000 population in region k up to lag 2. Hospitalisations are defined as the number of Covid-19 related hospitalisations per 1,000 population in the commuting zone. Containment policies are those introduced by the DPCM of November 3.

Table E.3: Impact of work from home and epidemiological conditions on housing demand (OLS)

	P(Contacts> 0)					
	(1)	(2)	(3)	(4)	(5)	(6)
Work-from-home (WFH)	0.0021***	0.0014***	0.0016***	0.0017***	-0.0005	0.0010**
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0006)	(0.0005)
Hospitalisations (Hosp)	-0.0024	-0.0015	-0.0020	-0.0019	-0.0093**	0.0019
	(0.0023)	(0.0024)	(0.0024)	(0.0023)	(0.0039)	(0.0026)
WFH*Private garden		0.0031***				
		(0.0008)				
Hosp*Private garden		-0.0015				
		(0.0019)				
WFH*Terrace			0.0014**			
			(0.0007)			
Hosp*Terrace			-0.0006			
			(0.0017)			
WFH*Single-family home				0.0025***		
				(0.0008)		
Hosp*Single-family home				-0.0012		
				(0.0018)		
WFH*Size = 50-85					0.0026***	
					(0.0006)	
WFH*Size = 85-115					0.0036***	
					(0.0007)	
WFH*Size = 115-145					0.0031***	
					(0.0009)	
WFH*Size > 145					0.0016*	
					(0.0008)	
Hosp*Size = 50-85					0.0026	
					(0.0024)	
Hosp*Size = 85-115					0.0048	
					(0.0043)	
Hosp*Size = 115-145					0.0104*	
					(0.0053)	
Hospitalisations*Size > 145					0.0120**	
					(0.0055)	
Log of population per m^2						-0.0013***
						(0.0004)
WFH*Log of population per m^2						-0.0002**
						(7.59×10^{-5})
Hosp*Log of population per m^2						0.0007***
						(0.0002)
Observations	16,192,805	16,192,805	16,192,805	16,192,805	16,192,805	16,007,615
R^2	0.1195	0.1197	0.1196	0.1196	0.1171	0.1198
Within R^2	0.0331	0.0333	0.0331	0.0332	0.0305	0.0331
Local housing market fixed effects	✓	✓	✓	✓	✓	✓
Region×Time dummies fixed effects	✓	✓	✓	✓	✓	✓

Notes: Standard errors are clustered at the province level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, price per m^2, price revision, time on market, number of days the ad has been visible during the month. Work-from-home is the percentage of the private sector employers experiencing work-from-home in the province. Hospitalisations are defined as the number of COVID-19 related hospitalisations per 1,000 population in the province.

Table E.4: Work-from-home and employment structure: first stage

	Work-from-home
Share ICT-Financial	0.494***
	(0.121)
Share bachelor	0.198**
	(0.0829)
Housing prices	0.377
	(0.286)
Change in housing prices	0.0640*
	(0.0382)
Change in listings	-0.0110
	(0.00729)
Hospitalisations	0.0309
	(0.0672)
Population	-0.000251
	(0.000236)
Income per capita	0.534***
	(0.117)
Surface	0.00779
	(0.0780)
Change in private sector employment	0.0269
	(0.0944)
Change in employment	-0.251
	(0.240)
Change in households bank deposits	-0.00246
	(0.0838)
Change in households bank loans	-0.0413
	(0.0880)
Change in labour income	0.0646
	(0.0415)
Short-term work scheme (CIG)	-144.6
	(134.5)
Change in car purchases	0.00693
	(0.0257)
Change in working hours	-0.0559
	(0.0455)
Share of permanent employees	-0.117***
	(0.0427)
Change in the share of permanent employees	-0.149**
	(0.0691)
Constant	-4.421*
	(2.437)
Observations	104
Adjusted R^2	0.802

Table E.5: Impact of work from home and epidemiological conditions on housing demand (IV)

	Single-family home (1)	Private garden (2)	Terrace (3)	Size (4)	Population density (5)
Work-from-home	0.00541** (0.00223)	0.00455** (0.00195)	0.00466*** (0.00166)	0.0000265** (0.0000105)	-0.000359 (0.000434)
Housing prices	-0.00977** (0.00397)	-0.00548 (0.00347)	-0.00188 (0.00294)	-0.0000173 (0.0000186)	0.000684 (0.000771)
Change in housing prices	-0.00211*** (0.000555)	-0.00172*** (0.000485)	-0.000796* (0.000412)	-0.00000679*** (0.00000260)	0.0000157 (0.000108)
Change in listings	0.0000762 (0.000105)	0.0000725 (0.0000915)	0.000107 (0.0000776)	0.00000121** (0.000000489)	0.0000431** (0.0000203)
Hospitalisations	0.00119 (0.000885)	-0.000361 (0.000774)	0.000348 (0.000656)	0.00000673 (0.00000414)	0.0000796 (0.000172)
Population	0.00000826*** (0.00000309)	0.00000306 (0.00000270)	0.00000699*** (0.00000229)	2.21e-08 (1.44e-08)	0.000000244 (0.000000600)
Income per capita	-0.00241 (0.00241)	-0.00124 (0.00211)	-0.00359** (0.00179)	-0.0000180 (0.0000113)	0.000349 (0.000469)
Surface	-0.00125 (0.00107)	-0.000446 (0.000935)	-0.00144* (0.000793)	0.00000848* (0.00000500)	-0.0000844 (0.000208)
Change in private sector employment	-0.00197 (0.00131)	0.000529 (0.00115)	0.000354 (0.000975)	0.00000207 (0.00000615)	-0.000293 (0.000256)
Change in employment	-0.000726 (0.00346)	-0.00118 (0.00303)	-0.00245 (0.00257)	-0.00000817 (0.0000162)	0.00149** (0.000673)
Change in households bank deposits	-0.000328 (0.00113)	0.00150 (0.000991)	0.000318 (0.000840)	-0.00000347 (0.00000530)	0.000183 (0.000220)
Change in households bank loans	0.000610 (0.00121)	0.000530 (0.00106)	-0.00106 (0.000900)	-0.00000282 (0.00000568)	-0.000267 (0.000236)
Change in labour income	-0.000227 (0.000612)	0.0000322 (0.000536)	-0.000756* (0.000454)	0.00000220 (0.00000287)	0.0000821 (0.000119)
Short-term work scheme (CIG)	0.378 (1.854)	0.0240 (1.622)	0.684 (1.375)	0.00955 (0.00868)	0.136 (0.361)
Change in car purchases	0.000361 (0.000354)	-0.000107 (0.000310)	0.000118 (0.000263)	0.000000850 (0.00000166)	0.00000793 (0.0000689)
Change in working hours	-0.0000467 (0.000639)	0.000446 (0.000559)	0.000599 (0.000474)	0.000000784 (0.00000299)	-0.0000196 (0.000124)
Share of permanent employees	0.000884 (0.000668)	0.000834 (0.000584)	0.000649 (0.000495)	0.00000784** (0.00000313)	-0.0000227 (0.000130)
Change in the share of permanent employees	0.0000121 (0.00101)	-0.000605 (0.000882)	0.00191** (0.000748)	0.00000412 (0.00000472)	0.000196 (0.000196)
Constant	-0.000221 (0.0342)	-0.0263 (0.0299)	0.0169 (0.0254)	-0.000275* (0.000160)	-0.00960 (0.00665)
Observations	104	104	104	104	104

Internet Appendix

F The Italian Housing Market Survey

F.1 Insights from real estate agents' assessments

The descriptive evidence based on the IHMS shows that at the onset of the health crisis real estate agents were overall pessimistic about the impact of the pandemic on potential buyers and prices, whereas they had divergent opinions regarding the supply of houses put on the market. These opinions radically changed as the epidemiological situation evolved and the households' reaction became more clear. To understand the initial pessimism of some agents, we should recall that the revival in housing demand has been largely heterogeneous across locations and dwelling types, both in the agencies' opinions and in online listings. Therefore, it is likely that, at least in an initial phase, agencies' expectations depended on the location and the features of the houses that they generally intermediate: Covid-19 has determined a shift in demand away from the largest and most representative share of the market (i.e. apartments in urban areas), which could explain why the aggregate figures based on the 2020 waves of IHMS depicted a gloomier situation compared to what emerged from Immobiliare.it since the re-opening of the economy in May 2020.[54]

We investigate this hypothesis by studying if the agents' assessment on the impact of the pandemic on demand and prices in 2020Q1, Q2 and Q3 is linked to possible changes in the prevailing characteristics of the housing demanded by their potential buyers, as well as in their motivation for buying a home, due to the Covid-19 outbreak. In particular, we regress the probability of an increase in the number of potential buyers (*potbuy_pos*) and in selling prices (*prices_pos*) over a set of dummies equal to one in case the agent replied that potential buyers are searching more for units which are either larger (*large_more*), or single-family (*indep_more*), or in need to be renovated (*toreno_more*), or endowed with outdoor spaces (*outdoor_more*) or located in peripheral or non-urban areas (*peri_more*). We also include dummies capturing the changes in potential buyers' motivations, namely if after the spread of the epidemic the share of potential buyers either changing home (*change_more*), or purchasing a first home for themselves or for their family members (*first_more*), or purchasing a second home for vacation/investment purposes (*invest_more*) or

[54] Moreover, there is a technical issue that could further rationalise why the agents' assessment on demand was less favourable. In the explaining notes of the survey questionnaire potential buyers are defined as the *number of potential purchasers who visited at least one property listed by your office*. As we reported in Section 4.1, the majority of agencies shifted at least in part from in-person visits to camera-assisted ones; to some extent they might have thus excluded such visits, inducing an underestimation of current and future potential buyers.

for other reasons (*other_more*) is higher with respect to the pre-Covid situation. Dummies for the geographic area are also included.

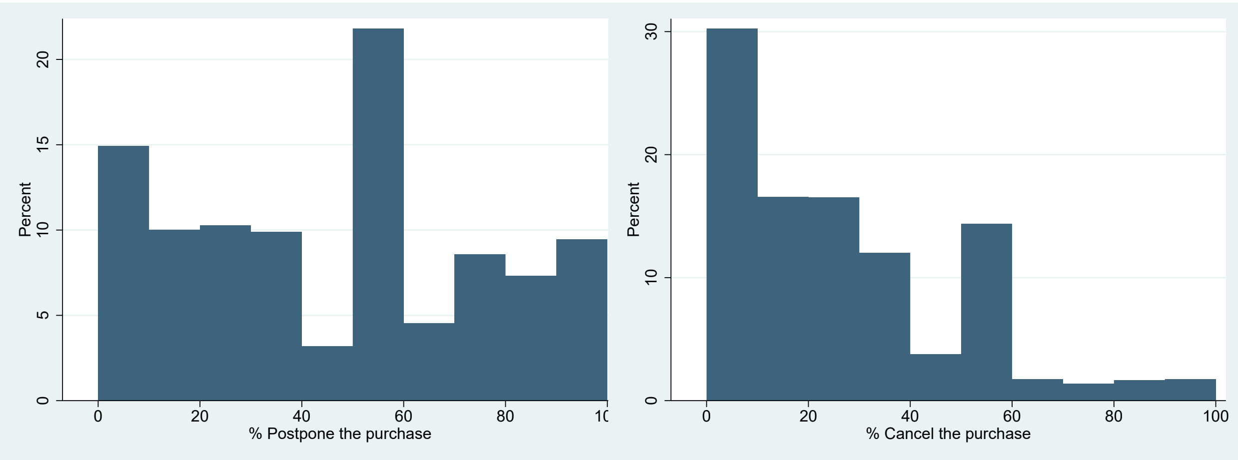
Table F.1 shows the marginal effects of a probit regression estimating the likeliness of agents declaring an increase in potential buyers according to their assessment on demand for certain houses' features, where weights are used in order to be representative of the whole market. A positive and significant association emerges for dwellings that are larger, single-family, in need to be renovated, with outdoor spaces units, as well as for second homes. For example, declaring that potential buyers are increasingly asking for single-family units or for second homes enhances the probability of agents pointing to a positive impact on potential demand by 0.14 points in both cases, which compares to an average observed probability of 0.31. The same regression for prices instead shows a significant association with houses with outdoor spaces only: if potential buyers ask more for this latter feature the probability of declaring a positive impact on prices is higher *ceteris paribus* by 0.04, which compares to an average observed probability of 0.09.

We then check whether agents' expected duration of the impact of the pandemic on potential buyers and prices is influenced by the same variables. In particular we consider the following question: "*How do you think the Covid-19 epidemic will influence the national housing market?*", which asks respondents first to assess if the impact of the pandemic had a positive, negative or neutral impact on potential buyers, and then asks the expected horizon of such impact. We construct a variable equal to 6 (months) if the horizon is 'end-2020', 12 if the horizon is 'mid-2021', 18 for 'end-2021' and 24 for a longer horizon. We split the sample among agents foreseeing a positive impact and those expecting a negative impact, and use the whole sample in order to control for the sign of the impact. Results are listed in Table F.2. It shows that the duration of the impact on the number of potential buyers is significantly lower – by about 1 month, which compares with an average duration of 14 months (12 the median) - for agents who sees the impact as negative and whose potential buyers became more interested in single-family homes after the pandemic. With reference to prices we instead do not detect any significant association with the characteristics of the dwellings.

Finally, we ask whether the longer-term agents' expectations are connected to some pandemic related structural breaks. In order to do so we run an ordered probit regression on the three possible answers (worse, same, better) to the question "*Considering the housing market only in your area, how will be like the performance compared with the current situation over the next 2 years?*". We find that agents are more likely to have favorable expectations if they see positive effects from the pandemic on potential buyers or house prices, while an increase in houses put on for purchase has no effect. Longer-run perspectives are slightly better in the South of Italy and somewhat worst in the North-East (Table F.3). Outcomes are similar if the dependent variable refers to the question "*What do you think the general situation in the housing market throughout Italy will be like compared with the current situation over the next 2 years?*", except that agencies operating in non-urban areas tend to express marginally more optimistic expectations (Table F.4).

Overall, the econometric analysis reveals that the real estate agents' optimism or pessimism about the evolution of housing demand in the early stages of the pandemic was tightly linked to the shift in household preferences. Such changes are detected mainly by the agencies which were active in the *winning* market segments, thus explaining their favorable prospects in connection to the newly popular locations and dwelling features.

Figure F.1: Impact of Covid-19 in 2020Q1, buyers' postponing and canceling of purchases



(a) *Share postponing purchase* (b) *Share canceling purchase*

Source: IHMS.

Table F.1: Probability of an expected positive impact of Covid-19 on potential buyers and prices

	Potential buyers	**Prices**
large_more	0.0962***	0.023
	[0.0327]	[0.0188]
indep_more	0.136***	0.0211
	[0.0303]	[0.0176]
torenov_more	0.0786**	0.00354
	[0.0315]	[0.0174]
outdoor_more	0.0846**	0.0445**
	[0.0378]	[0.0188]
periph_more	0.0425	0.0214
	[0.0331]	[0.0200]
change_more	-0.003	0.025
	[0.0288]	[0.0177]
home1_more	0.0224	-0.0159
	[0.0351]	[0.0189]
home2_more	0.143***	0.0367
	[0.0380]	[0.0230]
other_more	-0.0475	0.0221
	[0.0532]	[0.0350]
_Iareag4_2	-0.0446	0.0103
	[0.0366]	[0.0219]
_Iareag4_3	-0.0255	-0.0342*
	[0.0353]	[0.0177]
_Iareag4_4	-0.0488	-0.0484***
	[0.0353]	[0.0162]
Observations	1403	1403
obs. prob	0.311	0.0924

Notes: The Table reports the marginal effects of a probit regression, with robust standard errors in brackets. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F.2: Expected duration of the impact of Covid-19 on potential buyers and prices

	Duration pot. buyers pos.	Duration pot. buyers neg.	Duration pot. buyers	Duration prices pos.	Duration prices neg.	Duration prices
	(1)	(2)	(3)	(4)	(5)	(6)
large_more	0.201	0.493	0.366	1.544	0.295	0.446
	[0.643]	[0.539]	[0.417]	[1.299]	[0.479]	[0.447]
indep_more	-0.364	-1.055**	-0.792*	0.686	-0.728	-0.549
	[0.725]	[0.491]	[0.412]	[1.418]	[0.469]	[0.445]
torenov_more	-0.478	-0.431	-0.46	-0.222	-0.576	-0.417
	[0.613]	[0.529]	[0.402]	[1.267]	[0.474]	[0.443]
outdoor_more	1.034	0.61	0.659	-3.96	0.767	0.403
	[1.068]	[0.631]	[0.541]	[2.415]	[0.552]	[0.547]
periph_more	0.727	0.596	0.618	-0.64	0.631	0.456
	[0.680]	[0.532]	[0.420]	[1.464]	[0.462]	[0.445]
change_more	0.577	-0.0443	0.173	0.919	-0.276	-0.106
	[0.644]	[0.489]	[0.389]	[1.206]	[0.439]	[0.417]
home1_more	-1.104	0.186	-0.284	-1.116	0.543	0.365
	[0.732]	[0.538]	[0.432]	[1.658]	[0.484]	[0.462]
home2_more	-0.368	0.0612	-0.234	0.0458	-0.00217	-0.0943
	[0.721]	[0.623]	[0.468]	[1.278]	[0.527]	[0.486]
other_more	2.467**	-1.032	0.236	0.245	-0.131	0.023
	[0.995]	[0.790]	[0.629]	[1.790]	[0.795]	[0.737]
_Iareag4_2	0.3	0.217	0.235	0.93	0.785	0.92
	[0.848]	[0.648]	[0.515]	[1.532]	[0.620]	[0.573]
_Iareag4_3	-0.847	0.336	-0.195	2.947*	0.636	1.023**
	[0.781]	[0.626]	[0.486]	[1.595]	[0.536]	[0.512]
_Iareag4_4	-0.289	0.741	0.294	4.305**	0.822	1.183**
	[0.850]	[0.616]	[0.500]	[1.949]	[0.528]	[0.509]
covid_c6_2			0.206			
			[0.193]			
covid_c6_3						0.567*
						[0.313]
Constant	13.86***	13.89***	13.72***	17.27***	14.21***	13.57***
	[1.103]	[0.685]	[0.632]	[2.272]	[0.577]	[0.653]
Obs.	421	639	1060	124	829	953
R-squared	0.032	0.016	0.011	0.112	0.017	0.019

Notes: Robust standard errors in brackets. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F.3: Expected performance of the own housing market 2 years ahead

var25_2	Coef.	Robust Std. Err.	z	pvalue	[95% Conf.	Interval]
covid_c6_1_imps						
noimpact	0.028787	0.05348	0.54	0.59	-0.07603	0.133606
positive	0.006829	0.04415	0.15	0.877	-0.0797	0.093356
covid_c6_2_imps						
noimpact	0.333308	0.05236	6.37	0	0.230692	0.435925
positive	0.690778	0.04974	13.89	0	0.593288	0.788267
covid_c6_3_imps						
noimpact	0.5584	0.04451	12.55	0	0.471168	0.645633
positive	0.818193	0.07622	10.73	0	0.668806	0.96758
2.sstr1	-0.00469	0.0383	-0.12	0.902	-0.07977	0.070379
areag4						
2	-0.1871	0.04907	-3.81	0	-0.28327	-0.09092
3	-0.00474	0.05059	-0.09	0.925	-0.10389	0.094411
4	0.122528	0.0511	2.4	0.016	0.022373	0.222683
periodo						
20202	0.136816	0.05032	2.72	0.007	0.038184	0.235447
20203	0.108394	0.05102	2.12	0.034	0.008397	0.208391
20204	0.199038	0.05335	3.73	0	0.094468	0.303609
/cut1	-0.00145	0.05506			-0.10937	0.106478
/cut2	0.878487	0.05619			0.768366	0.988609

Notes: The Table shows the results of an ordered probit regression on the IHMS question *Considering the housing market only in your area, how will be like the performance compared with the current situation over the next 2 years?*. The possible outcomes are: worse, same, better.

Table F.4: Expected performance of the Italian housing market 2 years ahead

var23ay	Coef.	Robust Std. Err.	z	pvalue	[95% Conf.	Interval]
covid_c6_1_imps						
2	0.214069	0.046511	4.6	0	0.122909	0.305229
3	0.09858	0.038736	2.54	0.011	0.022659	0.174501
covid_c6_2_imps						
2	0.160674	0.046799	3.43	0.001	0.068949	0.252399
3	0.175699	0.043682	4.02	0	0.090083	0.261315
covid_c6_3_imps						
2	0.952999	0.043397	21.96	0	0.867942	1.038056
3	1.27683	0.073083	17.47	0	1.133591	1.42007
2.sstr1	-0.12769	0.033264	-3.84	0	-0.19288	-0.06249
areag4						
2	0.19664	0.044169	4.45	0	0.110071	0.283209
3	-0.1392	0.042677	-3.26	0.001	-0.22284	-0.05555
4	-0.21859	0.04785	-4.57	0	-0.31238	-0.12481
periodo						
20202	0.270077	0.045689	5.91	0	0.180529	0.359626
20203	0.1535	0.044918	3.42	0.001	0.065462	0.241538
20204	0.31753	0.046516	6.83	0	0.22636	0.4087
/cut1	-0.91927	0.050903			-1.01904	-0.81951
/cut2	-0.15471	0.048516			-0.2498	-0.05962
/cut3	0.369028	0.04899			0.273009	0.465046
/cut4	0.880998	0.050523			0.781974	0.980022
/cut5	2.465948	0.065034			2.338484	2.593412
/cut6	3.092857	0.078312			2.939369	3.246345
/cut7	3.505902	0.099482			3.310921	3.700883
/cut8	3.733466	0.116573			3.504987	3.961946

Notes: The Table shows the results of an ordered probit regression on the IHMS question *What do you think the general situation in the housing market throughout Italy will be like compared with the current situation over the next 2 years?*. The possible outcomes are: worse, same, better.

F.2 Covid-19 related questions

Immediate impact (2020Q1)

A4.2 Considering the **potential buyers your office assisted before the COVID-19 epidemic** that you have been able to contact again after re-opening:

	Percentage of the potential buyers	I cannot answer
A4.2a What **percentage of potential buyers** intend to **postpone the purchase of a property because of the epidemic**?	|_____|	|__|
A4.2b What **percentage of potential buyers no longer intend to purchase a property because of the epidemic**?	|_____|	|__|

A11.1 Considering the homes brokered by your agency, in your opinion, **has the COVID-19 epidemic caused an increase in the number of buyers withdrawing from a purchase or renegotiating transactions,** such as a previously signed preliminary contract or a pre-accepted proposal.

- ❑ No
- ❑ Yes
- ❑ Don't know

A11.2 Which of the following situations have you come across most frequently?

(up to three responses possible)

- ❑ The buyer withdrew from the transaction because of a change in income or employment situation
- ❑ The buyer withdrew from the transaction because of difficulties in obtaining a mortgage
- ❑ The buyer withdrew from the transaction for other known or unknown reasons
- ❑ The seller withdrew from the transaction because they no longer intend to sell the home
- ❑ The seller withdrew from the transaction for other known or unknown reasons
- ❑ The parties renegotiated the selling price
- ❑ The parties postponed the date of the deed of sale because one of them had temporary difficulties

A12 Considering the **potential sellers who had given your agency a mandate to sell before the COVID-19 epidemic:**

	Percentage of the potential sellers	I cannot answer
A12a What **percentage of potential sellers** intend to **postpone the sale of a property because of the epidemic?**	|_____|	|__|
A12b What **percentage of potential sellers no longer intend to sell a property because of the epidemic?**	|_____|	|__|

Questions asked multiple times (from 2020Q1 onwards) on influence and duration of impact

C6 How do you think the **COVID-19 epidemic** will influence the national housing market?

	Impact of the COVID-19 epidemic					Expected duration (if there is an impact)[1]			
	Very negative	Negative	No impact	Positive	Very positive	Until end-2020	Until mid-2021	Until end-2021	Even longer
Homes on the market	❑	❑	❑	❑	❑	❑	❑	❑	❑
Number of potential buyers	❑	❑	❑	❑	❑	❑	❑	❑	❑
Selling prices	❑	❑	❑	❑	❑	❑	❑	❑	❑

[1]For the survey waves referring to 2020Q4, 2021Q1 and 2021Q2 the possible responses changed as follows: 'Impact already over', 'until mid 2021', 'until end 2021', 'until mid 2022', 'even longer'.

Questions about the dwellings' characteristics demanded: expected and realized (2020Q2, Q3)

A4.1 Could you tell how the prevailing characteristics of the housing demanded by potential buyers have changed since before the Covid-19 outbreak? [2020Q2]

Accomodation feature	Decreasing	Stable	Rising
Large housing units	❐	❐	❐
Independent housing units (e.g. villas, cottages)	❐	❐	❐
Houses to renovate	❐	❐	❐
Availability of outdoor spaces (balcony, terrace, garden)	❐	❐	❐
Access to internet connectivity	❐	❐	❐
Peripheral or non-urban area	❐	❐	❐

A3.1. Consider the transactions that you intermediated and that ended with a deed transfer **between April and September 2020**. indicate **how the following characteristics of the houses have changed compared to the same period of the previous year September 2019)**? [2020Q3]

Housing features	Lower	About the same	Higher	I do not know
Average size (square meters)	❐	❐	❐	❐
Average price	❐	❐	❐	❐
Share of independent housing units out of total sales	❐	❐	❐	❐
Share of housing units with available outdoor space out of total sales	❐	❐	❐	❐
Share of housing units in excellent condition or recently renovated out of total sales	❐	❐	❐	❐

Questions about the potential buyers and their motivation (2020Q2, Q3)

A4.2 Could you cluster potential buyers according to their motivation for buying a home? [2020Q2]

	Percentuale				
	Home change	Purchase of the first home for yourself or for family members	Purchase of a second house for investment purposes	Other	Total
Before the Covid-19 epidemic	I__I	I__I	I__I	I__I	100
After the Covid-19 epidemic	I__I	I__I	I__I	I__I	100

A3.2. Consider the transactions that you intermediated and that ended with a deed transfer **between April and September 2020**. Please indicate **how the following characteristics of the buyers have changed compared to the same period of the previous year (April-September 2019)**? [2020Q3]

Buyer characteristics	Lower	About the same	Higher	I do not know
Average age of buyers	❐	❐	❐	❐
Percentage of those who bought their primary residence	❐	❐	❐	❐
Percentage of those who changed homes (purchase close to a sale)	❐	❐	❐	❐
Percentage of those who had urgent need to take possession of the home	❐	❐	❐	❐

A4.2. Could you cluster potential buyers according to their motivation for buying a home in **october-december 2020**? [2020Q4]

Percentuale				
Home change	Purchase of the first home for yourself or for family members	Purchase of a second house for investment purposes	Other	Total
|__|	|__|	|__|	|__|	100

Questions on the persistence of the impact (2021Q1)

A11 Consider as a benchmark the homes sold by your agency in 2019, before the pandemic, and their features. In your view, how will the demand for homes with the following characteristics change over the next three years?

	Decrease	No change	Increase	Don't know- Not applicable
Detached residential units	☐	☐	☐	☐
Homes with outdoor spaces	☐	☐	☐	☐
Large homes	☐	☐	☐	☐
Homes in non-urban or suburban areas	☐	☐	☐	☐

A12 (if you answered "increase" to at least one of the questions in A11) What role does the possibility of remote working have on these expectations?

1. No role
2. Small role
3. Somewhat significant role
4. Very significant role
5. Don't know

G Online listings: additional evidence and robustness

Table G.1: Descriptive statistics - Physical characteristics

	N = 2,892,645
Size (m^2)	
minimum	35
median (IQR)	100 (74.00, 138.00)
mean (sd)	117.88 ± 71.10
maximum	550
Property type	
Multi-family residential dwelling	2,267,555 (78)
Single-family home	625,090 (22)
Floor level	
Ground floor	623,335 (23)
Floor level: 1-3	1,566,886 (57)
Floor level: 4-	289,056 (11)
Multi-level	271,219 (10)
Unknown/Missing	142,149 (4.91%)
Rooms	
Number of rooms: 1	63,509 (2)
Number of rooms: 2	525,590 (19)
Number of rooms: 3	978,348 (35)
Number of rooms: 4	759,286 (27)
Number of rooms: 5 or more	462,480 (17)
Unknown/Missing	103,432 (3.58%)
Bathrooms	
Number of bathrooms: 1	1,598,152 (56)
Number of bathrooms: 2	1,015,326 (36)
Number of bathrooms: 3 or more	227,896 (8)
Unknown/Missing	51,271 (1.77%)
Terrace	
Terrace: No	1,820,031 (63)
Terrace: Yes	1,072,614 (37)
Balcony	
Balcony: No	1,197,811 (41)
Balcony: Yes	1,694,834 (59)
Maintenance status	
To be renovated	255,329 (9)
Good conditions	1,148,733 (42)
Very good conditions	985,381 (36)
New-built	343,519 (13)
Unknown/Missing	159,683 (5.52%)
Kitchen type	
Cooking corner	487,321 (21)
Small kitchen	266,283 (11)
Large kitchen	1,578,593 (68)
Unknown/Missing	560,448 (19.37%)
Utility room	
Utility room: No	2,120,431 (73)
Utility room: Yes	772,214 (27)
Basement	
Basement: No	1,846,879 (64)
Basement: Yes	1,045,766 (36)

Garage	
No parking slot/private garage	1,518,300 (52)
Parking slot	230,004 (8)
Private garage	1,144,341 (40)
Garden type	
Without garden	1,506,216 (52)
Shared garden	506,825 (18)
Private garden	879,604 (30)
Porter	
Porter: No	2,767,496 (96)
Porter: Yes	125,149 (4)
Elevator	
Elevator: No	1,786,012 (62)
Elevator: Yes	1,106,633 (38)
Heating type	
Centralised heating system	538,206 (22)
Independent heating system	1,962,148 (78)
Unknown/Missing	392,291 (13.56%)
energy class2	
Energy efficiency: high	258,264 (12)
Energy efficiency: intermediate	445,859 (20)
Energy efficiency: low	1,484,328 (68)
Unknown/Missing	704,194 (24.34%)

Table G.2: Descriptive statistics - Asking prices

	Percentile					Mean	Standard Dev.
	5	25	50	75	95		
Full sample							
Price	55,000	110,000	169,000	270,000	578,333	226,222	217,455
Price per s.m.	636	1,147	1,673	2,462	4,500	1,998	1,286
2018							
Price	57,500	111,667	170,000	270,000	590,000	230,403	224,218
Price per s.m.	667	1,182	1,703	2,480	4,444	2,016	1,261
2019							
Price	55,000	110,000	168,000	268,000	571,500	225,225	220,300
Price per s.m.	625	1,125	1,640	2,400	4,355	1,949	1,254
2020							
Price	55,000	110,000	169,000	270,000	570,000	225,623	217,506
Price per s.m.	608	1,111	1,641	2,429	4,524	1,973	1,309

Notes: All values are in euro.

Table G.3: Descriptive statistics - Local housing markets

	Percentile					Mean	Std. dev.
	1	25	50	75	99		
Population	9.0	326.0	924.0	2478.5	21988.8	2401.6	4636.8
Households	4.0	140.0	384.0	1004.5	9369.1	995.7	2024.2
Housing units	9.0	247.0	617.0	1462.0	11163.8	1343.3	2374.6
Share of owner-occupied (perc.)	45.5	69.9	75.8	80.8	92.2	74.7	9.4
Average asking price	34468.8	108651.0	150866.7	206105.8	634709.6	175341.4	121038.2
Average asking price per sm	316.7	825.0	1150.1	1586.3	4699.9	1351.2	876.9
Listings	1.0	8.0	28.0	95.0	1536.4	123.0	346.3
Census tracts	1.0	2.0	5.0	10.0	123.0	11.5	23.8

Notes: This table reports statistics about the distribution of some relevant variables across local housing markets: *(i)* the number of population, households and dwellings; *(ii)* the share of homeowners; *(iii)* the average asking prices; *(iv)* the annual average number of listings; *(v)* the number of census tracts included in the local housing markets.

Figure G.1: Placement of the seller contact form within the ad web page

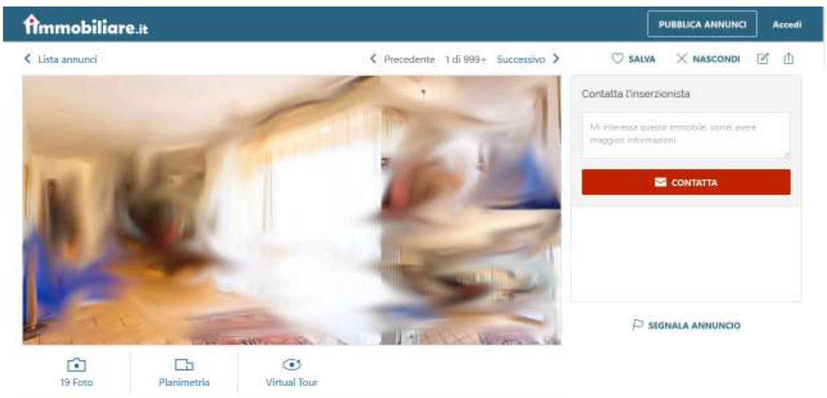
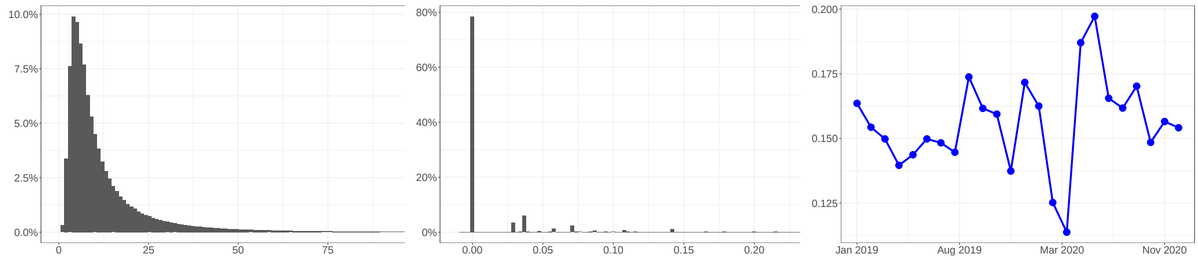


Figure G.2: Distribution of daily *clicks* and *contacts*



(a) *Clicks* (b) *Contacts* (c) *Ratio contacts / clicks*

Notes: Distribution of daily *clicks* (panel a) and *contacts* (panel b) in the 100 most populous commuting zones in Italy over the years 2018-2020. For panel (c), ratio between average daily *contacts* and *clicks* per ad (multiplied by 100) from January 2019 to December 2020.

Figure G.3: Sample selection: distribution of the 100 most populous commuting zones in Italy

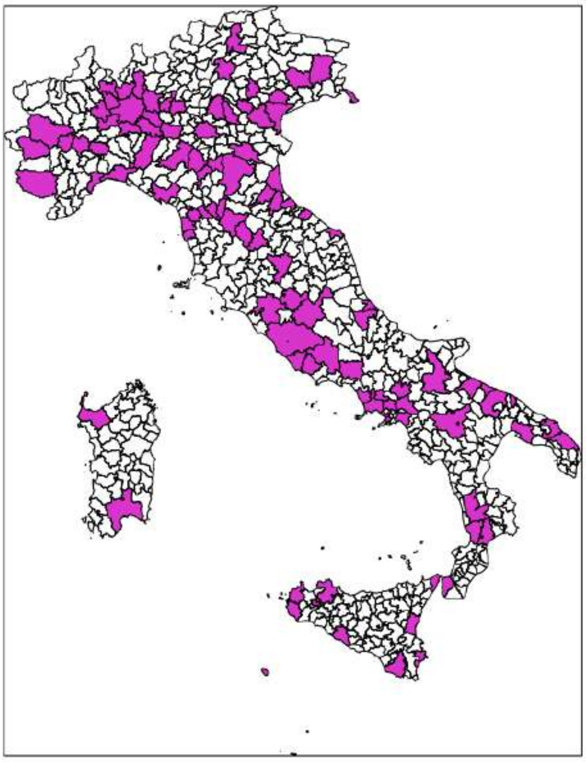
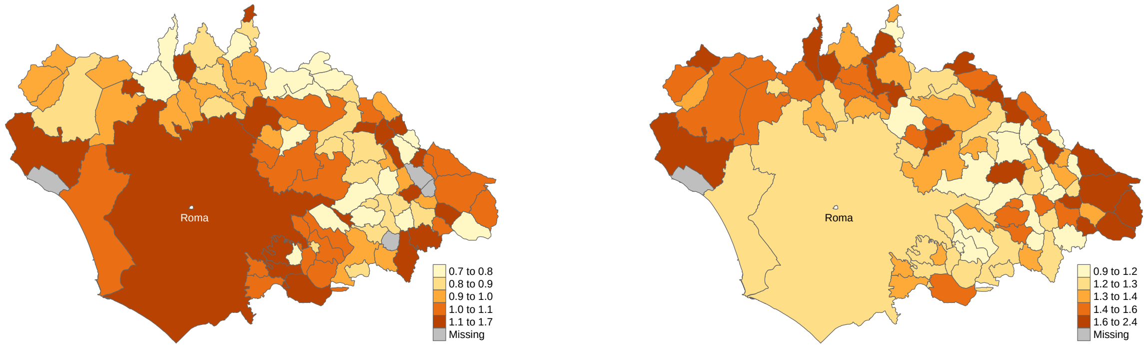


Figure G.4: Housing search activity in the commuting area of Rome

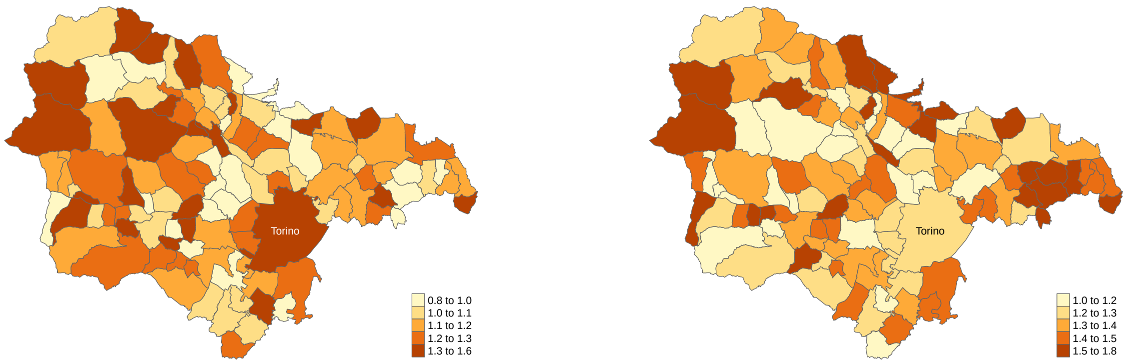


(a) *Ratio of the number of daily average clicks in 2019 and 2018*

(b) *Ratio of the number of daily average clicks in 2020 and 2019*

Notes: ratio of the number of daily average clicks during the period May-December of 2020 and 2019. Darker polygons are the municipalities with the larger increase in search activity. The scales of the charts are different as they represent the quintiles of the distribution in each year.

Figure G.5: Housing search activity in the commuting area of Turin

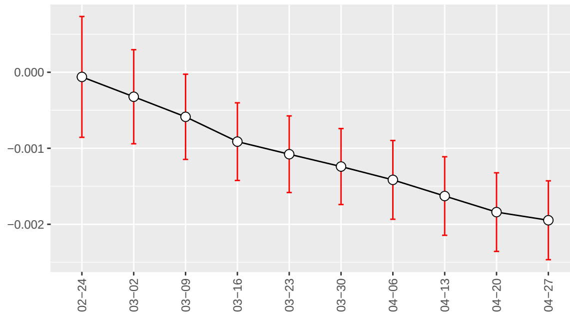


(a) *Ratio of the number of daily average clicks in 2019 and 2018*

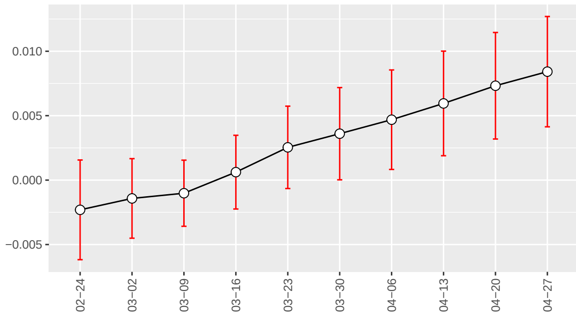
(b) *Ratio of the number of daily average clicks in 2020 and 2019*

Notes: ratio of the number of daily average clicks during the period May-December of 2020 and 2019. Darker polygons are the municipalities with the larger increase in search activity. The scales of the charts are different as they represent the quintiles of the distribution in each year.

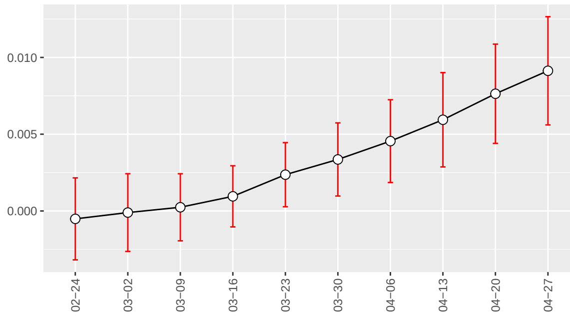
Figure G.6: Relative interest in dwelling characteristics and location - Regression discontinuity design



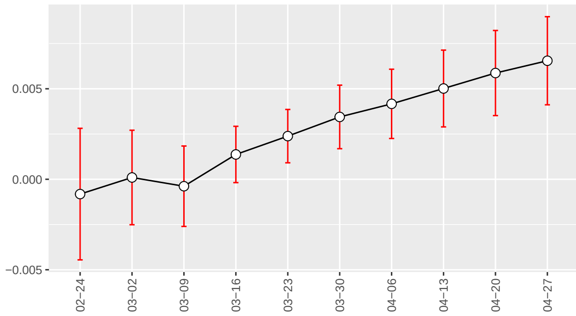
(a) *Population per* m^2



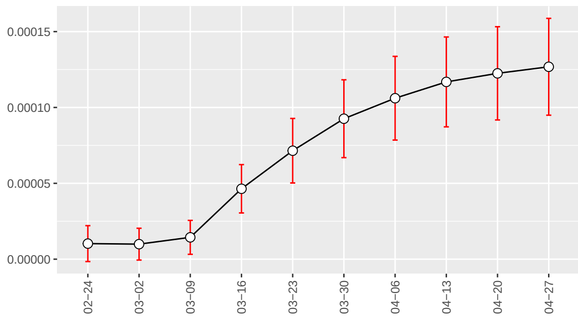
(b) *Property type*



(c) *Garden*



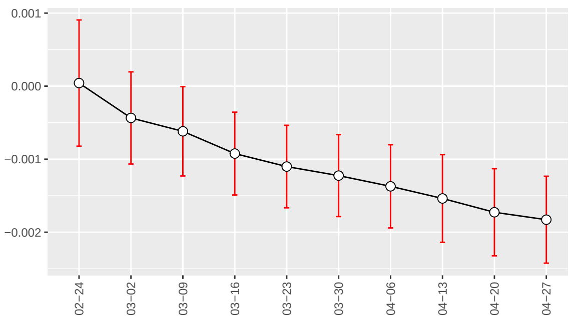
(d) *Terrace*



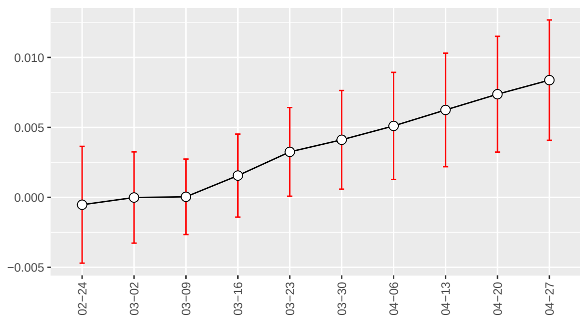
(e) *Floor area*

Notes: In these charts we report for each variable of interest the estimates of β from the following variation of model (1): $y_{i,k,t} = \alpha_{k,t} + \beta C_t X_i + \gamma X_i + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,k,t}$, where $y = 1$ if the number of contacts is strictly positive and C is a dummy equal to 1 from February 21, 2020 onward. Data are weekly and fixed effects are set at the local housing market level. The initial estimation sample is from February 3 to February 24; then, we gradually increase the sample by one week up to April 27. Standard errors are clustered at the commuting zone level.

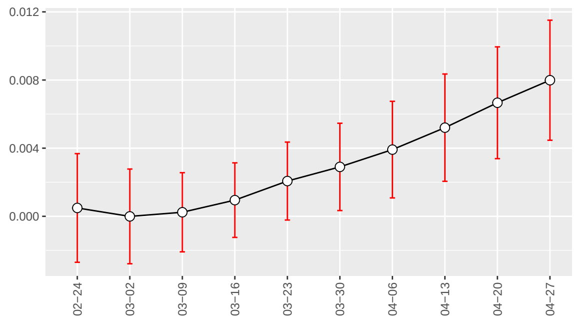
Figure G.7: Relative interest in dwelling characteristics and location - Fixed supply



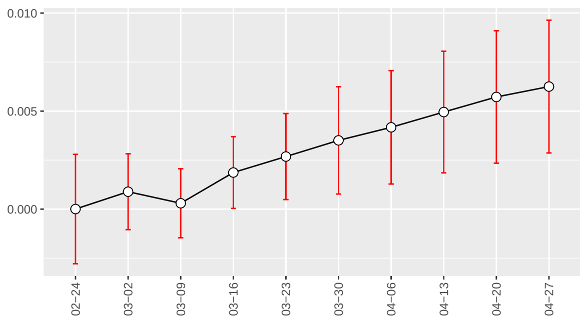
(a) *Population per* m^2



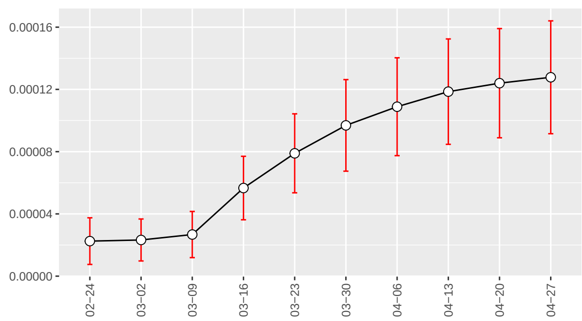
(b) *Property type*



(c) *Garden*



(d) *Terrace*



(e) *Floor area*

Notes: In these charts we report for each variable of interest the estimates of β from the following extension of model (1): $y_{i,k,t} = \alpha_i + \beta C_t X_i + \gamma_{k,t} + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,k,t}$, where $y = 1$ if the number of contacts is strictly positive and C is a dummy equal to 1 from February 21, 2020 onward. Data are weekly and fixed effects are set at the local housing market level. The initial estimation sample is from February 3 to February 24: then, we gradually increase the sample by one week up to April 27. We include only the ads that have been online before and after February 21. Standard errors are clustered at the commuting zone level.

Table G.4: Effects of Covid-19 on housing demand (Full sample)

	Log(Clicks)		P(Contacts> 0)		
	(1)	(2)	(3)	(4)	(5)
(Intercept)			0.186***		
			(0.012)		
Mar-Apr 2020	-0.058***	-0.044*	-0.036***	-0.030***	-0.027***
	(0.020)	(0.025)	(0.002)	(0.002)	(0.004)
Post May 2020	0.347***	0.356***	0.054***	0.067***	0.070***
	(0.018)	(0.020)	(0.003)	(0.004)	(0.005)
Observations	16,316,092	16,316,092	16,316,092	16,316,092	16,316,092
R^2	0.358	0.480	0.028	0.079	0.128
Within R^2	0.254	0.278		0.034	0.038
Commuting zone×Month fixed effects	✓			✓	
Local housing market×Month fixed effects		✓			✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month. Fixed effects control for monthly place-specific seasonality.

Table G.5: Effects of Covid-19 on housing demand by location (Full sample)

	Log(Clicks)			P(Contacts> 0)		
	(1)	(2)	(3)	(4)	(5)	(6)
Suburbs	-0.216***			-0.054***		
	(0.028)			(0.008)		
Rural areas	-0.326***			-0.064***		
	(0.057)			(0.018)		
Mar-Apr 2020*Suburbs	-0.049			0.014***		
	(0.030)			(0.003)		
Post May 2020*Suburbs	0.016			0.015***		
	(0.022)			(0.005)		
Mar-Apr 2020*Rural areas	0.042			0.028***		
	(0.027)			(0.003)		
Post May 2020*Rural areas	0.096***			0.017***		
	(0.020)			(0.005)		
Log of population per m^2		0.014***	2.73×10^{-5}		0.002***	-0.002***
		(0.003)	(0.0010)		(0.0008)	(0.0003)
Mar-Apr 2020*Log of population per m^2		-0.004**	-0.002**		-0.004***	-0.002***
		(0.002)	(0.0009)		(0.0004)	(0.0004)
Post May 2020*Log of population per m^2		-0.012***	-0.003***		-0.005***	-0.001***
		(0.001)	(0.0009)		(0.0006)	(0.0003)
Observations	16,316,092	16,130,789	16,130,789	16,316,092	16,130,789	16,130,789
R^2	0.392	0.385	0.531	0.084	0.083	0.153
Within R^2	0.237	0.228	0.253	0.031	0.030	0.034
Commuting zone×Time dummies fixed effects	✓	✓		✓	✓	
Local housing market×Time dummies fixed effects			✓			✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table G.6: Effects of Covid-19 on *contacts* by dwellings' characteristics (Full sample)

	P(Contacts> 0)			
	(1)	(2)	(3)	(4)
Single-family home	0.048***	0.048***	0.042***	0.039***
	(0.003)	(0.003)	(0.003)	(0.003)
Terrace	0.026***	0.024***	0.026***	0.023***
	(0.004)	(0.004)	(0.004)	(0.004)
Private garden	0.044***	0.052***	0.052***	0.050***
	(0.003)	(0.003)	(0.003)	(0.003)
Size (m^2)	-0.0007***	-0.0007***	-0.0007***	
	(5.24×10^{-5})	(5.24×10^{-5})	(5.24×10^{-5})	
Size = 50-85				-0.018***
				(0.005)
Size = 85-115				-0.027***
				(0.009)
Size = 115-145				-0.049***
				(0.010)
Size > 145				-0.129***
				(0.011)
Mar-Apr 2020*Private garden	0.004***			
	(0.001)			
Post May 2020*Private garden	0.028***			
	(0.002)			
Mar-Apr 2020*Terrace		0.005***		
		(0.001)		
Post May 2020*Terrace		0.008***		
		(0.002)		
Mar-Apr 2020*Single-family home			0.001	
			(0.002)	
Post May 2020*Single-family home			0.024***	
			(0.003)	
Mar-Apr 2020*Size = 50-85				0.003
				(0.003)
Post May 2020*Size = 50-85				0.005**
				(0.003)
Mar-Apr 2020*Size = 85-115				0.0006
				(0.005)
Post May 2020*Size = 85-115				0.009**
				(0.004)
Mar-Apr 2020*Size = 115-145				0.002
				(0.005)
Post May 2020*Size = 115-145				0.013***
				(0.005)
Mar-Apr 2020*Size > 145				0.014***
				(0.005)
Post May 2020*Size > 145				0.018***
				(0.006)
Observations	16,316,092	16,316,092	16,316,092	16,316,092
R^2	0.153	0.153	0.153	0.151
Within R^2	0.034	0.034	0.034	0.031
Local housing market×Time dummies fixed effects	✓	✓	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table G.7: Effects of COVID-19 on *contacts* by dwellings' characteristics and location (Full sample)

	P(Contacts>0)	
	(1)	(2)
Suburbs	-0.052***	
	(0.008)	
Rural areas	-0.059***	
	(0.018)	
Log of population per m^2		0.002**
		(0.0008)
Mar-Apr 2020*Single-family home	-0.006***	-0.005***
	(0.002)	(0.002)
Post May 2020*Single-family home	0.015***	0.013***
	(0.002)	(0.002)
Mar-Apr 2020*Terrace	0.006***	0.006***
	(0.001)	(0.001)
Post May 2020*Terrace	0.010***	0.010***
	(0.002)	(0.002)
Mar-Apr 2020*Private garden	0.008***	0.008***
	(0.002)	(0.002)
Post May 2020*Private garden	0.031***	0.030***
	(0.002)	(0.002)
Mar-Apr 2020*Size = 50-85	0.005**	0.006**
	(0.003)	(0.003)
Post May 2020*Size = 50-85	0.007*	0.007**
	(0.003)	(0.003)
Mar-Apr 2020*Size = 85-115	0.003	0.003
	(0.005)	(0.005)
Post May 2020*Size = 85-115	0.007	0.007*
	(0.004)	(0.004)
Mar-Apr 2020*Size = 115-145	0.002	0.002
	(0.005)	(0.005)
Post May 2020*Size = 115-145	0.004	0.004
	(0.005)	(0.005)
Mar-Apr 2020*Size > 145	0.014***	0.013***
	(0.004)	(0.004)
Post May 2020*Size > 145	-0.006	-0.005
	(0.007)	(0.007)
Mar-Apr 2020*Suburbs	0.012***	
	(0.003)	
Post May 2020*Suburbs	0.005	
	(0.005)	
Mar-Apr 2020*Rural areas	0.025***	
	(0.003)	
Post May 2020*Rural areas	0.001	
	(0.006)	
Mar-Apr 2020*Log of population per m^2		-0.003***
		(0.0004)
Post May 2020*Log of population per m^2		-0.003***
		(0.0006)
Observations	16,316,092	16,130,789
Commuting zone×Time dummies fixed effects	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table G.8: Effects of Covid-19 on *clicks* by dwellings' characteristics

	Log(Clicks)				
	(1)	(2)	(3)	(4)	(5)
Size (m^2)	-0.002***	-0.002***	-0.002***		
	(0.0001)	(0.0001)	(0.0001)		
Single-family home	0.282***	0.282***	0.284***	0.255***	0.274***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Terrace	0.105***	0.101***	0.105***	0.095***	0.093***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Private garden	0.129***	0.133***	0.133***	0.125***	0.117***
	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)
Mar-Apr 2020*Private garden	-0.017***				0.006
	(0.006)				(0.004)
Post May 2020*Private garden	0.023***				0.030***
	(0.006)				(0.004)
Mar-Apr 2020*Terrace		0.014***			0.008***
		(0.003)			(0.003)
Post May 2020*Terrace		0.015***			0.007***
		(0.004)			(0.003)
Mar-Apr 2020*Single-family home			-0.049***		-0.104***
			(0.008)		(0.007)
Post May 2020*Single-family home			-0.0001		-0.057***
			(0.009)		(0.008)
Size = 50-85				-0.040	-0.039
				(0.024)	(0.025)
Size = 85-115				-0.013	-0.013
				(0.043)	(0.044)
Size = 115-145				-0.061	-0.062
				(0.049)	(0.049)
Size > 145				-0.275***	-0.281***
				(0.046)	(0.046)
Mar-Apr 2020*Size = 50-85				0.004	0.003
				(0.014)	(0.014)
Post May 2020*Size = 50-85				0.022***	0.021***
				(0.007)	(0.007)
Mar-Apr 2020*Size = 85-115				-0.010	-0.008
				(0.020)	(0.021)
Post May 2020*Size = 85-115				0.026**	0.026*
				(0.013)	(0.013)
Mar-Apr 2020*Size = 115-145				0.0008	0.014
				(0.020)	(0.021)
Post May 2020*Size = 115-145				0.036**	0.038**
				(0.015)	(0.015)
Mar-Apr 2020*Size > 145				0.034	0.082***
				(0.021)	(0.019)
Post May 2020*Size > 145				0.068***	0.080***
				(0.016)	(0.014)
Observations	11,717,459	11,717,459	11,717,459	11,717,459	11,717,459
R^2	0.518	0.518	0.518	0.515	0.515
Within R^2	0.256	0.256	0.256	0.251	0.251
Local housing market×Time dummies fixed effects	✓	✓	✓	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table G.9: Effects of Covid-19 on *clicks* by dwellings' characteristics and location

	Clicks	
	(1)	(2)
Suburbs	-0.184***	
	(0.033)	
Rural areas	-0.300***	
	(0.068)	
Mar-Apr 2020*Single-family home	-0.095***	-0.097***
	(0.009)	(0.009)
Post May 2020*Single-family home	-0.037***	-0.036***
	(0.009)	(0.008)
Mar-Apr 2020*Terrace	0.014***	0.012***
	(0.004)	(0.004)
Post May 2020*Terrace	0.015***	0.014***
	(0.003)	(0.003)
Mar-Apr 2020*Private garden	0.012***	0.006
	(0.004)	(0.005)
Post May 2020*Private garden	0.047***	0.045***
	(0.005)	(0.006)
Mar-Apr 2020*Size = 50-85	-0.005	-0.009
	(0.019)	(0.019)
Post May 2020*Size = 50-85	0.024**	0.023**
	(0.009)	(0.010)
Mar-Apr 2020*Size = 85-115	-0.019	-0.024
	(0.028)	(0.029)
Post May 2020*Size = 85-115	0.021	0.020
	(0.016)	(0.016)
Mar-Apr 2020*Size = 115-145	-0.0002	-0.004
	(0.026)	(0.027)
Post May 2020*Size = 115-145	0.026	0.024
	(0.018)	(0.018)
Mar-Apr 2020*Size > 145	0.076***	0.073***
	(0.022)	(0.023)
Post May 2020*Size > 145	0.066***	0.063***
	(0.020)	(0.020)
Mar-Apr 2020*Suburbs	-0.044	
	(0.031)	
Post May 2020*Suburbs	0.008	
	(0.024)	
Mar-Apr 2020*Rural areas	0.066**	
	(0.027)	
Post May 2020*Rural areas	0.093***	
	(0.022)	
Log of population per m^2		0.021***
		(0.003)
Mar-Apr 2020*Log of population per m^2		-0.004*
		(0.002)
Post May 2020*Log of population per m^2		-0.009***
		(0.002)
Observations	11,717,459	11,591,151
R^2	0.374	0.369
Within R^2	0.246	0.240
Commuting zone×Time dummies fixed effects	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month.

Table G.10: Effects of Covid-19 on housing demand by location (controlling for average housing prices)

	Log(Clicks)			P(Contacts> 0)		
	(1)	(2)	(3)	(4)	(5)	(6)
Suburbs	-0.176***			-0.037***		
	(0.028)			(0.008)		
Rural areas	-0.303***			-0.052***		
	(0.046)			(0.014)		
Average housing prices	0.408***	0.407***		0.150***	0.149***	
	(0.024)	(0.027)		(0.006)	(0.006)	
Mar-Apr 2020*Average housing prices	0.052*	0.056**		-0.003	-0.004	
	(0.029)	(0.027)		(0.005)	(0.005)	
Post May 2020*Average housing prices	-0.002	-0.003		-0.015***	-0.014***	
	(0.008)	(0.009)		(0.003)	(0.003)	
Mar-Apr 2020*Suburbs	-0.040			0.007***		
	(0.031)			(0.002)		
Post May 2020*Suburbs	0.005			0.003		
	(0.020)			(0.004)		
Mar-Apr 2020*Rural areas	0.071**			0.019***		
	(0.029)			(0.003)		
Post May 2020*Rural areas	0.089***			-0.002		
	(0.019)			(0.005)		
Log of population per m^2		0.019***	0.0007		0.003***	-0.002***
		(0.003)	(0.001)		(0.0006)	(0.0004)
Mar-Apr 2020*Log of population per m^2		-0.003	-0.002**		-0.003***	-0.002***
		(0.002)	(0.001)		(0.0004)	(0.0005)
Post May 2020*Log of population per m^2		-0.011***	-0.003***		-0.004***	-0.001***
		(0.001)	(0.001)		(0.0006)	(0.0004)
Observations	11,716,668	11,590,420	11,590,420	11,716,668	11,590,420	11,590,420
R^2	0.422	0.417	0.518	0.098	0.097	0.142
Within R^2	0.304	0.297	0.256	0.060	0.059	0.040
Commuting zone×Time dummies fixed effects	✓	✓		✓	✓	
Local housing market×Time dummies fixed effects			✓			✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month. Average housing prices are computed as the average asking price in 2018-2019 at the local market level.

Table G.11: Effects of COVID-19 on *contacts* by dwellings' characteristics and location (controlling for average housing prices)

	P(Contacts> 0)	
	(1)	(2)
Suburbs	-0.035***	
	(0.008)	
Rural areas	-0.048***	
	(0.014)	
Log of population per m^2		0.003***
		(0.0006)
Average housing prices	0.144***	0.144***
	(0.006)	(0.006)
Mar-Apr 2020*Average housing prices	-0.004	-0.005
	(0.005)	(0.005)
Post May 2020*Average housing prices	-0.013***	-0.011***
	(0.003)	(0.003)
Mar-Apr 2020*Single-family home	-0.008***	-0.008***
	(0.002)	(0.002)
Post May 2020*Single-family home	0.013***	0.011***
	(0.003)	(0.003)
Mar-Apr 2020*Terrace	0.005***	0.005***
	(0.002)	(0.002)
Post May 2020*Terrace	0.012***	0.012***
	(0.002)	(0.002)
Mar-Apr 2020*Private garden	0.008***	0.007***
	(0.002)	(0.002)
Post May 2020*Private garden	0.034***	0.032***
	(0.002)	(0.002)
Mar-Apr 2020*Size = 50-85	0.002	0.001
	(0.005)	(0.005)
Post May 2020*Size = 50-85	0.012***	0.012***
	(0.004)	(0.004)
Mar-Apr 2020*Size = 85-115	-0.002	-0.002
	(0.008)	(0.008)
Post May 2020*Size = 85-115	0.015**	0.015**
	(0.006)	(0.006)
Mar-Apr 2020*Size = 115-145	-0.0003	-0.0008
	(0.008)	(0.008)
Post May 2020*Size = 115-145	0.015**	0.015**
	(0.006)	(0.006)
Mar-Apr 2020*Size > 145	0.013*	0.012
	(0.007)	(0.007)
Post May 2020*Size > 145	0.009	0.009
	(0.009)	(0.009)
Mar-Apr 2020*Suburbs	0.005**	
	(0.002)	
Post May 2020*Suburbs	-0.006	
	(0.004)	
Mar-Apr 2020*Rural areas	0.017***	
	(0.003)	
Post May 2020*Rural areas	-0.017***	
	(0.005)	
Mar-Apr 2020*Log of population per m^2		-0.003***
		(0.0004)
Post May 2020*Log of population per m^2		-0.001*
		(0.0006)
Observations	11,716,668	11,590,420
Commuting zone×Time dummies fixed effects	✓	✓

Notes: Standard errors are clustered at the commuting zone level. Control variables include property type, size, private garden, terrace, garage, balcony, elevator, distance from the centroid of the commuting zone, price per m^2, price revision, time on market, number of days the ad has been visible during the month. Average housing prices are computed as the average asking price in 2018-2019 at the local market level.

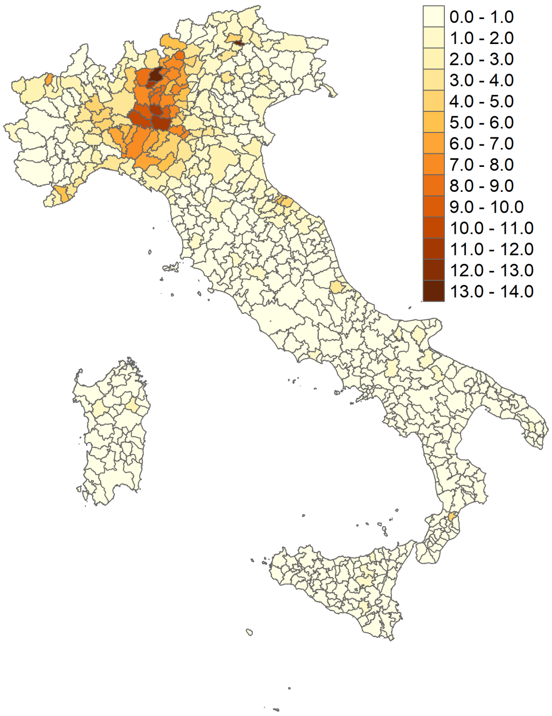
Table G.12: Relationship between actual housing transactions and *contacts*

	Transactions					
	(1)	(2)	(3)	(4)	(5)	(6)
Contacts per listing	0.035	-0.023				
	(0.031)	(0.023)				
Contacts per listing - Lag 1	0.322***	0.113***	0.265***	0.070***	0.250***	0.067***
	(0.061)	(0.027)	(0.052)	(0.017)	(0.052)	(0.017)
Contacts per listing - Lag 2	-0.028	0.004				
	(0.026)	(0.018)				
Contacts per listing - Lag 3	-0.065**	-0.041**				
	(0.033)	(0.016)				
Contacts per listing - Lag 4	0.115***	0.088***				
	(0.024)	(0.021)				
Year 2020*Contacts per listing - Lag 1					0.025*	0.006
					(0.015)	(0.010)
Observations	792	792	1,089	1,089	1,089	1,089
R^2	0.986	0.994	0.985	0.994	0.985	0.994
Province fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓		✓		✓	
Quarter fixed effects	✓		✓		✓	
Year×Quarter fixed effects		✓		✓		✓

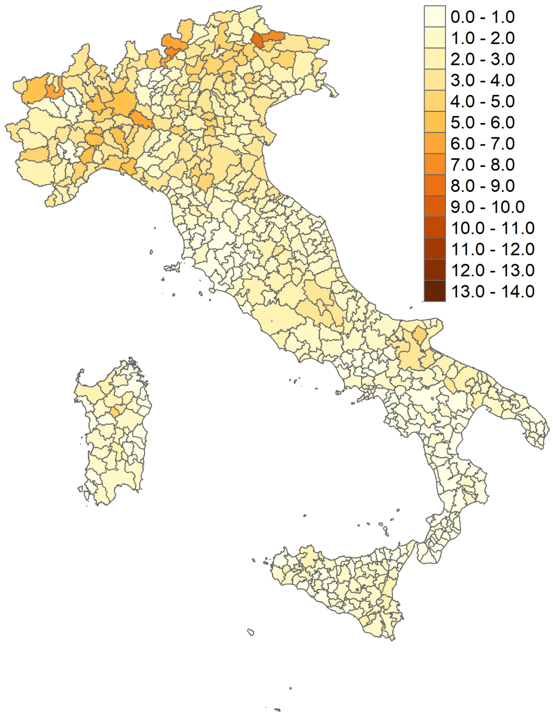
Notes: Standard errors are clustered at the province level. All variables are in log.

H Other data

Figure H.1: Covid-19 hospitalisations in the commuting areas



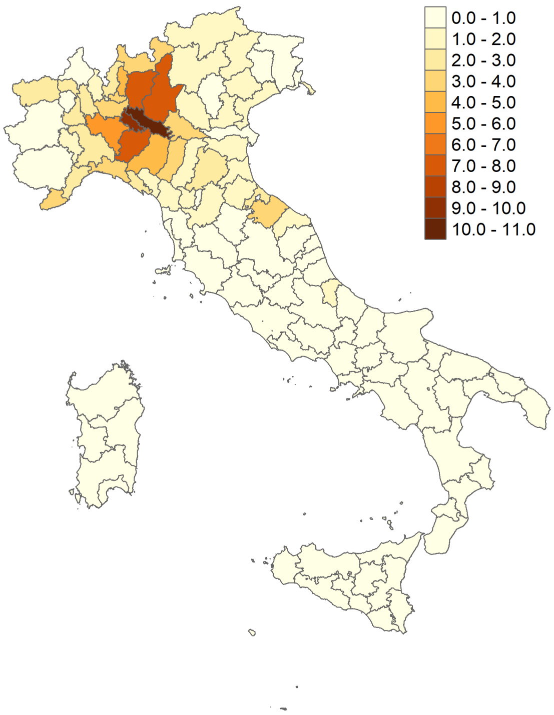
(a) *February-August*



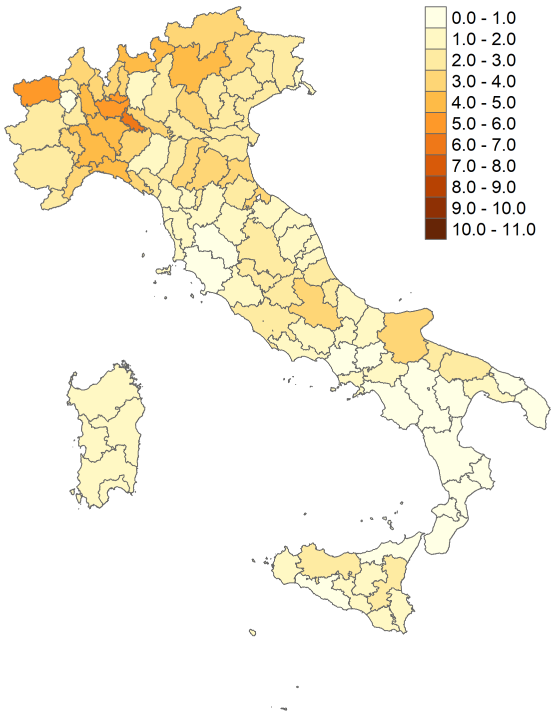
(b) *September-December*

Source: Istituto Superiore di Sanità (ISS, Italian National Institute of Health). *Notes:* Number of Covid-19 hospitalisations per 1,000 persons across commuting areas.

Figure H.2: Covid-19 hospitalisations in the provinces



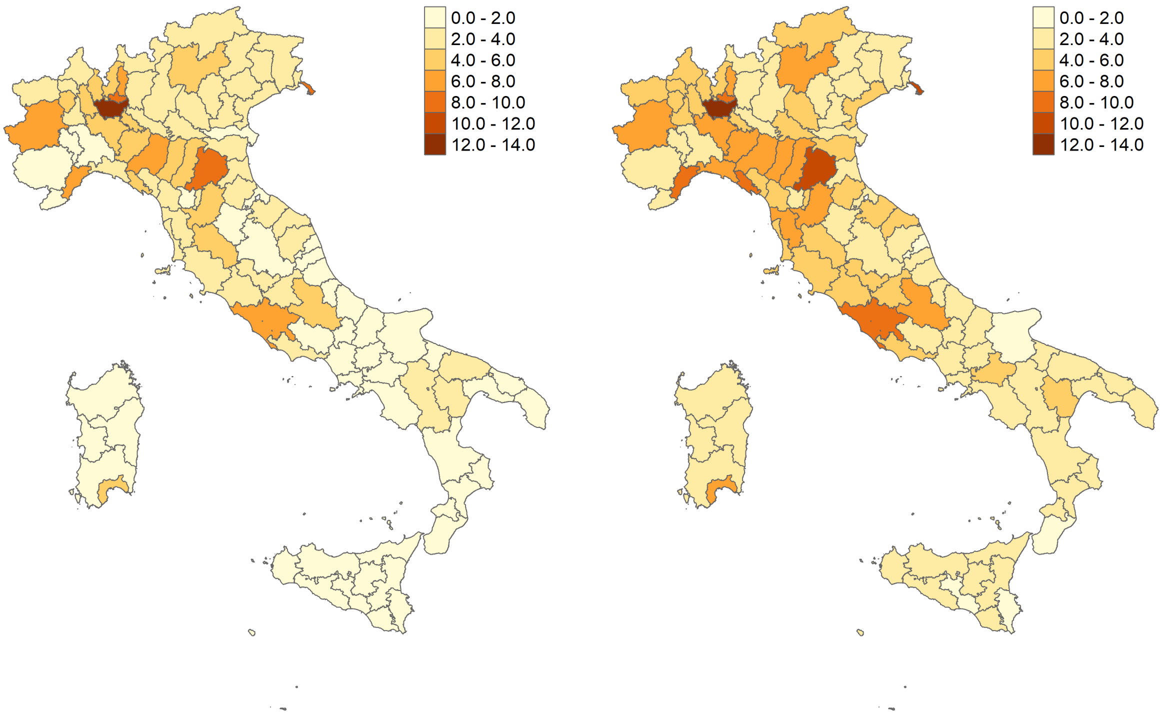
(a) *February-August*



(b) *September-December*

Source: Istituto Superiore di Sanità (ISS, Italian National Institute of Health). *Notes:* Number of Covid-19 hospitalisations per 1,000 persons across provinces.

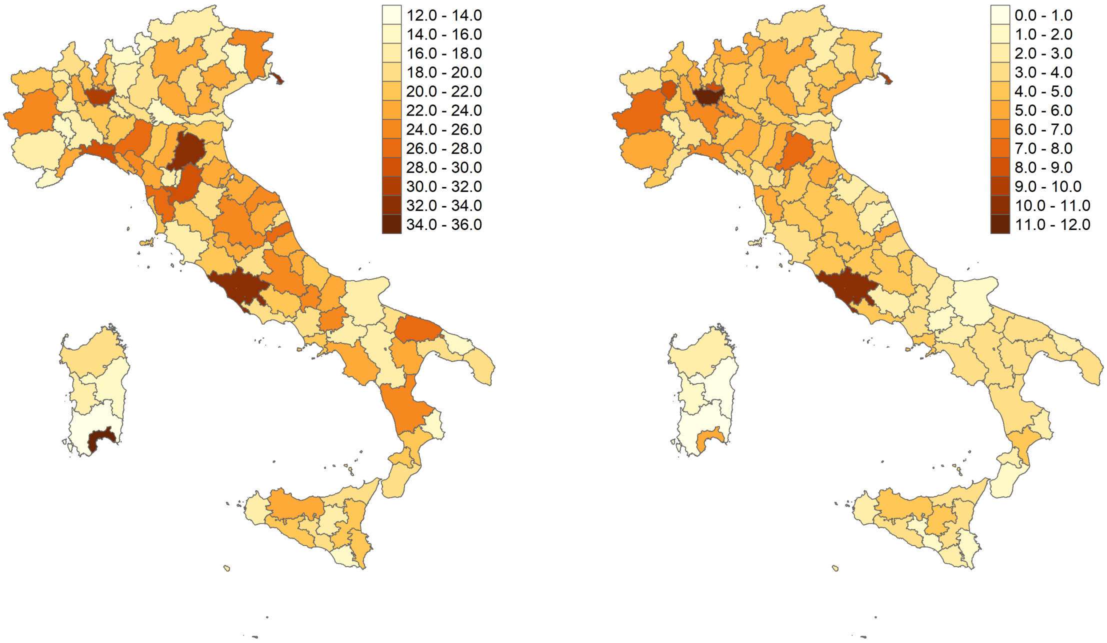
Figure H.3: The changing patterns in work-from-home



(a) *Private sector* (b) *Whole economy*

Source: Labour Force Survey. *Notes*: Difference (percentage points) in the share of workers experiencing work-from-home across provinces between 2020 and 2019.

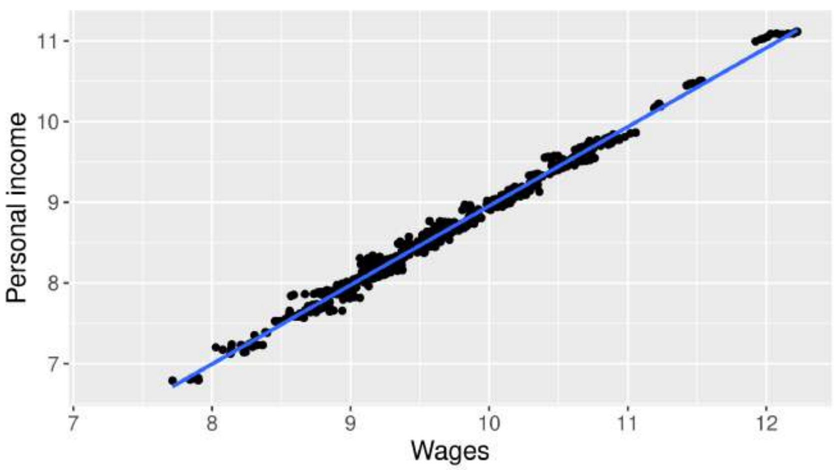
Figure H.4: Education and sectoral specialisation of private sector worker



(a) *Workers with a bachelor* (b) *Workers in the ICT and financial sectors*

Source: Labour Force Survey. *Notes*: Shares (percentage points) of workers in 2019 having a bachelor degree and those of workers in the ICT and financial sectors over all private sector workers.

Figure H.5: Tax returns and labour income



Source: Labour Force Survey (wages) and Ministry of Economy and Finance (personal income). *Notes*: Each dot represent a province-year over the period 2016-2019.

I Channels of transmission: additional evidence and robustness checks

Table I.1: Impact of work-from-home and epidemiological conditions on housing demand (OLS)

	P(Contacts> 0)			
	(1)	(2)	(3)	(4)
Work-from-home	0.0020***	0.0015	0.0020***	0.0021***
	(0.0004)	(0.0013)	(0.0004)	(0.0004)
Work-from-home (whole economy)		0.0005		
		(0.0011)		
Hospitalisations			0.0003	-0.0024
			(0.0040)	(0.0023)
Deaths			-0.0087	
			(0.0072)	
Observations	16,192,805	16,192,805	16,192,805	16,192,805
R^2	0.1195	0.1195	0.1195	0.1195
Within R^2	0.0331	0.0331	0.0331	0.0331
Local housing market fixed effects	✓	✓	✓	✓
Region×Time dummies fixed effects	✓	✓	✓	✓

Table I.2: Epidemiological conditions and employment structure

	Hospitalisations		
	(1)	(2)	(3)
Share ICT-Financial	-0.013	0.006	0.168
	(0.046)	(0.071)	(0.076)
Share Bachelor	0.001	0.008	-0.060*
	(0.011)	(0.013)	(0.023)
Work-from-home	0.014	-0.013	0.065
	(0.016)	(0.025)	(0.034)
(Intercept)			
Observations	428	428	428
R^2	0.753	0.606	0.467
Region×Quarter fixed effects	✓		
Region fixed effects		✓	
Quarter fixed effects		✓	✓

Table I.3: IV diagnostics (2 instruments)

	Single-family home (1)	Private garden (2)	Terrace (3)	Size (4)	Population density (5)
Work-from-home	0.00541**	0.00455**	0.00466***	0.0000265**	-0.000358
	(0.00223)	(0.00195)	(0.00166)	(0.00000105)	(0.000434)
Anderson LM statistic	32.585	32.585	32.585	32.585	32.585
$\chi^2(2)$ p-value	0.0000	0.0000	0.0000	0.0000	0.0000
Sargan statistic	0.035	0.689	0.272	3.035	0.055
$\chi^2(1)$ p-value	0.556	0.407	0.602	0.0815	0.8149
Endogeneity test for endogous regressors	2.661	1.924	3.417	2.287	0.361
$\chi^2(1)$ p-value	0.1029	0.1655	0.0645	0.1305	0.5480

Table I.4: Impact of work-from-home and epidemiological conditions on demand for dwellings' characteristics and location (OLS)

	Single-family home (1)	Private garden (2)	Terrace (3)	Size (4)	Population density (5)
Work-from-home	0.00247** (0.00122)	0.00235** (0.00107)	0.00221** (0.000896)	0.0000137** (0.00000571)	-0.000574** (0.000242)
Housing prices	-0.00855** (0.00379)	-0.00457 (0.00334)	-0.000864 (0.00279)	-0.0000120 (0.0000178)	0.000773 (0.000754)
Change in housing prices	-0.00183*** (0.000513)	-0.00152*** (0.000452)	-0.000567 (0.000378)	-0.00000559** (0.00000241)	0.0000358 (0.000102)
Change in listings	0.0000311 (0.0000979)	0.0000387 (0.0000863)	0.0000698 (0.0000721)	0.00000102** (0.000000460)	0.0000398** (0.0000195)
Hospitalisations	0.00128 (0.000859)	-0.000293 (0.000757)	0.000424 (0.000633)	0.00000713* (0.00000404)	0.0000862 (0.000171)
Population	0.00000918*** (0.00000295)	0.00000375 (0.00000260)	0.00000775*** (0.00000217)	2.61e-08* (1.39e-08)	0.000000312 (0.000000587)
Income per capita	0.000136 (0.00175)	0.000665 (0.00154)	-0.00147 (0.00129)	-0.00000688 (0.00000823)	0.000536 (0.000349)
Surface	-0.00148 (0.00103)	-0.000617 (0.000908)	-0.00163** (0.000759)	0.00000749 (0.00000484)	-0.000101 (0.000205)
Change in private sector employment	-0.00160 (0.00126)	0.000806 (0.00111)	0.000662 (0.000927)	0.00000368 (0.00000591)	-0.000266 (0.000251)
Change in employment	-0.00223 (0.00324)	-0.00231 (0.00285)	-0.00370 (0.00238)	-0.0000147 (0.0000152)	0.00138** (0.000644)
Change in households bank deposits	-0.000415 (0.00110)	0.00143 (0.000970)	0.000246 (0.000811)	-0.00000385 (0.00000517)	0.000177 (0.000219)
Change in households bank loans	0.000303 (0.00117)	0.000300 (0.00103)	-0.00132 (0.000858)	-0.00000416 (0.00000548)	-0.000290 (0.000232)
Change in labour income	0.0000802 (0.000565)	0.000262 (0.000498)	-0.000500 (0.000416)	0.00000353 (0.00000266)	0.000105 (0.000113)
Short-term work scheme (CIG)	0.0234 (1.791)	-0.242 (1.578)	0.388 (1.319)	0.00801 (0.00841)	0.110 (0.357)
Change in car purchases	0.000458 (0.000339)	-0.0000335 (0.000299)	0.000199 (0.000250)	0.00000127 (0.00000159)	0.0000151 (0.0000676)
Change in working hours	-0.000193 (0.000615)	0.000336 (0.000542)	0.000477 (0.000453)	0.000000148 (0.00000289)	-0.0000303 (0.000123)
Share of permanent employees	0.000460 (0.000595)	0.000516 (0.000525)	0.000295 (0.000438)	0.00000600** (0.00000280)	-0.0000538 (0.000119)
Change in the share of permanent employees	-0.000437 (0.000942)	-0.000941 (0.000830)	0.00154** (0.000694)	0.00000216 (0.00000442)	0.000163 (0.000188)
Constant	-0.0131 (0.0323)	-0.0359 (0.0285)	0.00613 (0.0238)	-0.000331** (0.000152)	-0.0106 (0.00643)
Observations	104	104	104	104	104
Adjusted R^2	0.230	0.256	0.158	0.255	0.132

Table I.5: Impact of work-from-home and epidemiological conditions on housing demand (IV, one instrument: share of employees in the ICT and financial sectors)

	Single-family home (1)	Private garden (2)	Terrace (3)	Size (4)	Population density (5)
Work-from-home	0.00486** (0.00240)	0.00387* (0.00210)	0.00503*** (0.00181)	0.0000341*** (0.0000117)	-0.000317 (0.000471)
Housing prices	-0.00954** (0.00395)	-0.00520 (0.00345)	-0.00203 (0.00299)	-0.0000204 (0.0000193)	0.000667 (0.000776)
Change in housing prices	-0.00206*** (0.000557)	-0.00166*** (0.000486)	-0.000829** (0.000421)	-0.00000750*** (0.00000272)	0.0000117 (0.000109)
Change in listings	0.0000678 (0.000105)	0.0000621 (0.0000914)	0.000113 (0.0000791)	0.00000133*** (0.000000511)	0.0000438** (0.0000206)
Hospitalisations	0.00121 (0.000877)	-0.000340 (0.000767)	0.000337 (0.000664)	0.00000649 (0.00000429)	0.0000782 (0.000172)
Population	0.00000843*** (0.00000307)	0.00000327 (0.00000268)	0.00000688*** (0.00000232)	1.97e-08 (1.50e-08)	0.000000231 (0.000000604)
Income per capita	-0.00193 (0.00252)	-0.000656 (0.00220)	-0.00390** (0.00191)	-0.0000246** (0.0000123)	0.000312 (0.000495)
Surface	-0.00129 (0.00106)	-0.000499 (0.000927)	-0.00141* (0.000803)	0.00000907* (0.00000519)	-0.0000811 (0.000209)
Change in private sector employment	-0.00190 (0.00131)	0.000614 (0.00114)	0.000309 (0.000989)	0.00000111 (0.00000639)	-0.000298 (0.000257)
Change in employment	-0.00101 (0.00346)	-0.00153 (0.00302)	-0.00226 (0.00262)	-0.00000428 (0.0000169)	0.00151** (0.000680)
Change in households bank deposits	-0.000345 (0.00112)	0.00148 (0.000981)	0.000329 (0.000849)	-0.00000324 (0.00000549)	0.000184 (0.000221)
Change in households bank loans	0.000553 (0.00121)	0.000460 (0.00105)	-0.00102 (0.000913)	-0.00000203 (0.00000590)	-0.000263 (0.000237)
Change in labour income	-0.000170 (0.000615)	0.000103 (0.000537)	-0.000794* (0.000465)	0.00000140 (0.00000300)	0.0000776 (0.000121)
Short-term work scheme (CIG)	0.312 (1.840)	-0.0578 (1.608)	0.728 (1.393)	0.0105 (0.00900)	0.141 (0.362)
Change in car purchases	0.000379 (0.000352)	-0.0000841 (0.000308)	0.000106 (0.000267)	0.000000597 (0.00000172)	0.00000652 (0.0000693)
Change in working hours	-0.0000740 (0.000635)	0.000412 (0.000555)	0.000617 (0.000480)	0.00000116 (0.00000310)	-0.0000175 (0.000125)
Share of permanent employees	0.000805 (0.000675)	0.000736 (0.000590)	0.000701 (0.000511)	0.00000894*** (0.00000330)	-0.0000165 (0.000133)
Change in the share of permanent employees	-0.0000718 (0.00101)	-0.000708 (0.000882)	0.00197** (0.000764)	0.00000528 (0.00000493)	0.000203 (0.000198)
Constant	-0.00264 (0.0341)	-0.0292 (0.0298)	0.0185 (0.0258)	-0.000241 (0.000167)	-0.00942 (0.00671)
Observations	104	104	104	104	104

Table I.6: Relation between instruments and housing demand before the epidemic

	Single-family home (1)	Private garden (2)	Terrace (3)	Size (4)	Population density (5)
Share ICT-financial	0.0008	0.005***	0.0007	-4.57×10^{-6}	0.0002
	(0.001)	(0.0010)	(0.0007)	(9.52×10^{-6})	(0.0002)
Share bachelor	0.0003	-0.0009**	0.0003	$-1.38 \times 10^{-5***}$	-0.0002***
	(0.0005)	(0.0004)	(0.0003)	(4.03×10^{-6})	(6.44×10^{-5})
Population	0.010***	0.011***	0.011***	-0.0002***	0.0003
	(0.003)	(0.002)	(0.002)	(2.29×10^{-5})	(0.0004)
Surface	-0.008***	-0.008***	-0.005***	0.0001***	0.001***
	(0.003)	(0.002)	(0.002)	(2.38×10^{-5})	(0.0004)
(Intercept)	-0.036	-0.046*	-0.096***	0.001***	-0.013***
	(0.029)	(0.026)	(0.018)	(0.0003)	(0.004)
Observations	208	208	208	208	208
R^2	0.143	0.316	0.302	0.485	0.094
Adjusted R^2	0.126	0.303	0.288	0.475	0.076