Near-Miss Climate Catastrophe and Local Adaptation

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Abstract

The 2022 forest fire in Landes and Gironde was France's second largest forest fire in the past two centuries. Despite its extensive coverage, the fire had no direct casualties, and few structures were destroyed. The Landes's fire was a near-miss event: its consequences could have been much more catastrophic. In 1949, the same region was subject to the largest and most deadly forest fire on record in France. We investigate whether a salient but near-miss extreme climatic event acts as a catalyst for adaptation strategies. We assemble a rich set of data to investigate households' intentions and actual internal migration decisions. We also link migration outcomes with housing market outcomes. We find evidence of an intention gap, i.e., a difference between intended and actual migrations, and these intentions are mostly supply-side driven. In particular, we observe an increase in listings in the impacted regions, but no strong effect on incoming and outgoing migrations. We also observe a small increase in transactions and an increase in the supply of short-term rentals. Overall, our results suggest that the secondary home housing market was the most impacted, and there are important barriers to internal migrations.

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1 Introduction

Atmospheric greenhouse gas concentrations have now reached levels such that physical climate risks will become significantly more severe. Extreme climatic events will increase in both intensity and frequency, and critical climate tipping points could also be crossed (Lee et al., 2023). Therefore, implementing more ambitious adaptation policies is unavoidable. A key factor determining a local economy's capacity to adapt to these multifaceted climate risks is households' ability to migrate. Understanding how climate risks influence households' location choices and the policy tools that can enable these decisions is therefore of utmost importance. However, significant frictions exist, particularly in the labor and housing markets, which pose substantial barriers to relocation. These frictions create an intention gap: a disparity between desired and actual migrations.

In this paper, we examine the role of a near-miss extreme climate event as a driver of internal migration decisions. The underlying hypothesis is that a salient and potentially severe extreme event can act as an information shock that encourages households to adapt and relocate. We leverage a unique event to test this hypothesis: the 2022 Landes forest fires, which was France's second-largest forest fire in its recent history. Fortunately, these fires were not as destructive as they could have been. There were no casualties, and few structures were destroyed despite the fire's significant size. However, the 2022 Landes fire served as a reminder that this region is highly vulnerable to wildfires. France's largest and deadliest forest fire, which claimed 82 lives in 1949, also occurred in this area. The Landes Forest is a notable example of a man-made ecosystem misadapted to climate change. It is the largest artificial forest in Western Europe, consisting of a single tree species, the maritime pine, introduced in the 19th century. This monoculture transformed extensive areas of coastal wetlands into forests susceptible to fires, which, due to climate change, are projected to become much more frequent and destructive. The Landes forest and the 2022 fire provide an ideal setting to test how a near-miss extreme climate event can serve as a catalyst for local adaptation strategies. This context suggests that households should be aware of their high vulnerability given the nature of the ecosystem, past experiences of extreme events, and the wide array of policies in place to manage and prevent forest fires.

We have assembled a rich set of outcome variables to study internal migration decisions starting from intention to actual moving decisions. In particular, we use household-level data about housing searches from the French online real estate platform SeLoger and actual reallocation behaviors from the mailing redirection service from La Poste. These two datasets provide a unique and in-depth view of households' responses to realized climate risks. We then collected comprehensive data on France's residential housing market: flow and stock of listings, number of transactions, and prices. Finally, we also collected data about the short-term rental market.

Our empirical strategy consists of comparing the evolution of intentions and migration flows between municipalities impacted by the 2022 Landes fire and a group of matched comparable municipalities. We use the fire start date to define the beginning of the treatment with possible heterogeneous effects. Our main specification uses a synthetic difference-in-differences and matching approach to compare impacted municipalities (treated) with other similar regions (control). From a methodological point of view, our proposed approach is inspired by the recent literature on quantitative trade and worker migrations. There is a rich and growing literature investigating the spatial reallocation of labor in response to local economic shocks (Blanchard et al., 1992; Greenwood, 1997; Cadena & Kovak, 2016) which also studies the role of climate change on workers' location choice (Albert et al., 2021). For our main empirical strategy, we employ the recently proposed method of synthetic difference-in-differences to better ensure comparability between affected areas and control group (Arkhangelsky et al., 2021).

Our results show that the 2022 Landes fire impacted intention and actual migration behaviors and the local real estate market in a nuanced way. We document that the forest fires led to an increase in the number of available properties, both in terms of the stock of listings and additional listings posted each month, in the affected regions—an increase of 12.4% in the stock of listings and 23% in the rate of posted listings, respectively. The increase in the number of offered properties is not followed by a change in demand. This is true for both intention to move and actual reallocation decisions. We observe no changes in search intensity, first measured with the number of clicks on listings and, second, measured by the number of requests for further documentation about a property. We also distinguish search intensity for three categories of platform users: users located outside the treated regions who searched for properties located inside treated regions, users located inside the treated regions who searched for properties located outside treated regions, and users located inside the treated regions who searched for properties located inside treated regions. For all three categories, we do not observe strong and robust evidence that the forest fire changes intentions to move. We also do not document significant changes in actual migration patterns along the same three margins. There are neither more people moving into the affected region nor more people moving out from there in comparison to the control group.

Although migration patterns remain unchanged, we still document an increase of about 8% in terms of real estate transactions post fire. We posit different explanations for the additional increase in available properties but unchanged search and migration patterns. One is that more available properties does not translate into more interest, but shifts the market equilibrium more towards a "buyers" market with less interested parties per available unit. We do not observe a decrease in transaction prices though, which would likely complement such a market evolution. Another potential explanation for the observed pattern is that the agents that are offering their property as well as the incremental buyers of the additional transactions are investors into secondary homes or rental property. We do find some supportive evidence for investment behavior as well as adaptation strategies from property owners, that have their property listed but do not find increased interest through AirBnB. We document an increase in available listings in the forest fire region by approximately 5% in comparison to the control group. These additional listings are also met with increased reservations (9.5%) as well as a higher number of reserved days (12.8%). In terms of revenue and AirBnB rates we do not document significant differences between the affected region and the comparison group.

We also distinguish between the ownership and rental markets. We find that there is an increase in available properties both for sale and for rent, but no decrease in platform users' interest in both markets. The forest fire has not changed transaction prices, suggesting that the perception of forest fire risk has either not changed or was already fully reflected in the real estate market. Current residents seem to prefer to stay in the affected region, as they are not altering their real estate search behavior, indicating that the additional available properties are mainly secondary homes. This sudden increase in available properties leads to some additional transactions and an increase in short-term rental properties on AirBnB but does not significantly change the population's exposure to forest fire risk in the area.

This paper contributes to our understanding of the role of climate change and environmental factors on human migration. This literature has attracted considerable attention, recently summarized in several meta-analyses and review papers (e.g., Hoffmann et al. (2020); Millock (2015); Beine & Jeusette (2021); Moore & Dennis (2022)). Rapid environmental changes caused by extreme climatic events (ECEs) such as floods, droughts, and hurricanes have been recognized as key drivers of migration (Hoffmann et al., 2020). Internal migration is the more common response to these events, as individuals often relocate within their own country before contemplating crossing international borders (Moore & Dennis, 2022; Beine & Jeusette, 2021). Several factors, such as cultural and linguistic familiarity, proximity to social networks, and potential legal obstacles associated with international migration, explain why environmentally-induced migrations tend to be relatively local.

The bulk of the empirical evidence on the influence of ECEs on different economic outcomes, including migrations, comes, however, from developing economies (Kellenberg & Mobarak, 2011). The US is one important exception where several studies have investigated the impact of natural disasters on various measures of economic activity (e.g. McIntosh (2008); Strobl (2011), household reallocation (e.g. Boustan et al. (2020)), and the housing market (e.g., Sheldon & Zhan (2019)). In Western Europe, although climate risks are also important, empirical evidence remains scant (Hoffmann et al., 2021).

Although a link between physical climate risks and internal migrations has been established, the role of specific factors mediating this relationship is not yet well understood (Millock, 2015). The challenge comes from the fact that there are different channels by which climate risks could induce households to move to a new location and the lack of disaggregated data to test those mechanisms. Moreover, climate change, from the human perspective, is a slow-changing phenomenon. An important question is what particular climate-related events or information about such events impact households' decisions, and whether this can be captured empirically. The literature has distinguished between climatic events with a slow onset (e.g., change in yearly average temperature and precipitations) versus fast-onset events (e.g., heat waves, floods, and forest fires) to identify the impact of a changing climate (Cattaneo et al., 2019). Each type of event has its challenges. The behavioral response to the former is difficult to capture as it is confounded with long-term trends. Whereas the response to the latter, easier to identify, captures several intertwined mechanisms, such as the destruction of infrastructures, labor market disruptions, housing market frictions, changes in insurance premia, and information shocks, which makes it hard to understand why internal migrations occur.

When it comes to studying specific mechanisms that impact internal migration in response to or anticipation of ECEs, several recent studies have focused on information-based mechanisms, as it can be a policy lever that governments can easily adjust. For instance, variation in flood maps and at-risk designations has been exploited (Hino & Burke, 2021) to test whether households are well-informed about baseline flood risk and respond to new information about future exposure. There is also evidence that households have biased beliefs (Bakkensen & Barrage, 2022) about the underlying baseline climate risk and do not fully internalize new risk information . Other instruments might be more effective to inform households. Fairweather et al. (2024) investigates the voluntary disclosure of flood risk on a real estate platform and found that it impacted behaviors along several margins, from search to actual offers, and ultimately, was internalized in market prices. Another information channel might be the realization of past extreme events that increase the salience of a risk, without creating destruction. While large environmental disasters have been shown to induce stronger regulations, near-miss catastrophic events could operate in a more subtle manner, and be a catalyst for local adaptation behaviors. Bakkensen et al. (2019) show that hurricanes can increase flood risk salience, which is reflected in housing prices. Near-miss climatic events could, however, have the unintended consequence of decreasing preparedness efforts for catastrophic climatic events (Dillon et al., 2011) as individuals become over-optimistic in their ability to sustain such events (Tinsley et al., 2012). Their net impact of migrations might then be ambiguous.

Our contribution to this literature is threefold. First, we exploit a well-defined near-miss extreme climatic event that allows us to isolate the role of information salience on local adaptation behaviors. The 2022 Landes fire was unprecedented in size and media coverage, but destroyed very few structures and caused no casualties. The local labor market and infrastructures were, thus, unaffected, which provides the ideal context to test how ECEs can act as an information shock that induces adaptation.

Second, we are investigating a rich set of outcome variables to uncover the different margins by which households and the housing market may respond to such information shock. We start from intention to move to actual reallocations, and look at housing market outcomes. We also distinguish the ownership, long-term rental, and short-term rental markets, as they are all interconnected and are each subject to different types of frictions.

Third, we provide empirical evidence for a region and type of climate risk that have received little attention in this literature. The culture, institutions, and policy context in Europe differ from those of developing and developed economies. It is thus crucial to empirically investigate this setting. Compared to other natural disasters, forest fires are also relatively less documented despite their severe and destructive potential.[1]

The rest of the paper is organized as follows. Next, we discuss the institutional setting. In Section 3, we describe the data. The empirical strategy is described in Section 4, and the results are presented in Section 5. Conclusions follow.

[1]Some recent studies have examined the effects of fires in California (Jia et al., 2020) and other studies show that these forest fires slightly increased out-migrations from risky areas (Sharygin, 2021) and reduced migrations (Winkler & Rouleau, 2020). (McConnell et al., 2021) find that areas with most destructive wildfires experienced a significant increase in outgoing migrations flows and no effect on incoming migration flows. Even short-term migrations increase to avoid wildfires smokes (Holloway & Rubin, 2022).

2 Institutional Setting: Wildfires in France

France is particularly exposed to wildfires. As of 2022, one in five municipalities (precisely 6,870) were exposed to such a risk.[2] The most vulnerable municipalities are located in the South of France, namely, Corsica, the Mediterranean coast, the Cévennes, the foothills of the Alps, the Pyrenees, and the Landes, due to the specific combination of vegetation types (conifers, scrubland) and climatic conditions (wind and heat). In some regions, the exposure to wildfire risk has been exacerbated by man-made interventions to local ecosystems. In the Landes, for example, in the nineteenth century, Napoleon III ordered the conversion of vast coastal wetlands into monoculture plantations of maritime pines, which led to the largest artificial forest in Western Europe.

The Landes forest is a case-in-point of climate mal-adaptation. The maritime pines turned wetlands into sand-like soil and created ideal conditions for forest fires. As a result, this is the region of France that has had the deadliest and largest forest fires. The 1949 Landes fire, which killed 82 persons, is the largest wildfire in France's recent history, and, in 2022, the second-largest wildfire occurred in the exact same region. However, unlike in 1949, the 2022 fire did not cause human casualties, and few structures were destroyed despite the fact that the area was then much more populated. This is partly attributable to the French Government's effort to put in place institutions and policies to prevent and manage wildfire risks.

France's wildfire management strategy first relies on a set of planning, management, and maintenance tools for forested areas. Key instruments include Forest Fire Protection Plans (PPFCI), urban planning documents, such as Territorial Coherence Schemes (SCoT), and Local Urban Plans (PLU). For high-risk areas, the Forest Fire Risk Prevention Plans (PPRIF) are regulations designed to reduce exposure to wildfires by prohibiting or limiting the construction and development of infrastructures.[3] When it comes to informing citizens, Municipal Information Documents on

[2] According to GASPAR ("Base nationale de Gestion Assistée des Procédures Administratives relatives aux Risques") which collects all climate events that led to public support for a given community and the respective timestamp.

[3] These documents also specify measures for prevention, protection, and safeguarding, as well as measures related to the planning, use, or operation of buildings, infrastructure, or cultivated and planted areas. To date, the number of approved PPRIFs is approaching 200, distributed as follows across France: 46% in the Provence-Alpes-Côte d'Azur region, 22% in the Occitanie region (where the Landes fires occurred), 18% in the Nouvelle-Aquitaine region, 9% in Corsica, and 5% elsewhere in the country.

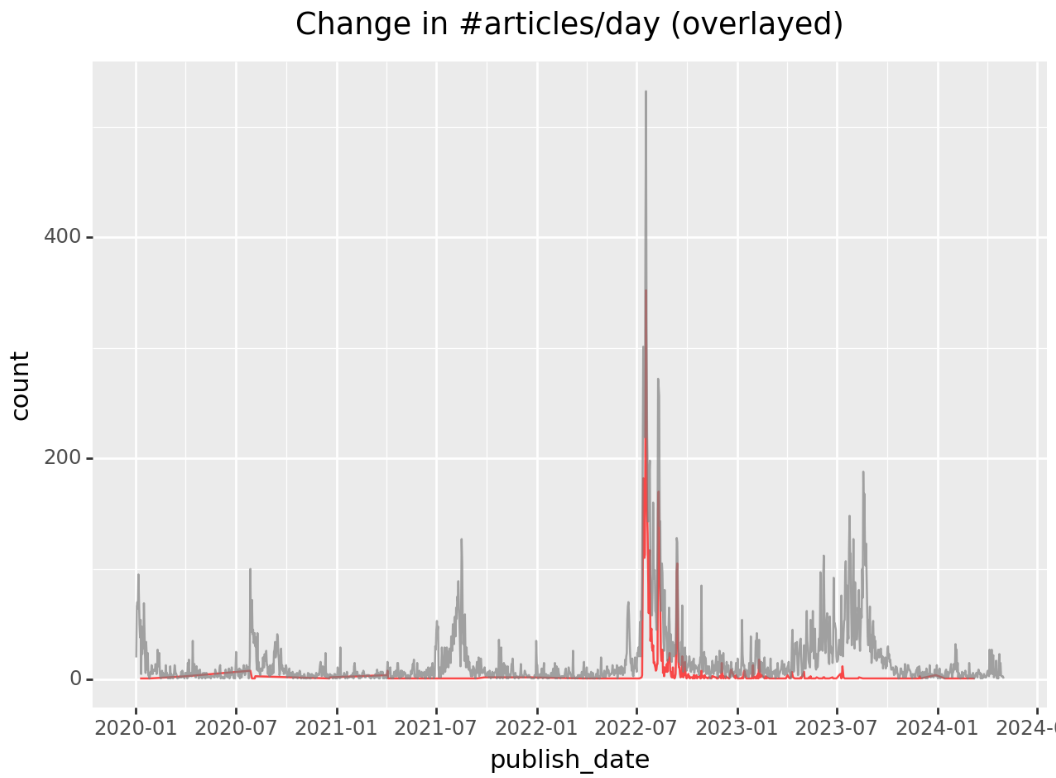
Major Risks (DICRIM) play a key role in raising awareness and informing local populations about wildfire risks, recommended behaviors during crises, and prevention measures. This tool aims to enhance community resilience by improving their ability to anticipate and respond to wildfires.

Despite the extensive set of policy instruments to make communities more resilient to wildfires, tools that help households anticipate future wildfire risks, and more generally climate risks, in their long-term location decisions are still lacking. For example, none of France's real estate platforms systematically provide information on such risks. In housing transactions, only certain climate-related risks must be disclosed, and these do not account for future climate change scenarios. Moreover, the rental market is not covered by any mandatory climate risk disclosure policies. Given the lack of information at crucial moments when households make housing decisions, extreme climatic events may raise awareness of such risks and act as a catalyst for relocating to safer areas. The 2022 Landes fire is an ideal case study to test this hypothesis. Although it did not cause significant human and material damages, it was an exceptionally salient event in France. As shown in Figure 1, it attracted an unusual amount of media coverage, compared to the coverage of other forest fires inside and outside France for other years, and lasted several months. As we explain next, we exploit the timing of the event and the sudden media coverage it attracted with fine-grained information about different types of behaviors, starting from intentions to move to actual migrations, together with housing market outcomes.

3 Data

We compile data from multiple sources to examine a comprehensive set of outcome variables. Our primary focus is on migration-related behaviors, their effects on housing market demand and supply, and, ultimately, their impact on housing market equilibrium. To this end, we collect data on online search behaviors, online requests to real estate agents, actual migrations tracked with change-of-address requests, property listings, housing transactions, and prices. Additionally, we distinguish between the rental and ownership markets. Finally, we incorporate data from the short-term rental market to provide a complete picture of the potential adjustments in the housing market. Below, we discuss in detail each of those outcome variables, after having presented how

Figure 1: Media Coverage of Forest Fires



Note: This figure presents the number of media articles on Landes and Gironde Forest Fires 2022 (red) vs overall Forest Fire coverage (gray). *Source: Common Crawl database, 2022.*

we define our treatment variable using forest fire data.

3.1 Forest Fire Data

We use two different forest fire data sources. First, we employ the European Forest Fire Information System (EFFIS), which has geocoded information on the occurrence and severity of forest fires, to identify regions impacted by forest fires during our sample period. Second, we use the Firelihood model, a probabilistic framework that predicts fine-grained wildfire risk across France (Pimont et al., 2023), to define control regions that we match with the treated ones.

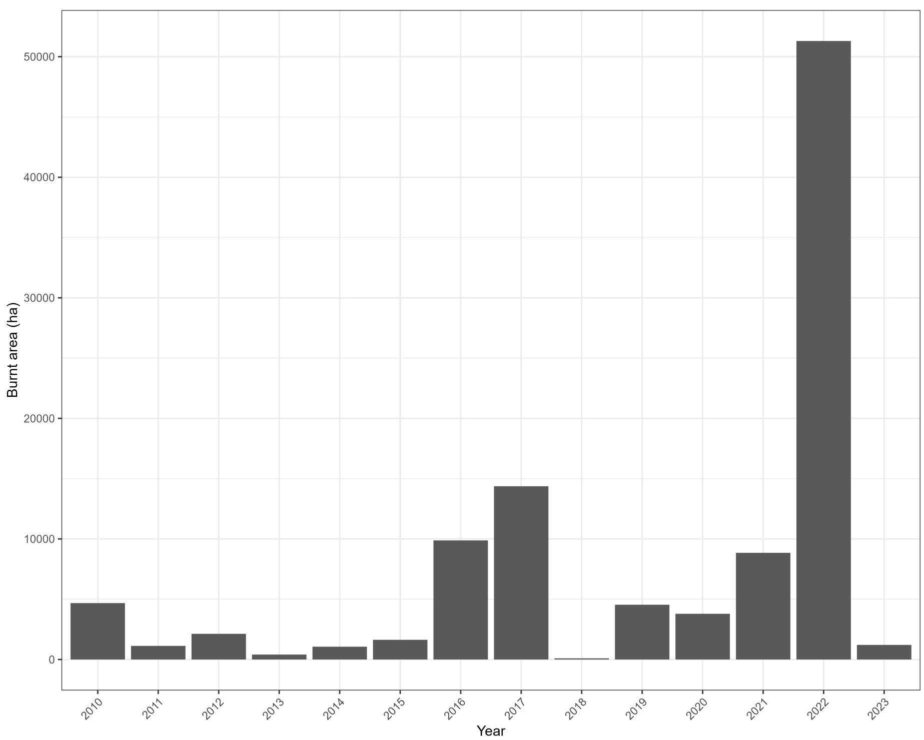
Realized Forest Fires - EFFIS

The EFFIS data[4] is the most reliable source of information on forest fires, based on satellite data

[4]The data are a component of the Copernicus program. They are available at: https://effis.jrc.ec.europa.eu/applications/data-and-services.

and complemented and validated with on-the-ground information. We use the data to compute the share of burnt area caused by a forest fire in a municipality, which is the intersect of the perimeter of the burnt area with that of the municipality. Figure Figure 2 shows how exceptional the year 2022 was in terms of forest fire intensity compared to other years. More than 50,000 ha of land was burnt between May and September 2022,[5] which is more than four times greater than the second and third highest observations in this sample period.

Figure 2: Distribution of annual burnt area caused by forest fires



Note: This figure presents the total annual burnt area between May and September based on the EFFIS database.

In the summer of 2022, there were various forest fires throughout France, but the main fires were geographically concentrated in the Gironde department (one of the ninety-size administrative divisions in mainland France), with 29,585 hectares burnt between May and September 2022. The

[5]Note that we report statistics on this restricted period, as it allows us to exclude any deliberate fires linked to controlled field-burning during the winter agricultural season—a historical agricultural practice in France referred as *écobuage*.

second most impacted department, the Var, had substantially less area burnt, about 2,630 hectares. Although the media refer to the 2022 forest fire as the Landes fires, it is somewhat a misnomer as it refers to the name of the immense forest massif in southwest France. The Landes department was in itself much less impacted, relative to the Gironde department and was only the 9th worst-hit department in 2022 with 1,183 hectares burnt (see Table Table 1).

Table 1: Burnt area by Département

	Département	Burnt Area (ha)
1	Gironde	29585
2	Var	2630
3	Finistère	1941
4	Ardèche	1767
5	Maine-et-Loire	1706
6	Bouches-du-Rhône	1680
7	Pyrénées-Orientales	1555
8	Aveyron	1388
9	Landes	1183
10	Alpes-de-Haute-Provence	1143

Note: This table presents the top 10 departments impacted by forest fires in France in terms of burnt area between May and September 2022 based on the EFFIS database. We focus on the summer months to avoid counting intended fires from agriculture practices.

The Landes and Gironde, two adjacent departments, were affected by 5 distinct fires between May and September 2022. The first reported fire in the region started on July 7, and the other fires started in July 12, July 31, August 9, and September 13, 2022 respectively. To define the start of our treatment period, we use the reported date of the first fire: July 7, 2022. Treated regions are defined at the municipality level, i.e., communes, which consist of 36,781 administrative divisions in France. In our main specification, we define a municipality as being treated if more than 3% of the municipality area was burnt by a forest fire during the summer of 2022. In the treated regions, we also include municipalities inside a buffer of 10 km around the municipality directly impacted to account for potential spillovers and smoke-related impacts. Figure Figure A.1 shows the location and variation in the intensity of burn areas among the treated regions.

Exposure to Forest Fires - the Firelihood model

We employ additional information on the potential forest fire risk to construct our control groups of communities. We employ a simplified version of the Firelihood model (Pimont et al., 2023), focusing exclusively on predicting the number of seasonal fires larger than 20 hectares rather than considering all fire activity larger than 1 hectare at a daily scale (Pimont et al., 2021).[6] The output of the model allows us to distinguish between at-risk regions and other regions. We use this information in our matching procedure to select municipalities with a similar level of exposure to forest fires as the ones impacted in 2022, but that were not recently impacted by forest fires.

3.2 Search, Migration, and Housing Market Data

Online housing searches data - SeLoger

The online searches database is provided by SeLoger, one of the main French online real estate platforms that has 6.3 million unique visitors per month in France[7]. The platform publishes listings of dwellings both to sell and to rent from realtors historically and from private individuals since July 2023. Thanks to Google Analytics, the firm tracks the use of its website and its application by users who have accepted cookies[8]. To follow their behavior on the platform, an anonymized identifier is assigned to each user as long as they remain on the same device, do not delete cookies, or are inactive for more than two months.[9] Several pieces of information on the search behavior of agents are gathered. Of particular importance for us is their geographic location while being

[6]The methodology involves estimating a probabilistic model that predicts the annual number of summer fires based on a fire danger metric calculated using the Fire Weather Index (FWI) and the raw vegetation sensitivity, which is mapped by the French National Forest Office (ONF). The national-scale model for France was calibrated using a mixed dataset covering the period 2008–2020, combining national and regional data sources with fire perimeters reconstructed from reanalyzed satellite data (EFFIS, FRY, and GlobFire datasets). The model includes a spatio-temporal component to account for regional variations in fire activity. This adjustment reflects the fact that, even with identical FWI values and vegetation sensitivities, fire occurrences are not homogeneous across the country. Regional differences in human activity, fire prevention and suppression strategies, as well as landscape structures, play a significant role in influencing fire outbreaks and dynamics.

[7]Source : Médiamétrie, NetRatings - February 2023.

[8]It represents between 65% to 75% of users.

[9]In order to avoid double counts of users, we focus on searches done only on the website and not on the application.

online[10] and the listings they click on including an exact timestamp. We employ the geolocations as a proxy for their place of residence.[11] Furthermore, we employ information on the listings that agents click on, including the type of transaction (to sell or to rent), the type of dwelling (house or apartment), and the city in which the dwelling is located. We build intention mobility flows between a user's residence and searched locations overall and separated by type of transaction. We observed search behavior from January 2021 to December 2023. We deduplicate the number of clicks by user, municipality of origin, and municipality of destination: in other words, we count the user one time if he performs several identical searches in a given month.[12] For each community-month, we distinguish between incoming, outgoing, and internal clicks and count each agent's action within that category.

Clicking on ads is the first step in a real estate search. However, users may click on an ad out of curiosity, without necessarily having a strong interest in buying or renting the property. The intention is more pronounced if the user wishes to contact the real estate agency to obtain more information and to visit the property he or she is interested in. We also have access to data of realtors contact forms filled in by users. In the same way as for clicks, we have access to an anonymous user identifier[13] and to the user's location at the time of the search. This allows us to study a stronger signal of interest, separate from clicks.

In addition to these statistics on user behavior, which are more indicative of demand, we also have access to the listings database, which enables us to study the supply side. In fact, in addition to the characteristics of the properties presented in the ads, we observe the dates of publication. Therefore, for each community-month, we are able to observe the supply of properties for rent and for sale on the platform. We measure supply in two ways: the stock (i.e., the number of active ads online) and the flow (i.e., the number of additional listings published in a given month).

[10] Geographical tracking is based on API addresses at a community level.

[11] To ensure the reliability of our findings, we constructed an alternative database, including only searches conducted between 7 p.m. and 8 a.m. This time window is presumed to more accurately reflect individuals being at home rather than at work.

[12] We aggregate the user-listing level data to a community-month level dataset, in order to make the data comparable with the observed migration data.

[13] The identifier is based on an encrypted e-mail address, which is a requirement to complete the form.

We present in Panel A of Table 2 some descriptive information on both the demand and supply behavior on the platform. As previously described, we distinguish between listings being online and additional listings being added on a community-month level between January 2021 and December 2023. We observe, on average, 267 listings being online in each community and 158 additional listings being posted. The distribution seems fairly centered, with the median being close to the mean. In terms of demand behavior, we see substantially more variation between communities. While, on average, 452 individuals clicked on listings being advertised in different communities than their current location, the median click rate is substantially lower at 48. This illustrates that there are various community-month combinations that receive almost no interest. For outgoing and internal clicks this pattern is even stronger, with more than 50% of the community-month observations not observing any clicks. The same patterns apply to the requests for additional information or contact ("leads").

Migration data -La Poste

The mail forwarding database is provided by La Poste, the near-monopoly leader in charge of mail distribution in France[14]. When French households move, whether they rent or own their dwelling, they can pay to redirect their mail from their old home to their new home for 6 or 12 months. Both origin and destination municipalities are known, enabling mobility flows to be built throughout France. Almost 2/3 of French movers take out a mail forwarding contract. Despite its incomplete coverage of the universe of household migrations in France, these data are highly representative.[15] A key advantage of La Poste data, in comparison of census data, is that they are almost in real-time, as we know the starting date of the contract. We can use this information to define moves that were plausibly impacted by the start of the forest fires in July 2022. In particular, we compute a proxy for the date of the decision to relocate, which is three months before the starting

[14]Despite the opening up to private competition for mail weighing less than 50 grams in 2011, market shares of La Poste remain high.

[15]A comparison between household mobility flows based on La Poste mail redirections between January 1, 2017 and January 1, 2018, and mobility flows from INSEE's "Fichier détail migrations résidentielles" over the same period shows a correlation of 0.97 for both inter- and intra-Departmental mobility flows.

date of the contract.[16] The three months cut-off thus corresponds to the approximate average between tenants' and buyers' moving times.[17] Note that households can use La Poste to subscribe to temporary mail forwarding contracts, which is common in France for households who wish to forward mail to their secondary residences or vacation homes. We also observe those contracts. In that case, we retain the starting date of the contract without delaying it by 3 months.

Similarly, to the clicks and request forms, we again aggregate the data based on the mail forwarding contracts to a community-month level measure and distinguish between incoming, outgoing and internal mobility flows. We do this for our three outcomes of interest: permanent migrations of households, temporary migrations of households, and firms migration.

In Panel B of Table 2 we present descriptive statistics of the migration data. On average, we observe 152 people moving into our communities and 132 out each month. We also observe some within community moves of 52 households on average. We see substantially fewer temporary and firm migrations. Overall, our selected sample seems to attract more people than leaving, with all the incoming averages being higher than the outgoing movements. Again, the distribution seems tilted towards zero, with some variables having the majority of observations being zero on a community-month level. The lower number of observations for the permanent migration variables is because we lag these outcome variables by 3 months, as aforementioned.

Housing Market Outcomes - DV3F

We rely on address-level geolocated real estate market data provided by CEREMA (Centre d'études et d'expertise sur les risques, l'environnement, la mobilité et l'aménagement) to study market outcomes. This dataset, called DV3F, encompasses all real estate transactions that occurred on French territory between January 2010 and June 2023, excluding for historical reasons the three Metropolitan départements Bas-Rhin, Haut-Rhin and Moselle. In addition to numerous

[16] As a robustness check, we consider alternative moving times of one month, which is closer to that of a renter in a tight housing market area due to the shorter required period of notice, and five months, which is closer to that of a buyer, taking into account the time to obtain a loan, for notaries to gather information, etc.

[17] In the La Poste data, we cannot distinguish renters and homeowners as we do not have any information on the status of subscribers (tenant versus buyer, age, gender, profession, etc.). We can, however, distinguish between private households and firms, however, and thus also include these two different outcome variables in our analysis.

Table 2: SUMMARY STATISTICS

	Mean	Sd	Min	Median	Max	N
Panel A: SeLoger Platform						
Nb Listings (stock)	267	165	0	264	1006	90,684
Nb Listings (Flow)	158	147	0	144	923	90,684
Clicks (In)	452	245	0	48	1324	90,684
Clicks (Out)	84	235	0	0	1352	90,684
Clicks (Int)	46	152	0	0	1318	90,684
Leads (In)	124	152	0	88	897	90,684
Leads (Out)	39	121	0	0	978	90,684
Leads (Int)	12	6	0	0	879	90,684
Panel B: LaPoste Migration						
Permanent HH (In)	152	122	0	144	716	85,646
Permanent HH (Out)	132	119	0	88	754	85,646
Permanent HH (Int)	52	93	0	0	779	85,646
Temporary HH (In)	84	109	0	88	664	90,684
Temporary HH (Out)	62	91	0	0	734	90,684
Temporary HH(Int)	12	44	0	0	621	90,684
Companies (In)	15	43	0	0	448	85,646
Companies (Out)	12	4	0	0	466	85,646
Companies (Int)	06	3	0	0	565	85,646
Panel C: Real Estate market						
Nb Transactions	124	121	0	88	814	68,013
Median Price (Eur/m^2)	849	53	06	853	1096	88,770
Panel D: AirBnB						
Nb Listings	288	167	0	278	1005	90,684
Nb Bookings	365	193	0	378	1145	90,684
Nb Booking days	467	223	0	49	1277	90,684
Revenue (Total)	906	351	0	98	1789	90,684
Rate (Eur/Day)	521	104	0	534	892	83,700

Note: This table presents summary statistics of our main variable of interest. Data sources are described in text.

transaction characteristics (such as surface area, number of rooms, construction periods, prices, etc.), this dataset provides the date of signature of the deed of sale. As with mail forwarding data, we consider a proxy for purchase decision date which is 3 months before the date of signature. We consider two outcome variables aggregated on a month-community level and again lagged by three months: the total number of transactions and the median price per square meter.[18]

Panel C of Table 2 illustrates summary statistics for the real estate data. On average, there are 124 properties sold in a community-month observation at a price of 849 Euros per square meter of area. There is again quite some variation in terms of both transactions and prices, with prices ranging from six Euros to upwards of 1000 Euros. The lower number of observations is a consequence of the three-month lag that we apply, as well as the shorter time coverage of the

[18]If there was no transaction in a given community-month, we interpolate the evolution linearly between the two closest observations.

dataset available. Currently, DV3F data collection has only been updated till June 2023.

Short-term Rentals - AirDNA

To evaluate the impact of fires on tourism activity, we use data from AirDNA, a company that systematically collects short-term rental (STR) listing information from AirBnB.[19] This rich dataset offers detailed insights into the STR market. It covers all municipalities in France from January 2016 to December 2023. We consider the following four outcome variables aggregated on a monthly time step at the municipality level over the period 01/2021-12/2023: the total number of booked days, the number of nights booked (total nights during which a listing is reserved), the average daily rate (the price of the listing per night), and the total revenue generated by the hosts. We focus only on listings that include the entire home as a booking and not separate rooms within a dwelling.

We present in Panel D of Table 2 some summary statistics of the AirBnB outcomes. On average, our sample consists of communities with 288 listings, that were booked 365 times for a total of 467 days. The average AirBnB host generated revenue of approximately 906 Euros each month. We again observe quite some heterogeneity in the distribution of our outcome variables with various community-month observations not having any active AirBnB listing. The distribution of most variables seems quite centered, with average and median values being close to each other. Data coverage for the daily rate is slightly lower, as we observe the price only if actual bookings were taking place since the hosts have the opportunity to adjust prices on the platform.

4 Empirical Strategy

We leverage the spatial and temporal variations in the incidence of the 2022's forest fires to first estimate households' behavioral responses along different dimensions that identify demand and supply effects. We consider various types of outcome variables to the study behavioral responses:

[19] AirDNA also collects data from HomeAway. Our analysis focuses exclusively on AirBnB listings since many properties are cross-listed on multiple platforms, making it challenging to distinguish unique listings accurately.

intentions to move based on the SeLoger platform data with different intensities (clicks and leads), intention to sell based on stock and flow of listings on the platform, actual definitive and temporary moving decisions based on mail forwarding contracts for households and firms, and housing market equilibrium outcomes such as the number of transactions, level of prices. Finally, we investigate short-term renting supply and daily rates, and short-terms demand effects based on the number of reservations, reserved days, and revenue through AirBnB data.

To estimate the average treatment effect on the treated (ATT) of the impact of the 2022 forest fires on the various outcomes, we first define group of treated and control regions at the municipality level. On the one hand, the treated municipalities are based on the five severe forest fires that burnt at least 3% of the municipal area between July and September 2022 in the Landes forest (see the Data section) in a single event. The treated region directly impacted comprises of 16 municipalities with burnt surface areas exceeding 3%. We additionally include 104 surrounding municipalities based on a 10 km buffer zone around the most affected area. This inclusion is based on the fact that the entire area is comparable in terms of vegetation and forest fire risk.[20] On the other hand, the definition of the control group of comparable municipalities not impacted by the 2022 fires in the Landes forest results from a two-step matching procedure. In the first step, we define the pool of municipalities from which control municipalities will be selected. We consider all municipalities in mainland France,[21] except for municipalities that themselves experienced more than 3% forest fire related burnt areas[22] or municipalities within the départements of Bas-Rhin, Haut-Rhin and Moselle, due to data availability.[23] From this filtered national pool, we determine the control group based on a matching approach with a ratio of 1:20. In total, our sample consists of 120 municipalities treated and 2,399 control units.[24]

Specifically, our matching approach to determine the control group is based on a "nearest neighbor" method for continuous variables and an "exact matching" method for categorical vari-

[20] We define different buffer zones in our robustness checks.

[21] excluding Corsica (due to its unique geographic and touristic specificities)

[22] this ensures that control units were not directly exposed to severe wildfires since May 1, 2010

[23] The real estate transaction dataset DV3F does for historical reasons not include those regions, see data section.

[24] There is one municipality within the treatment group that could not be matched to 20 control units based on our matching approach and thus only has 19 control units.

ables. We match on four variables: population density, touristic function rate, [25], and a 5-class likelihood score for the estimated occurrence of seasonal wildfires exceeding 20 hectares and a quintile factor variable measuring the median real estate price. This matching procedure is performed for two reasons. On the one hand, we want to ensure that our control group is as comparable as possible to the affected area both in terms of real estate market outcomes as well as in terms of hypothetical forest fire risk. On the other hand, we ensure that our control group is not affected by potential spillover effects from our treatment area, thus limiting the hypothetical pool of control units to a small share of communities spread throughout France but not in close proximity to the affected region (Butts, 2021).[26]

Second, we resort to a synthetic difference-in-difference (SDID) estimator. Indeed, despite our matching approach, a graphical inspection of the evolution of most of our outcomes of interest suggests that there are still potential unobserved influences or seasonality patterns violate the parallel trend assumptions between our treatment area and the control group for a subset of our outcome variables .[27] In order to determine a causal effect, we therefore use a synthetic difference-in-difference (SDID) estimator, which combines the advantages of the difference-in-differences estimator and synthetic control groups (Arkhangelsky et al., 2021). One of the main advantages of SDID is a re-weighting of time periods and observations of the control group to create a weighted average that best matches the pre-treatment evolution of the treated observation. In comparison to the synthetic control method a shift in the level of the observed evolution is viable as long as the evolution is parallel (Abadie, 2021). We define outcomes with the generic variable Y_{it}, which measures the outcome for municipality i in month t.[28] Our estimation model reads as follows:

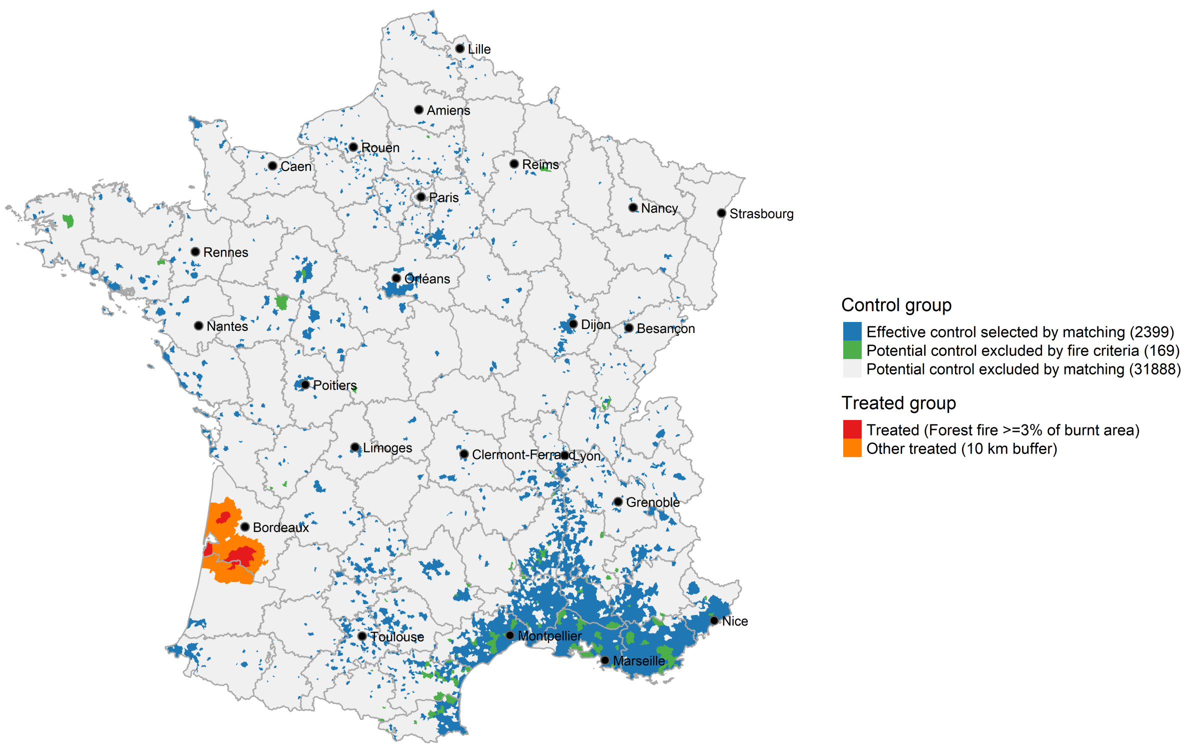
[25] The touristic function rate is defined as the ratio of a municipality's tourist accommodation capacity (i.e., the number of tourists it can accommodate) to the number of permanent residents. This indicator computed by INSEE provides a piece of information on tourism development.

[26] In 2022 there were 34,816 communities in France, which means we only focus on approximately 7% most closely related communities as a control group.

[27] We illustrate in Figure A.2 the average of the monthly incoming and outgoing migration flows between treatment and control group as an example.

[28] The dyadic outcomes based on origin and destination observation are aggregated for a municipality i. Then, three variables for each outcome of interest are defined based on the direction of flow (i.e., outgoing, incoming or internal).

Figure 3: Treated and Control Regions



Note: This map depicts our treated regions, which are communities where more than 3% of the area was burnt in Summer 2022 and the available and set of potential and selected control regions based on our matching approach.

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \arg\min_{\tau,\mu,\alpha,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{1}$$

where treatment assignment is defined in $W_{it} = Fire_t \times Treated_i$. $Fire_t$ is a binary variable equal to 1 in every month past the start of severe forest fires in July 2022, $Treated_i$ is a binary variable equal to 1 if the municipality is in the treated group. The matrix W_{it} summarizes the assignment of individual observations on a community-month level into the groups on these two dimensions.[29] The estimate, $\hat{\tau}^{sdid}$ is obtained from a two-way fixed effect regression in which α_i is a municipality fixed effect and β_t is a month fixed effect. Consequently, the SDID procedure chooses optimal individual weight $\hat{\omega}_i^{sdid}$ and time weight $\hat{\lambda}_t^{sdid}$ in order to match the pre-trends of the control group and treatment group and identifies the average treatment effect on the treated (ATET).

Note that most of our outcome variables of interest, such as clicks, migration flows or number of listings represent count variables that are bounded at zero. The distribution of most variables is centered at or close to zero and has a relatively long tail. To ensure that our model can account for zero observations, but that the effects are not driven by a small number of outlier community-month observations, we transform our dependent variables using the inverse hyperbolic sine transformation. Hence, all our outcomes of interest, Y_{it} are a transformation of the underlying variable in levels (y_{it}):

$$Y_{it} = ihs(y_{it}) = ln(y_{it} + (y_{it}^2 + 1)^{(1/2)}$$

5 Results

In this section, we present our findings. We first present short-term behavioral responses and focus on intentions to move captured by search behaviors. We then investigate supply-side intentions and look into listings. We follow with an analysis of actual moves and, then, of housing market outcomes. We conclude with an analysis of the short-term rental market.

5.1 Effects on Intentions

We first document the effects on intentions captured by online platform search behaviors. In this context, we define intentions as behaviors on the real estate platform that indicate some form of interest but not a formal commitment (yet). We distinguish between supply-side and demand-side related intentions. We define two related supply-side measures of intention to move: the amount of

[29] One can distinguish between four groups, treated-pre-treatment, treated-post-treatment, control-pre-treatment and control-post-treatment. In our setting, the treatment allocation follows a block structure (i.e., each treated unit receives treatment at the same point in time).

active listings on the platform ("stock") as well as the amount of newly listed properties ("flow") in a given month and community. For demand-side measures of intention, we also define two distinct but related measures. First, we measure the number of generated clicks by unique users on the listings, a so-called page view for a listing, and aggregate all clicks at the community-month level. We distinguish between incoming, outgoing, and internal flows based on the origin-destination location pair of each user, given we know the geolocation of the user where the search emerged and the location of the listing. A click on a listing is a relative weak signal of interest. Our second measure is the number of leads, which are requests made to listing advertisers to obtain additional documentation or a potential viewing. Such behavior represents a slightly higher level of intention to move.

Table 3 presents the estimation results of our main specification. The average treatment effect on the treated indicates a significant increase in both the stock and the flow of advertised active listings on the platform (columns (1) and (2)). This means that in the region affected by the fire more properties were advertised in comparison to the control group. On average, in the period after the forest fire, the affected communities had approximately 23% more active listings. This is in line with a 12.4% increase in the average additional flow of advertised listings each month after the forest fire relative to the control communities. These increases in the stock and flow thus suggest that there are more properties being listed on the platform and they, on average, tend to stay online longer.

Looking at the demand-side related measures of intentions, the increase in intention to sell was, however, not necessarily met with an increase in search behaviors. Both internal and incoming migrations, measured by clicks or leads, remain stable between the control and treatment groups following the forest fire. It is important to note here, that this null result captures the interests of new users. Mechanically, one would expect the total number of clicks to increase given that there are more properties available in the impacted regions. However, our demand-side measures of intention rule out this mechanical effect as we deduplicate clicks and leads by the same unique user for a given listing. Hence, our result illustrates that there were neither more nor less interested new users looking at properties in the treated communities relative to the control group.[30]

Looking at intentions to move out of the treated areas, we do not find a significant difference, compared to the control areas, in the search behavior either. Given the increase in advertised listings, one would expect the households to potentially be looking for replacement housing, which would translate into more search behaviors. There are different potential explanations for this result. First, the additional supply on the market might be predominantly secondary properties. In such a case, households might be searching for replacing them. We provide evidence below that such behavior might be present. Second, households who listed their properties after the fire might have been already active in the market prior to the event. Our measure of search intensity captures the behaviors of additional users. If the set of existing users remains the same but searches more, we do not capture the effect. Third, households selling their property might want to understand first what the market value and potential selling price are before searching for a replacement.

Table 3: Demand and Supply effects measured as intentions & search behavior

Dependent variable:	Supply		Demand - clicks			Demand - leads		
	(1) Stock	(2) Flow	(3) In	(4) Out	(5) Int	(6) In	(7) Out	(8) Int
Fire effect	0.2305*** (0.0332)	0.1239*** (0.0305)	0.0741 (0.0629)	0.0214 (0.0331)	0.0013 (0.0208)	-0.0724+ (0.0394)	-0.0412 (0.0300)	-0.0116 (0.0162)
N	90,684	90,684	90,684	90,684	90,684	90,684	90,684	90,684

Note: This table presents the average estimated effect of a synthetic difference in differences specification comparing treated communities with a matched sample of control communities at a ratio 1 to 20 as described in the data section. Standard errors are clustered at a community level and estimated via bootstrap with 100 replications. The dependent variable is indicated in the top row of the table. Treatment is defined as being a community that is within 10 km of communities that had at least 3% of their area burned. In total there are 120 treated communities and 2,399 control communities. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

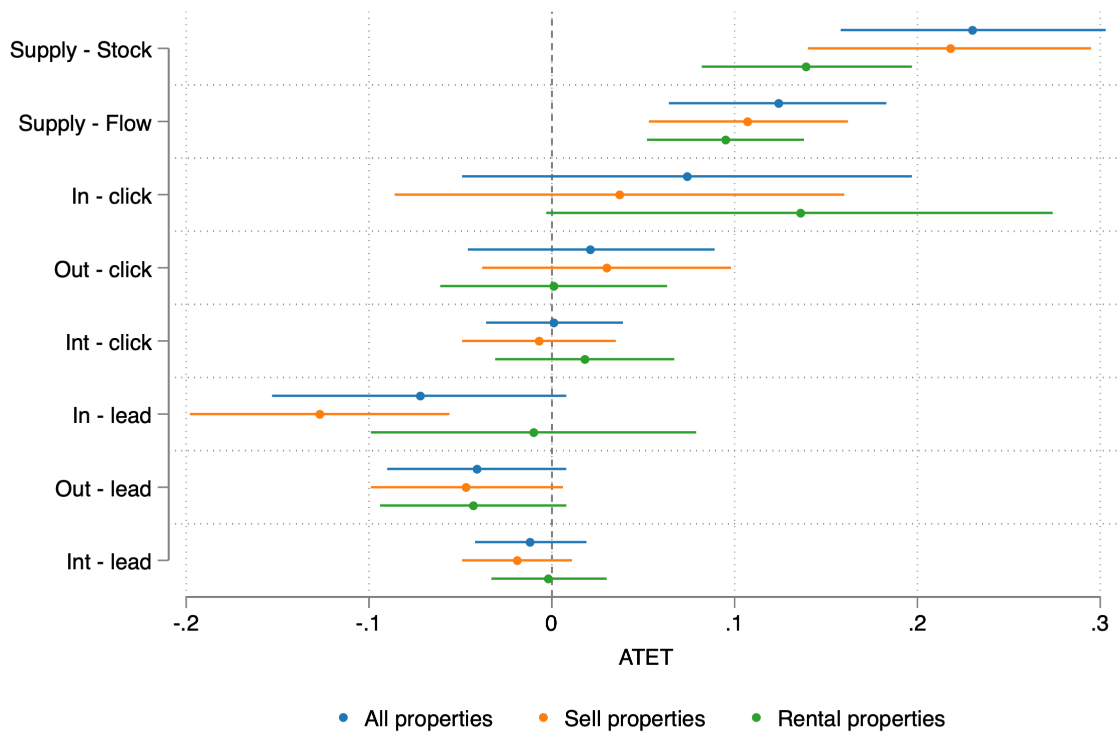
To better understand our results and potential heterogeneity in the effects, we also estimate each of our outcomes for rental and ownership properties separately and depict the results in Figure 4. The stock and flow of both rental and ownership properties are increasing, with a

[30] We do find some evidence for decreased interest to live in the treated communities, when we define demand based on incoming leads. We find a decrease of 7.2% in the number of users that generated a lead for properties listed in the treated communities in comparison to the control groups, but this reduction is marginally statistically significant at the 10% level.

more pronounced supply shock in the ownership market. Furthermore, we also differentiate between houses and apartments. The detailed results are depicted in Figure A.3. These results are consistent with the previous results as we observe a larger increase in houses for sale, which are predominantly offered in the ownership market, relative to apartments.

In terms of search behavior, we do not observe substantial differences between the rental and ownership markets. There is some evidence of a slight increase in click rates on rental properties within the affected area by people living outside. On the other hand, there seems to be a substantial difference in higher commitment interest from people intending to purchase properties in the forest fire area. We find a significant decrease in leads generated by properties in the affected area requested by people living in other areas in comparison to incoming interest into the control group. The outgoing search behavior of people living in the affected area does not appear to significantly differ from the control group in terms of clicks and we find borderline significant effects in terms of a reduction of leads originating in the treated areas. Differences between rental and seller properties are negligible here.

Figure 4: Renter and Seller Market Intentions



Note: This figure presents the estimated coefficients and the corresponding 95% confidence interval from a synthetic DiD estimation with bootstrapped standard errors. Dependent variable according to description on the vertical axis. We differentiate between all properties as the baseline result and between properties for sale and for rental.

There is a small discrepancy in the results between clicks and leads , as it appears that initial interest from people outside the community seems to be unaffected or has even slightly increased, while more serious interest in the form of requests for additional information or viewings is slightly decreased. To ensure that this discrepancy is not caused by misclassification of users' location at the time of their search, we perform an additional estimation. We also estimate the number of clicks from users where we filter observations based on time of the day and only use clicks that occurred between 7pm and 8am. This assumes that during those times of the day most people are at home and thus will be more likely classified to their current residence rather than, for instance, their workplace. The results are presented in Figure A.4.

Overall, the 2022 forest fire led to an economically and statically significant increase in the supply of listed properties for sale in the affected areas. However, this increase in supply was not met with a change in search behaviors either in terms of outgoing, internal, or incoming migrations in the affected areas. These patterns suggest that households had the intention to reduce their financial exposure to such an event by selling their properties but might not have had the intention to migrate to different regions, which suggests that important frictions to migrations exist. Next, we investigate how these intentions translate into actual migrations and impact housing market outcomes.

5.2 Effects on Migrations

We present the estimates for net migrations in Table 4. As before, we differentiate between incoming, outgoing and internal migrations to the affected areas. Furthermore, La Poste data allow us distinguishing between permanent migration and temporary migrations. We do not find a statistically significantly different effect between the affected region and the control area in terms of permanent migration. If anything, migration seems to be slightly hindered, in particular within community moves seem to be slightly lowered. We observe approximately 3.4% less internal moves in the affected area in comparison to the control group in the post-fire period. For temporary moves the effect is slightly lower at 1.9%. Both effects are only marginally statistically significantly different from zero at the 10% level. This pattern of no observed migration flows or even reduced migration flows is consistent with the estimated demand-side intention effects documented above. The increase in the supply of listed properties was, therefore, not met with an increase in search, but also did not lead to an increase in migratory flows.

One challenge to estimate the impact of the forest fire on migration flows is the fact that actual moving, both on the rental and ownership markets, are delayed by administrative procedures. Typically, rental contract have a notice period and selling a property takes time. As discussed before, we lag the moving date observed in La Poste by three months to capture the lag between the decision to move and the actual decision date. To ensure that results are not driven by this

Table 4: Effects on Migration - Permanent & Temporary

Dependent variable:	Definitive			Temporary		
	(1) In	(2) Out	(3) Int	(4) In	(5) Out	(6) Int
Fire effect	-0.0166	-0.0257	-0.0338	-0.0043	0.0007	-0.0186+
	(0.0188)	(0.0195)	(0.0216)	(0.0195)	(0.0137)	(0.0103)
N	85,646	85,646	85,646	90,684	90,684	90,684

Note: This table presents the average estimated effect of a synthetic difference in differences specification comparing treated communities with a matched sample of control communities at a ratio 1 to 20 as described in the data section. Standard errors are clustered at a community level and estimated via bootstrap with 100 replications. The dependent variable is household migration flows and the direction is indicated in the top row of the table. We distinguish between permanent and temporary relocation. Treatment is defined as being a community that is within 10 km of communities that had at least 3% of their area burned. In total there are 120 treated communities and 2,399 control communities. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

hypothesis, we re-estimated the model considering a lag of one and five months. The results are presented in Table Table B.1. There are still no significant effect on either internal or outgoing migration in the affected communities after the forest fire, and we find a small and marginally statistically significant decrease at the 10% level when we lag the incoming migration by five months.

In Table 5 we illustrate the effect of the forest fire on firms' migratory flows. We again use the La Poste data to differentiate between internal, incoming and outgoing migrations from companies. The pattern of migration flows from commercial agents is similar to the one of households. We observe no statistically significant changes in both outgoing and incoming migratory flows between the treatment and control groups following the fires. There is a small decrease in within-community moves in the treatment region following the fires. This effect, however, is again only statistically significant at the 10% level.

Table 5: Effects on Migration - Companies

Dependent variable:	Firm migration		
	(1) In	(2) Out	(3) Int
Fire effect	0.0018	-0.0027	-0.0152
	(0.0130)	(0.0124)	(0.0095)
N	85,646	85,646	85,646

Note: This table presents the average estimated effect of a synthetic difference in differences specification comparing treated communities with a matched sample of control communities at a ratio 1 to 20 as described in the data section. Standard errors are clustered at a community level and estimated via bootstrap with 100 replications. The dependent variable is migration flows from companies and the direction is indicated in the top row of the columns. Treatment is defined as being a community that is within 10 km of communities that had at least 3% of their area burned. In total there are 120 treated communities and 2,399 control communities. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

5.3 Effects on Housing Market

How did the increase in the supply of listed properties impacted the housing market? In this subsection, we study the impact of the 2022 forest fires on the number of transactions and housing market prices using the same empirical strategy. In Table 6, column (1) shows that there was an economically and statistically significant increase in the number of transactions in the impacted regions—an increase of approximately 8% compared to the control region. In column (2) of Table 6, we report the estimate on transaction prices, which is positive, small, but not statistically significant.

As for the migration data, both the price and the number of transaction variables are lagged by three months to account for a lag in adjustments in the housing market in response to the forest fires. To assess the robusteness of our results with respect to this assumption, we lag the outcomes by one month or five months. The results are presented in Table B.2. When we reduce

Table 6: Effects on Markets - Real Estate & AirBnB

Dependent variable:	Real estate		Air BnB				
	(1) Trans.	(2) Price	(3) List	(4) Res.	(5) Days	(6) Rev.	(7) Rate
Fire effect	0.0802***	0.0261	0.0576+	0.0951*	0.1280+	0.1792	-0.0269
	(0.0202)	(0.0168)	(0.0322)	(0.0469)	(0.0704)	(0.1308)	(0.0471)
N	68,013	54,864	90,684	90,684	90,684	90,684	73,980

Note: This table presents the average estimated effect of a synthetic difference in differences specification comparing treated communities with a matched sample of control communities at a ratio 1 to 20 as described in the data section. Standard errors are clustered at a community level and estimated via bootstrap with 100 replications. The dependent variables are real estate transactions, transaction prices and AirBnB market outcomes. For AirBnb we observed listings, reservations, reserved days, revenue and daily rates. Treatment is defined as being a community that is within 10 km of communities that had at least 3% of their area burned. In total there are 120 treated communities and 2,399 control communities. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

the lag, the effect for the number of transactions is slightly smaller but still present; when we increase the lag, the effect is slightly larger. In both specifications, the direction and extent of the effects are similar, and the point estimates are not statistically significantly different from the estimate of the baseline specification. As previously we find no effect on real estate market prices.

Overall, the results suggest that the 2022 forest fires moved the housing market to an equilibrium where more properties were offered, and eventually sold in the impacted areas. At the same time, there is weak evidence that the event led to a change in the intention and actual migrations. This suggests that households' first adaptation margin to such a shock was to reduce the exposure to their housing capital by selling properties. However, without a change in the net flow of households in the impacted regions, an increase in housing transactions can only be possible if there is an active secondary-home market, which we investigate next.

5.4 Effects on Short-Term Rentals

In France, the secondary home market has always been historically important, especially in tourist regions such as the ones impacted by the 2022 forest fire. In recent years, short-term rentals through the AirBnB platform have become an important drivers in local housing market. In our housing transaction data, we do not observe what property sold was used for before and after the transactions, which would have allowed to test directly whether the increase in listed and sold properties were primarily directed for the secondary market, and short-term rentals. As an alternative, we investigate directly the impact of the 2022 forest fires on properties offered through the AirBnB platform.[31]

In columns (3) - (7) of Table 6, we document three results. First, there is a significant increase in additional properties listed on AirBnB after the forest fires. In particular, we find that there are approximately 5.8% more listings in the treated areas post-fire. Second, these additional listings were also accompanied by an increase in the number of reservations of 9.5% and the number of days reserved of 12.8%. Finally, we do not observe significant changes in terms of total revenue and daily rates, which are both not statistically significantly different from zero. However, the signs of the effects suggest that the increase in listings on Airbnb, which are also met with more demand, was also accompanied by slightly lower prices per day.

There are two potential forces in the short-term rental market that could explain our results. First, investors who have been observing the market in the Landes region took advantage of the increase supply in properties due to the fire to purchase secondary homes as investment property. Second, existing homeowners might have decided to list their property as a temporary investment, while they were not yet able to find sellers at their desired conditions.

5.5 Robustness Checks

We conduct a series of robustness checks to asses our hypotheses in constructing the outcome and treatment variables, empirical specifications, and estimation procedures. In the previous subsections, we already presented some robustness checks, where we control for specific variable definitions within the subgroup of variables, such as the lagged period in housing transactions and migratory flows, as well as the distinction between clicks filtered based on the time of the day or not. In this subsection, we present a comprehensive set of robustness checks for our empirical

[31] focus on AirBnB outcomes that relate to entire property listings. Hence, we filter for listings that rent-out the entire house or apartment, but not single rooms within an apartment.

strategy, which we apply for all our main outcomes of interest. We conduct the following four additional estimations: Inference via jackknife instead of bootstrapped standard errors, reduced treatment radii of 5Km around the affected area or 0Km (i.e., only directly affected communities) and outcome measure aggregated on a quarterly level. These robustness checks allow us to illustrate whether our results are pre-dominantly driven by specification decisions or if they are robust to different procedures or data aggregation. The quarterly aggregation in particular is motivated by accounting for potential seasonality patterns in real estate markets to ensure that our results are not driven by few outlier observations in particular month-community combinations.

We follow the previous outline and document the additional estimation in separate graphs again differentiating into listings and search effects, migration effects, housing market, and short-term rental outcomes. The results are depicted in Figure A.5, Figure A.6 and Figure A.7. The results with respect to platform behavior are relatively robust and similar. We still document an increase in both additional listings as well as listings being online in each specification. In terms of demand-side measure of intentions to move, both measured with clicks and as requests for additional information, the pattern is also consistent. The confidence intervals of the results from the zero treatment radius specification are relatively wide. This is predominantly due the a reduction in sample size. In our baseline specification with the 10Km treatment radius, 104 communities were treated. Once we remove the radius from the treatment definition, only includes 16 communities are in the treatment group. The specification with a zero treatment radius is also the one that offers results that differ with respect to the migration outcomes. If we only consider the 16 communities that were directly impacted by the forest fires, we do observe a statistically significant effect on incoming migration flows. Results for both outgoing and internal flows remain consistent and also the results for temporary and firm migration remain the same, i.e., close to zero. In terms of housing market outcomes, the results remain consistent and unchanged between the different specifications. We still document a modest increase in transactions with unchanged or slightly increased prices. In terms of AirBnB, there are more property listings, that are reserved more often and for longer periods, but do not necessarily lead to higher revenue or higher rates.

6 Conclusion and Further research

We investigate the role of a near-miss extreme climatic event as a driver of household adaptation. The 2022 forest fires in the Landes forest offer an ideal natural experiment to test how an extreme climatic event, with potentially severe impacts but that did not cause large-scale material or human damages, can act as an information shock. We use rich and comprehensive data to document the different margins of adaptation and the sequence by which households respond to such a shock. At the onset, we study supply and demand-driven intentions to migrate. We find an economically large increase in listed properties in the impacted region but not a significant increase in new households looking for properties. Households' adaptation response thus starts with the intention to liquidate housing assets before searching for a new location.

Neither the increase in listed properties nor the small changes in search behavior translate into changes in migratory flows. Migration frictions were thus more important in comparison to the potential change in perceived risks induced by the forest fires. Although the 2022 Landes fire was France-second largest in its history, it was not a catalyst for households' adaptation behaviors. This question the role of near-miss extreme climatic events as a substitute of other adaptation policies that aim to inform households.

Although there were no significant changes in households leaving the affected area, there was, nonetheless, an increase in the number of transactions in the impacted region. We posit that the secondary-home market played an important role in this context. We find evidence of an increase in activity in the short-term Airbnb market, which suggests that new buyers were investors and not actually primary residents who moved into the affected areas. This result suggests an important but underlook mechanism by which local housing market could adapt to climate risks. The secondary-home market offered for short-term rentals may hold more value in regions exposed to extreme but infrequent climate risks.

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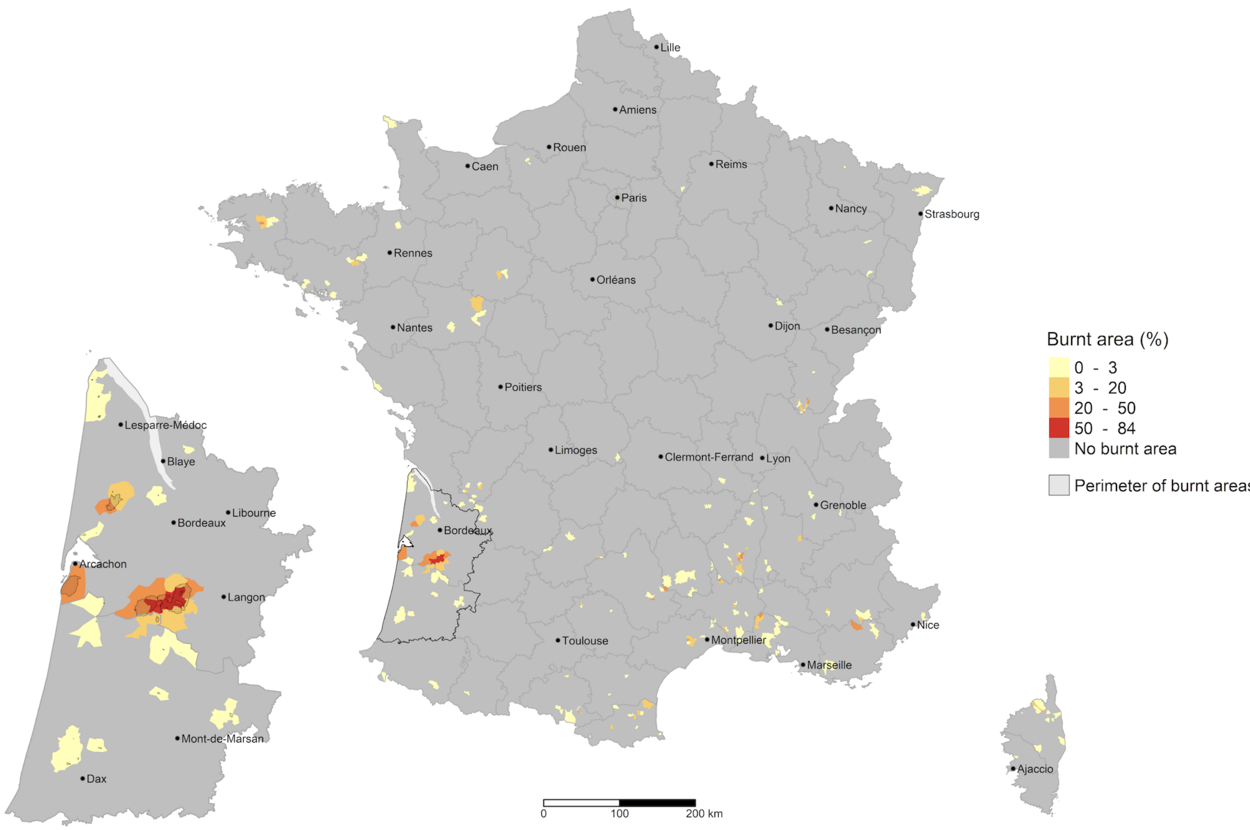
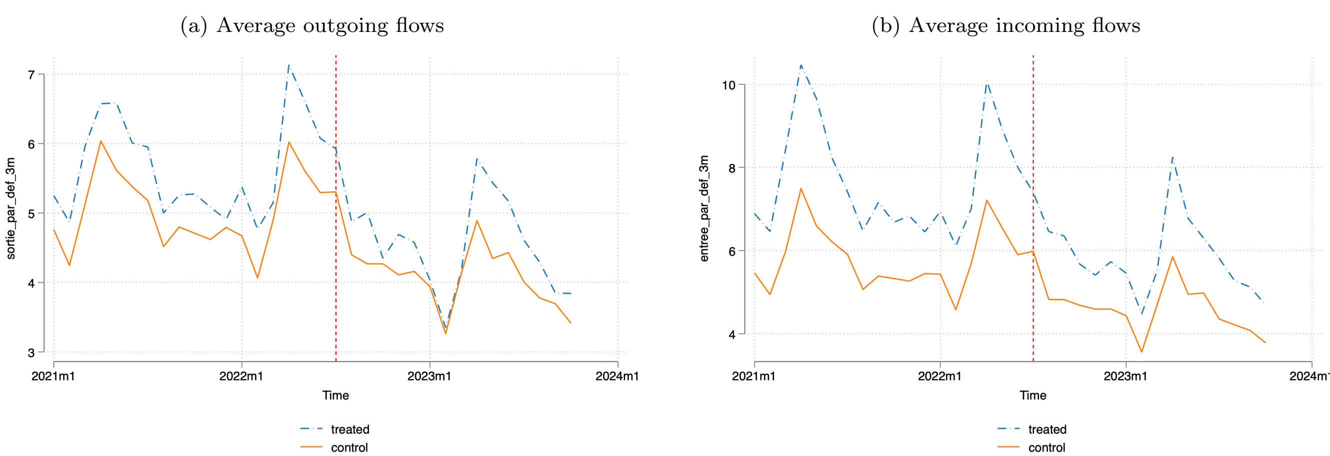
A Additional Figures

Figure A.1: Percentages of burnt areas by community



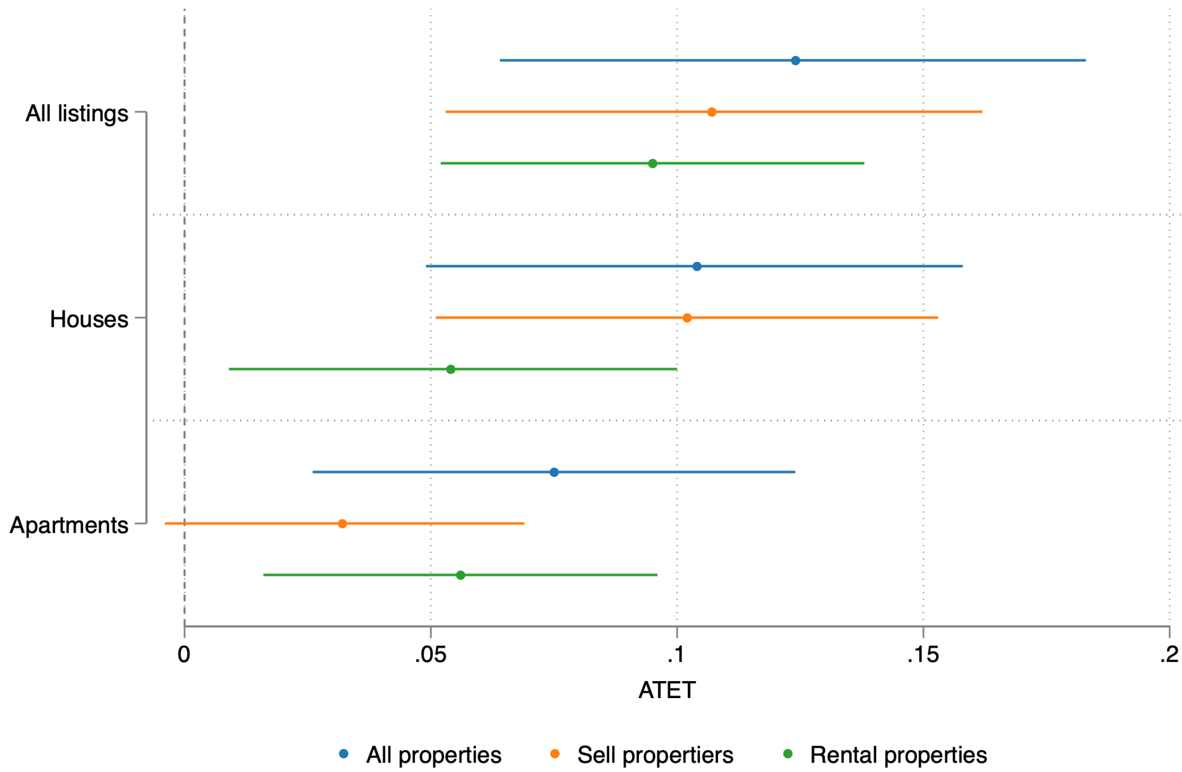
Note: This figure presents the share of burnt area on a community level in the year 2022 only accounting for fires between May and September. The share is calculated based on the forest fire footprints from EFFIS.

Figure A.2: Evolution of Migration Levels



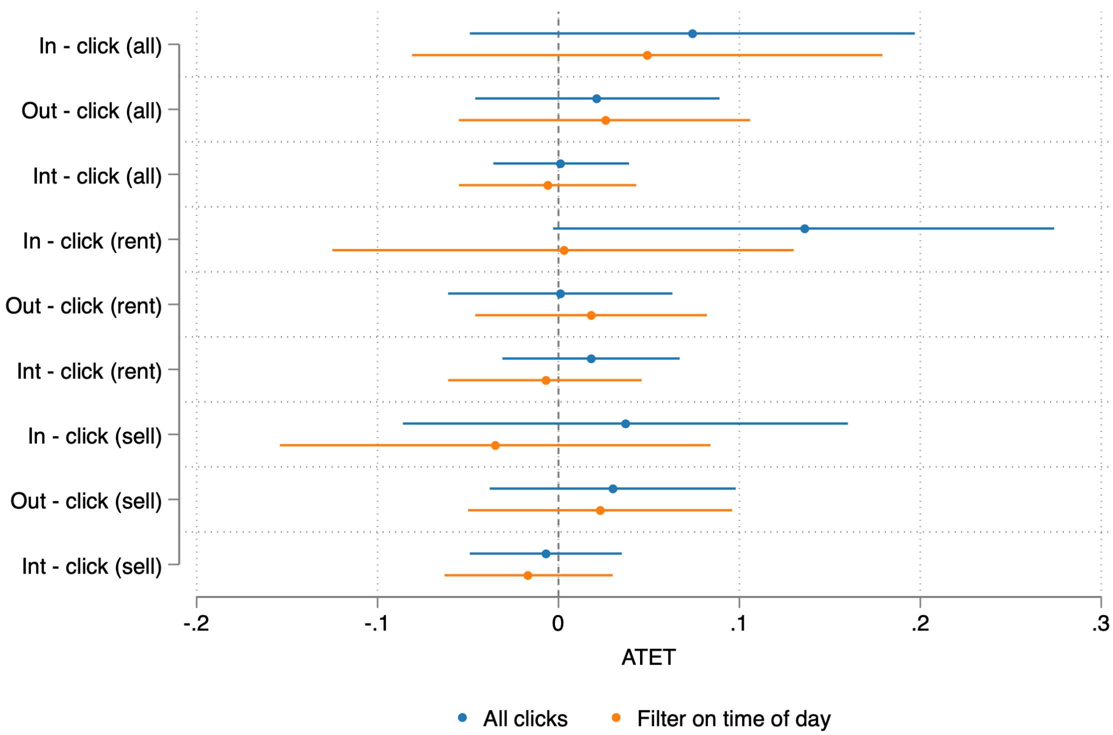
Note: The left graph depicts the average number of outgoing migration flows between our treatment and our control group depicted for each month. The right graph illustrates the same aggregate measure for incoming flows.

Figure A.3: Additional Listings - By Dwelling Type



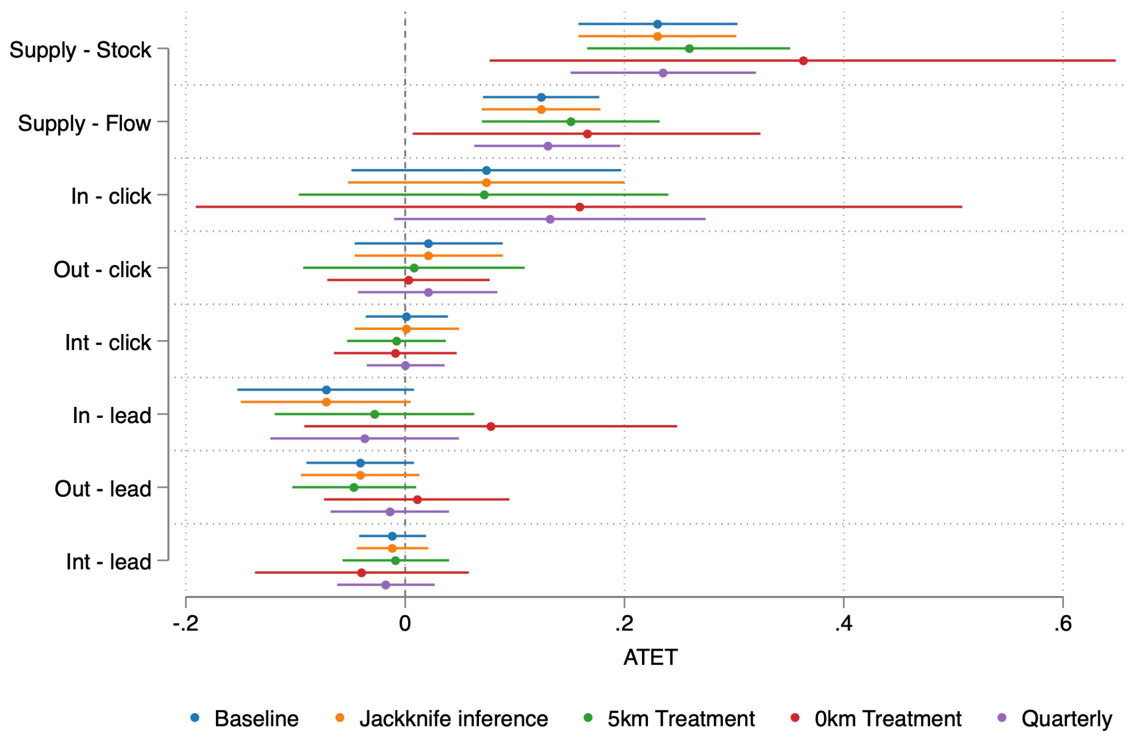
Note: This figure presents the estimated coefficients and the corresponding 95% confidence interval from a synthetic DiD estimation with bootstrapped standard errors. Dependent variable according to description on the vertical axis measures the monthly additional number of advertisements with a category and community. We differentiate between all properties as the baseline result and between properties for sale and for rental.

Figure A.4: Number of clicks - overall and filtered



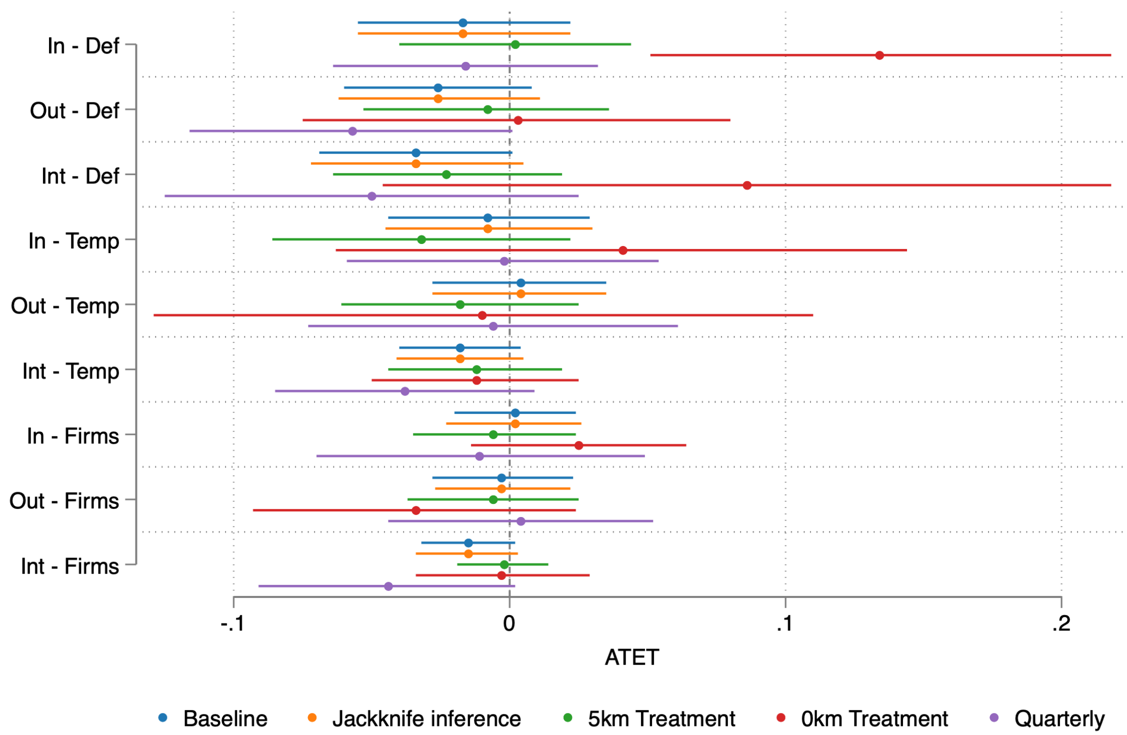
Note: This figure presents the estimated coefficients and the corresponding 95% confidence interval from a synthetic DiD estimation with bootstrapped standard errors. Dependent variable according to description on the vertical axis. We differentiate between all searches and filtered searches occurring between 7pm and 8am and thus likely geocoded to current place of residence.

Figure A.5: Robustness - Listings & Search Behavior



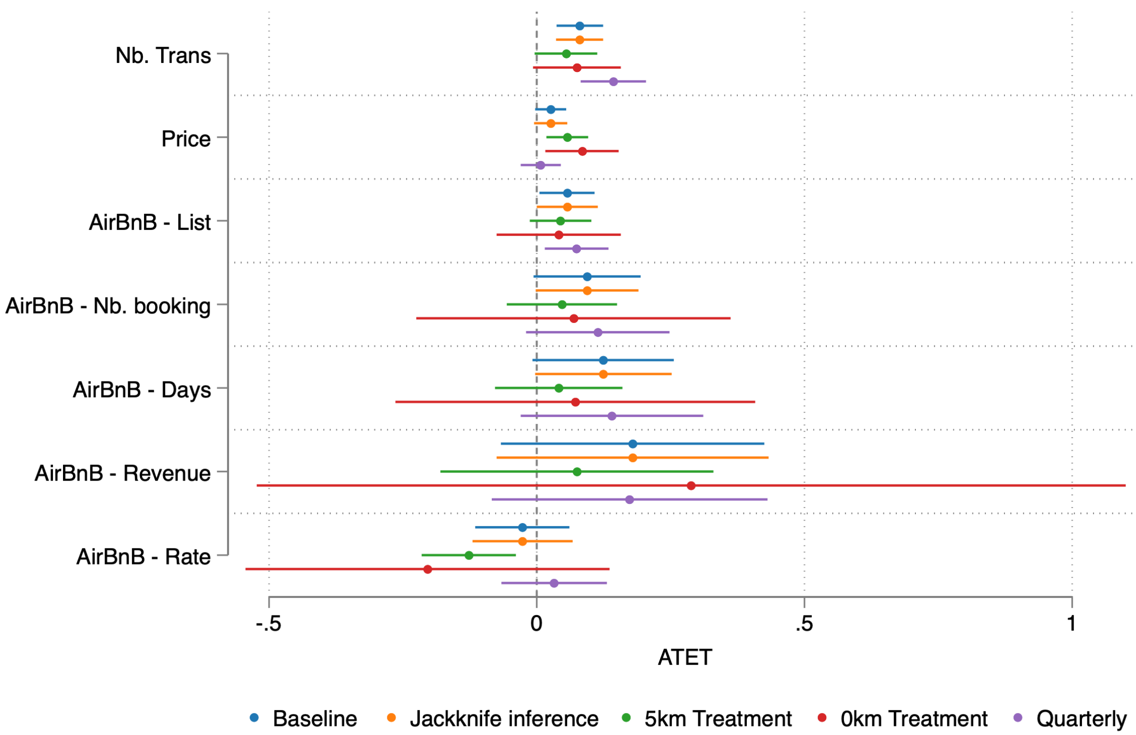
Note: This figure presents the estimated coefficients and the corresponding 95% confidence interval from various synthetic DiD estimations. Dependent variable according to description on the vertical axis. We illustrate the baseline model of a 10Km Treatment radius with bootstrapped standard errors on a month-community level and compare the results to alternative specifications. Jackknife is a different inference method with the same result. 5Km and 0Km are reduced treatment radii definitions and quarterly represents a dataset aggregated on a quarter-community level.

Figure A.6: Robustness - Migration



Note: This figure presents the estimated coefficients and the corresponding 95% confidence interval from various synthetic DiD estimations. Dependent variable according to description on the vertical axis. We illustrate the baseline model of a 10Km Treatment radius with bootstrapped standard errors on a month-community level and compare the results to alternative specifications. Jackknife is a different inference method with the same result. 5Km and 0Km are reduced treatment radii definitions and quarterly represents a dataset aggregated on a quarter-community level.

Figure A.7: Robustness - Real Estate Markets



Note: This figure presents the estimated coefficients and the corresponding 95% confidence interval from various synthetic DiD estimations. Dependent variable according to description on the vertical axis. We illustrate the baseline model of a 10Km Treatment radius with bootstrapped standard errors on a month-community level and compare the results to alternative specifications. Jackknife is a different inference method with the same result. 5Km and 0Km are reduced treatment radii definitions and quarterly represents a dataset aggregated on a quarter-community level.

B Additional Tables

Table B.1: Effects on Migration - Robustness

Dependent variable:	1 month lag			5 month lag		
	(1) In	(2) Out	(3) Int	(4) In	(5) Out	(6) Int
Fire effect	0.0021 (0.0164)	-0.0138 (0.0181)	-0.0138 (0.0163)	-0.0340+ (0.0186)	-0.0189 (0.0187)	-0.0253 (0.0167)
N	90,684	90,684	90,684	78,089	78,089	78,089

Note: This table presents the average estimated effect of a synthetic difference in differences specification comparing treated communities with a matched sample of control communities at a ratio 1 to 20 as described in the data section. Standard errors are clustered at a community level and estimated via bootstrap with 100 replications. The dependent variable is household migration flows and the direction is indicated in the top row of the columns. Treatment is defined as being a community that is within 10 km of communities that had at least 3% of their area burned. In total there are 120 treated communities and 2,399 control communities. In comparison to Table 4 we lag the flows here by either 1 month or 5 month instead of 3 months. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table B.2: Effects on Real Estate Markets - Robustness

Dependent variable:	1 month lag		5 month lag	
	(1) Trans	(2) Price	(3) Trans	(4) Price
Fire effect	0.1013*** (0.0187)	-0.0153 (0.0197)	0.0719** (0.0261)	0.0070 (0.0176)
N	73,051	57,681	62,975	54,150

Note: This table presents the average estimated effect of a synthetic difference in differences specification comparing treated communities with a matched sample of control communities at a ratio 1 to 20 as described in the data section. Standard errors are clustered at a community level and estimated via bootstrap with 100 replications. The dependent variable is household migration flows and the direction is indicated in the top row of the columns. Treatment is defined as being a community that is within 10 km of communities that had at least 3% of their area burned. In total there are 120 treated communities and 2,399 control communities. In comparison to Table 6 we lag the flows here by either 1 month or 5 month instead of 3 months. + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.