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Behavioral changes in the housing market before and after the Covid-19 lockdown☆

André Kallåk Anundsen [a,*], Bjørnar Karlsen Kivedal [a,b], Erling Røed Larsen [a,c], Leif Anders Thorsrud [c]

[a] Housing Lab, Oslo Metropolitan University, Norway
[b] Østfold University College, Norway
[c] BI Norwegian Business School, Norway

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ABSTRACT

We exploit unique Norwegian day-by-day transaction and hour-by-hour bidding logs data in order to examine how market participants reacted to the spreading news of Covid-19 in early March 2020, the lockdown on March 12, and the re-opening on April 20. We observe changes on the date of the lockdown in transaction volumes, sell-prediction spreads, exploitative bidding behavior, and seller confidence. However, when we compare observed price developments with our estimated counter-factual price developments, we find that about half of the total fall in prices had already occurred before the lockdown was implemented. The re-opening completely reverses the lockdown effect on prices. We show that voluntary behavioral changes, as well as lockdown and re-opening effects, are visible in various measures of social mobility, and that changes in daily news sentiment correlate with the abnormal price movements during this period.

1. Introduction

The Covid-19 pandemic has sparked an on-going debate on how to balance positive medical results against negative economic outcomes. If the negative economic outcomes in the Spring of 2020 were fully caused by policy interventions, such as lockdown policies, the exact design of such policies are crucial. On the other hand, if the negative economic outcomes were mostly driven by voluntary and precautionary behavior among market participants, the role of policy intervention is less clear. In fact, a governmental induced lockdown might actually have a positive effect if it facilitates coordinated action among market participants and reduces uncertainty. This article uses novel Norwegian housing market data with ultrahigh granularity and asks three questions: (1) What changes in behavior do we detect in the days before the lockdown of Norway on March 12? (2) How large were reductions in transaction volumes, sell prices, and bidding activity in the days immediately following the lockdown? (3) What results do we observe following the partial re-opening on April 20?

The answers we find to these questions indicate that precautionary behavior put transaction volumes and sell prices on a downward trend before the lockdown on March 12. The lockdown itself is also associated with further reductions in transaction volumes and sell prices. House prices in the seven-day period between March 6 and March 12 were 3.7 percent lower than the estimated counter-factual without Covid-19, and house prices during the period March 13 to March 19 were 7.3 percent lower than the estimated counter-factual without Covid-19 and the lockdown on March 12. These results indicate both a voluntary behavior effect before lockdown and an additional policy effect after lockdown. We believe the key economic lesson from our study is that people voluntarily changed behavior before the lockdown policy. We document this change. The implication of these behavioral changes is that the proposition that it was the lockdown that impacted the economy negatively is incomplete. The takeaway is that without governmental intervention it is probable that behavioral changes in themselves could have affected the economy. However, although we do detect a change in our measure of economic sentiment, we do not find a similar clear change in the stock market, thus we cannot interpret our findings to encompass all sectors.

After the re-opening on April 20, transaction volumes and sell prices increased substantially. Moreover, we find that the tendency among bidders to extend lower opening bids relative to the ask price after

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* Corresponding author.
E-mail address: andrekal@oslomet.no (A.K. Anundsen).

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the lockdown. Sellers, on the other hand, display a higher tendency to accept lower bids after the lockdown. These tendencies are reversed after the re-opening.

We further triangulate the validity of our findings by holding them up against patterns from measures of social mobility and a unique daily business cycle sentiment index derived from news media coverage. Patterns in all of these datasets are consistent with what we find in the housing market. That is, voluntary behavioral changes, as well as lockdown and re-opening effects, are clearly visible in social mobility data, indicating that market participants indeed follow policy guidelines. Moreover, changes in daily news sentiment correlate with abnormal price movements during this period.

These findings are important for at least four reasons. First, they are important for policy. After lockdown, several commentators were seen to claim that the policy adversely affected the economy. However, such claims may be insufficient as explanations of the economic downturn. Our findings indicate that the economy would not have been unaffected had one not implemented policies. On the contrary, the economy would have been adversely affected even without policy interventions, due to voluntary adjustments in behavior. People responded to the Covid-19 pandemic, not only to the Covid-19 policies. This finding is not only consistent with Correia et al. (2020), who studied the Spanish flu, but also provides important empirical input to policy in the case of additional Covid-19 waves or future pandemics.

Second, not only is the housing market a liquid market involving asset values of such magnitudes that buyers and sellers make informed and well-thought-through decisions, it also has features found in a broad spectrum of other markets. It has a physical component in that buyers seek to inspect the house thoroughly before buying in order to examine the match between own preferences and house attributes. It has a digital component, since sellers advertise online and realtors may offer virtual tours in lieu of open houses. It has a financial component because the price is multiples of annual income. Finally, it is a necessary good because everybody needs shelter and somewhere to stay and sleep, but it has luxury components since the quality and address signal status. This makes the analysis relevant for also understanding developments in other markets.

Third, housing market developments are important for macroeconomic fluctuations (see e.g., Leamer (2007, 2015), Mian and Sufi (2011), Mian et al. (2013), Mian and Sufi (2014), and Aastveit et al. (2019)). That is, the aggregate value of homes affects aggregate household equity, and aggregate household equity affects aggregate demand. Since being able to move house oftentimes is a necessary condition for changing jobs, changes in house prices also affect labor market outcomes (Brown and Matsa, 2020). Moreover, the values at risk by Covid-19 measures were, and still are, substantial. Using Norway as an example, the market value of the housing stock is at approximately 2.5 times GDP.[1] What happens in a market with such aggregate value of assets affects the whole economy through e.g. wealth effects.

Fourth, the timeline of the spread of Covid-19 in Norway and the subsequent policy interventions is representative of much of Western Europe. In Norway, the first case of Covid-19 was registered on February 26. The news affected at least non-economic behavior, and individuals started to take precautionary steps. In the days leading up to the lockdown, parents kept kindergarten children and school pupils at home and refrained from usual leisure activities. Companies issued statements in which employees were encouraged to work from home. The Norwegian government ordered a lockdown in the afternoon on Thursday March 12. Employees were then ordered to work from home, schools were closed, and a number of non-essential businesses were shut down. The activity in the Norwegian economy decreased immediately and substantially. Monetary policy was changed on March 13 and March 20 by interest rate reductions – although it took some weeks before this was passed through to mortgage rates. On April 7, the Norwegian government announced a partial re-opening of the economy, starting on April 20. Thus, even if the Norwegian housing market is small and peripheral in the world economy, it may still be a market laboratory within which observers can study effects with a high degree of temporal resolution. In particular, we point to the temporal granularity of our daily data, which allows us zoom in on the days before and after policy.

Results from the analysis just before and just after the lockdown have the clearest causal interpretation. The reason why is that the behavioral changes before the lockdown cannot have been caused by policy changes that had not yet been implemented. The discontinuity in market effects on the lockdown date may plausibly be attributed to the lockdown. We substantiate this claim by showing that in placebo years differences before and after March 12 are statistically insignificant; only in 2020 is the difference statistically significant. However, in the interim period between the lockdown and the re-opening, the interpretation becomes more tenuous since the economy was affected by multiple of events and policies: (i) spreading news about Covid-19, (ii) spreading cases from Covid-19, (iii) the lockdown on March 12, (iv) monetary policy changes (interest rate cuts), and (v) fiscal policy changes (support packages). We do not attempt to differentiate between (i)–(v); we only estimate the difference between the actual and the counter-factual price development. Obviously, the motivation behind (iv) and (v) is to mitigate the economic effects of (i)–(iii).

Our analysis is based on daily transaction data and bidding logs in addition to a daily sentiment index, traffic data, and Google mobility data. Both the transaction data and the bidding logs originate from the institutional arrangement in Norway that all sales are arranged as ascending bid auctions, in which bids are legally binding and may be placed on digital platforms. The transaction data include the date on which the highest bid was accepted. Since bids and acceptances of bids are legally binding, transfer of ownership is legally locked-in on this date. This is a key attribute of the data because it lets us construct a daily house price ticker. Since the data also include hedonic attributes, we are in a position to control for composition and quality effects. The bidding logs are sourced from the same sales process, but also include the date and the time (in hours and minutes) when a bid was placed and the date and time of its expiry, in addition to unique bidder, realtor, and unit identification. This makes it possible to extend the analysis from only observing the outcome, i.e. the sell price, to also including observations on behavioral input into the process, i.e. the bids.

The methods we use are straight forward. In order to analyze the effects on prices, we first estimate a hedonic time dummy model that serves as a benchmark. The model involves a regression of the sell price onto a space spanned by a second order polynomial in size, type of house, type of ownership, type of lot ownership, dummies for number of bedrooms, zip codes, calendar month, Easter, Winter vacation, year, and weekdays. We then estimate the model using data prior to the period we study, i.e. from January 2, 2010, to February 13, 2020. Using this model, we predict prices, in a way that accounts for seasonal effects and intra-week price variation (Røed Larsen, 2021), from February 14 to April 30, 2020, and compare predicted prices with observed sell prices. As an extra precaution in handling intra-week prices, our chosen analytical periods are always multiples of weeks. The resulting spread, the difference between sell prices and predicted prices on predicted prices, are used to construct a daily ticker. This is our estimate on the difference between counter-factual developments in sell prices in absence of Covid-19 and policy interventions, and actual developments in sell prices with the presence of Covid-19 and policy interventions.

We also probe deeper by investigating seller and buyer behavior. We find a reduction in the number of clicks on internet ads in the weeks prior to lockdown, and that the number of ad clicks decreases

[1] The Norwegian GDP for the year 2017 in market value is 3300 billion NOK; see http://www.ssb.no. The firm Eiendomsverdi computed the market value of the Norwegian housing stock in September 2017 to be 8000 billion NOK (contact eiendomsverdi.no).

further after lockdown is implemented. The same is true for number of showings. While the number of viewers at the open house remains unchanged in the weeks preceding lockdown, it decreases markedly after lockdown. Number of bids and number of bidders reflect the extensive margin of bidding. The reason why is that when there are fewer bidders, sellers realize that the probability of a bidding war (Han and Strange, 2014) is small. Conversely, when there are multiple bidders, the probability of a bidding war is higher. Bidding wars are associated with higher sell prices. There are no changes in number of bids and number of bidders in the period we study, suggesting that the extensive margin is unaffected by the pandemic and the policy intervention. Since there is a clear reduction in number of viewers, we interpret this as an indication that the threshold for visiting the open house is increased, so that only people with a sufficient interest in purchasing the property visit the showing.

In order to study the intensive margin, we consider two measures: The first measure investigates whether buyers try to exploit the uncertainty induced by the pandemic. For this purpose, we construct an exploitative-bidding measure based on the percentage spread between an auction's opening bid and the ask price. Our second measure monitors the extent to which sellers want to off-hand the unit before things get worse. For this, we construct a seller confidence metric based on the spread between an accepted bid and the highest formerly rejected bid. We find that bidders' propensity to extend exploitative bids increases before the lockdown is implemented, which is consistent with behavioral changes among prospective buyers. After lockdown, we find a marked drop in seller confidence and a further increase in the propensity to extend exploitative bids.

This article foremost speaks to a growing literature investigating the economic consequences of the Covid-19 pandemic. The earliest batches of the Covid-19 literature were either theoretical studies of optimal control or macro-simulations (see e.g. Eichenbaum et al. (2020), Alvarez et al. (2021), Atkeson (2020), Baker et al. (2020), Caballero and Simsek (2020), Guerrieri et al. (2022), and Stock (2020)) or empirical studies of earlier pandemics (see Barro et al. (2020), Correia et al. (2020), Hassan et al. (2020), and Moser and Yared (2022)). A bouquet of other studies include Coibion et al. (2020), who used a large-scale survey to assess labor market effects; Ramelli and Wagner (2020), who look at stock prices; and Huang et al. (2020), who ask how to save China from an economic meltdown in the aftermath of the disease. Nicola et al. (2020) and Brodeur et al. (2021) provide overviews of how Covid-19 may affect different parts of the economy differently.

In a study of the 2003 SARS epidemic and the housing market, Wong (2008) found that property prices in Hong Kong dropped between 1–3 percent. However, effects of Covid-19 on the housing market is largely unexplored. Del Giudice et al. (2020) investigate effects of Covid-19 on the housing market in the region of Campania in Italy. However, they simulate the effects of Covid-19 on the housing market based on findings in the previous literature on the effects of crises, such as natural disasters and terrorism, and use data until 2019. The paper most related to ours is D'Lima et al. (2022), who look at house prices and listings in the U.S. during the Covid-19 pandemic. They find no effect on property prices, but document a drop in listings. Our paper is different from theirs in several ways. First, we study both policy effects and behavioral changes. Second, we dig into both buyer and seller behavior before, during, and after lockdown.

The novelty of our study lies in the application of using daily data from the housing market. This allows for a unique analysis of how households responded to the pandemic, both in the days prior to policy interventions as well as in the days following policy intervention. As such, although our contribution is foremost about housing market developments, it documents empirical patterns that are relevant for understanding expectation formation and the role of governmental intervention at a more general level.

The article is organized in the following way. The next section describes the data, the institutional setting, and presents the empirical techniques, while Section 3 lays out the empirical results. The final section summarize and suggests a few policy implications.

2. Institutional background, data, and empirical approach

In the following section, we first outline the institutional background of the Norwegian housing market. Next, we show a brief timeline of Covid-19 events in Norway, before we present the transaction and auction data. Finally, we outline our empirical approach.

2.1. Institutional background

The Norwegian housing market is organized in a way that makes it possible for buyers and sellers to interact and communicate seamlessly. When sellers want to sell their units, they place online advertisements on Finn.no. In this advertisement, the seller includes photos, a thorough description, an ask price, and an announcement of a date for an open house (public showing). Prospective buyers search the platform Finn.no, and make a short-list of which open houses to visit.

Shortly after the open house (typically the day after the last showing), an ascending bid English auction is arranged. Bids are placed by telephone, fax, or electronic submission using digital platforms. The realtor informs the participants (both active and inactive) of developments in the auction. Both bids and acceptances of bids are legally binding. Thus, the transfer of ownership is essentially locked-in at the exact moment a bid is accepted. The seller may decline any bid – even bids that are above the posted list price – and announce a new showing without adjusting the list price. While the seller has the right to decline any bid, it is illegal for the realtor to be involved in sales with an artificially low ask price. A realtor may therefore face the risk of being reported to the authorities for knowingly mispricing the unit if bids at, or above, the ask price are rejected.

When the auction is completed, every participant in the auction is entitled to see the bidding log, which provides an overview of all the bids that were placed during the auction. The timing is precisely logged by the realtors bid log system. It is this pair of date and time this article uses in the examination of the timeline of events.

In Norway, the time-on-market (TOM) typically is low, and in the capital Oslo, TOM often is less than four weeks and relatively frequently even lower than two weeks. Real Estate Norway reported that for March, 2020, the average TOM for Norway was 51 days and 20 days for Oslo.[2]

A detailed description of the institutional setting in Norway can be found in Anundsen et al. (2022).

2.2. Timeline of events

The first infection in Norway was announced in major media outlets late in the evening of February 26, 2020. In Fig. 1, we denote this event as the first of four major events in the development of the Covid-19 situation in Norway. The media coverage in early March was symptomatic for an increasingly worried population. As the situation in Italy grew worse and became acutely desperate, Norwegians also talked about what to do. Several companies instituted work-at-home policies. In many work-places, strategies and contingency plans were being sketched out.

The second key date was March 12. During that day, news came in that several Norwegian municipalities would implement local school shut-downs. Also, there were reports of nervousness in the population and that parents had kept pupils at home.[3] In the afternoon of March 12, on 2:00 PM, the Norwegian Prime Minister held a press conference

[2] Descriptions and reports in English here: https://eiendomnorge.no/housing-price-statistics/category936.html.

[3] The day before, March 11, the Danish Prime Minister had announced that Denmark would implement a lockdown. It is not unlikely that the actions taken in several Norwegian municipalities were linked to the Danish policy announcement, as Norway and Denmark share a long history and strong cultural bonds.

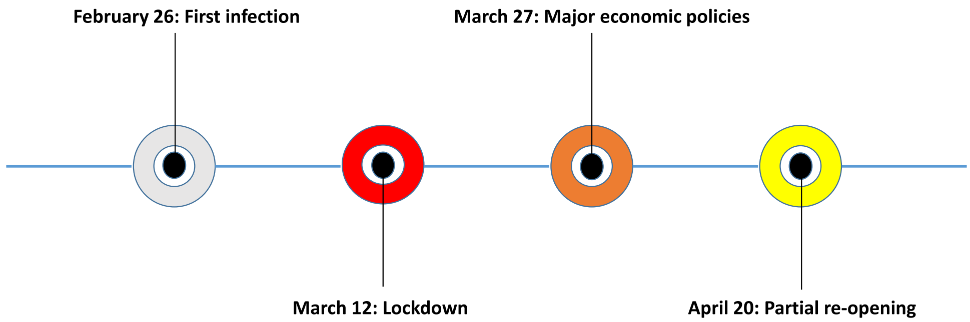


Fig. 1. Four key dates in the Covid-19 development in Norway, 2020. A full documentation of all dates and all policies would exhaust the space available. Online documentation exists at the Norwegian Ministry of Finance and the Norwegian Prime Minister's office at regjeringen.no. Health data and documentation in English can be found at the Norwegian institute of public health: fhi.no/en/.

in which a Norwegian lockdown was announced. Since our data indicate that 69.8 percent of auction bids are delivered before 2:00 PM on any given day, we classify March 12 as a pre-intervention date, and thus the first day of the post-intervention period is March 13.

In the aftermath of the lockdown, multiple policies were introduced. On March 27, a major package was announced to the public and proposed to the Parliament. It included economic relief packages to help funnel financial support to firms that had experienced at least thirty percent reduction in revenue in order to help such firms cover inevitable fixed costs. In addition, monetary policy changes were implemented through changes in the central bank's policy rates. On March 13, the central bank policy rate was reduced from 1.5 percent to 1.0 percent. On March 20, it was further reduced to 0.25 percent.

On April 7, a partial re-opening of the Norwegian society and economy was announced and the date was set to April 20. For symmetry, since we include March 12 in the pre-intervention period, we also include April 20 in the pre-reopening period.

2.3. Transaction data

We use transaction data from Eiendomsverdi, a private, bank-owned firm that specializes in constructing Automated Valuation Models (AVM) for banks and realtors, in addition to constructing the Norwegian house price statistics for Real Estate Norway.[4] The data contain the date on which the highest bid was accepted (sell date), the date the unit was put up for sale (listed) on the online platform Finn.no, the sell price, ask price, common debt, appraisal value, type of unit, type of lot, size of unit, size of lot, number of bedrooms, zip code, and city. The data span the time period from January 1, 2010, to April 30, 2020, and cover the capital Oslo. We use the period prior to February 14, 2020, to estimate our hedonic model, and then compare its predicted prices to actual sell prices in the period from February 14 during the pandemic.

We trim the data first by requiring that every observation has information on the sell price, the ask price, the common debt, the sell date, the size, and type of ownership (owner-occupier or co-op). Subsequently, we trim on the 0.1 and 99.9 percentiles for sell price, size, and sell price on size. Table 1 presents summary statistics for the period 2010–2020.

In Table 2, we present summary statistics for transactions in the 14-day period prior to, and including, the lockdown date March 12 (the pre-intervention period) and the 14 days post intervention. We see that the mean prices of the two periods are different. The pre-intervention mean is NOK 5,256,464, while the post-intervention mean is 4,815,018. However, because there also exist differences in the mean size and the mean square meter prices, not all of the differences in means can be interpreted as price reductions. That is, the difference in square meter price between pre-intervention and post-intervention is smaller on a percentage basis. By employing a hedonic model, we control for these compositional effects.

2.4. Bid-log data

We have acquired bid-log data from one of the largest real estate agencies in Norway, DNB Eiendom. The data cover the period from January 1 to April 30, 2020. The bid-log data comprise detailed information on every single bid in a transaction that led to a sale, and that was handled by a realtor employed by DNB Eiendom. We have information on each bid, the exact time at which the bid was placed, the exact time at which it expired, as well as the exact time of bid acceptance. The data set also includes a unique bidder id, which allows us to compute the number of bidders in each auction. In addition, we have info on number of clicks on the online advertisement, number of showings that have been organized, as well as number of showing participants (viewers).

We also have information on the ask price, the date when the unit was listed for sale, a separate identifier for the realtor handling the transaction, as well as different attributes of the unit (size, address, unit type, etc.).

These bid-log data are used to construct two measures that capture seller and buyer behavior. First, we calculate the percentage difference between the sell price and the highest rejected bid. We use this as a measure of seller confidence. Second, we calculate the distance between the opening bid and the ask price, and use this as a measure of exploitative bidding. Our thinking is that the former is indicative of how sellers view the economic environment in which they are selling, including the chances of selling the unit after a bidding war (Han and Strange, 2014). We propose that the latter, on the other hand, reflects how the buyers view the economic environment in which they are bidding.

Table 3 summarizes the bid-log data partitioned into pre-intervention and post-intervention. From Table 3, we observe that there is a marked decline in the number of ad clicks in the post-intervention period. There are also fewer showings, on average, and the number of viewers is halved. Although there are fewer people at the showings, there is no difference, or only small differences, in number of bidders per auction, number of bids per auction, and number of bids per bidder. These structural characteristics of the bidding process appear to remain intact throughout the crisis. We interpret this as a sign that only really interested parties show up at the showings in the post-intervention period.

In the pre-intervention period the distance between the sell price and the highest rejected bid (in days prior to the acceptance date) is 1.69. This means that, on average, the sell price is 1.69 percent higher than the highest rejected bid. After lockdown, it was 0.52 percent.

[4] These statistics are widely considered as the most comprehensive housing market statistics in Norway, and are used by ministries, the Central Bank, and financial companies.

Table 1
Summary statistics. Transaction data, Oslo, 2010–2020. Data are trimmed on the 0.1 and 99.9 percentile of sell price, size, and sell price/size. The reported statistics are for the trimmed data set. Size is measured in square meters, sell price in NOK, and share is given in percent.

	Min	25	Median Oslo	Mean	75	Max
Size	16	50	65	73.6	84	353
Sell price	747,000	2,505,399	3,326,171	3,943,824	4,588,297	19,070,656
Sell/size	12,671	41,828	53,546	56,319	68,660	136,190
Date	Jan 2 2010	Aug 21 2012	Mar 24 2015	Mar 15 2015	Oct 16 2017	Apr 30 2020
No. obs.			192,106			
Prct. share	Apartments		89.1			
Prct. share	Detached houses		3.8			

Table 2
Checks for balance. 14 days pre/post lockdown. Transaction data, Oslo 2020. Data are trimmed on the 0.1 and 99.9 percentile of sell price, size, and sell price/size. The reported statistics are for the trimmed data set. Size is measured in square meters, sell price in NOK, and share is given in percent.

Variable	Pre Lockdown		Post Lockdown	
	Mean	Std.	Mean	Std.
Size	74.5	34.8	70.4	34.0
Sell price	5,256,464	2,436,155	4,815,018	2,242,502
Ask price	5,120,188	2,388,980	4,817,731	2,320,044
Sell/size	73,487	19,096	71,959	18,666
No. obs.	733		513	
Perc. Apartment	89.6		92.0	
Perc. Detached	3.3		2.3	

Our interpretation is that seller confidence is affected by the policy intervention. Moreover, before lockdown the opening bid was 5.39 percent lower than the ask price. After lockdown, the opening bid is 6.75 percent lower than the ask. This exploitative bidding could indicate that buyers became aware of opportunities they potentially could, and did, take advantage of.

2.5. Empirical approach

To estimate counter-factual price developments, we construct a hedonic time dummy model that includes attributes determining match quality. The model is estimated on data covering the time before the Covid-19 outbreak in Norway, i.e. Jan 2 2010–Feb 13 2020. Then, we compare actual sell prices with the estimated counter-factual sell prices in the Covid-19 period.

More formally, the hedonic model is similar in spirit to Anundsen and Røed Larsen (2018) and Røed Larsen (2021), and is given by:

$$P_{h,t} = \alpha + \sum_k \beta_k X_{k,h} + \sum_R \theta_R D_{R,h,t} + \epsilon_{h,t}, \tag{1}$$

in which P denotes price, X is a collection of hedonic attributes and geographic location, D is a collection of time dummies, and ϵ is a stochastic element. Subscripts h, k, R, t refers to house, characteristic, time period, and date of sale. The k attributes in X comprise a second order polynomial in size, house type dummies, ownership type dummies, number of room dummies, interaction terms for apartment and size and squared size, and geographical dummies based on zip codes. The temporal dummies D comprise year, calendar month, dummies for Easter and the Norwegian Winter vacation (i.e. week 8 and 9), and weekdays (to control for intra-week price patterns). Notice here that, while many hedonic models use a log–log form, we use a linear polynomial set-up since the logarithm is a non-linear transformation that implies, due to Jensens inequality, a bias in price prediction.

We then use the estimated model to predict sell prices out-of-sample using the estimated time dummies for month, week number (eight or nine, or neither), weekday, and Easter vacation, and compare the observed sell prices with these predicted prices. The observed difference between sell prices and predicted prices, i.e. the residual, is divided by the predicted price and termed the prediction error. It measures the percentage deviation between observed and predicted price.[5] The R^2 from the estimated model is 0.83. Thus, observable attributes explain a great deal of the overall variation in prices in the sample period.

To test for differences in mean prediction errors (on a percentage basis) in the pre-intervention period versus the post-intervention period, we run regressions that include dummy variables for each week before and after lockdown.

3. Results

We first study transaction and bid-log data for the period around lockdown. Next, a similar analysis is conducted for the re-opening period. Finally, results for the whole period are evaluated against data on sentiment and social mobility.

3.1. The lockdown

Fig. 2 plots transaction volumes and prediction errors for Oslo for the 14-day period before and after lockdown. By visual inspection, we observe a clear reduction in transaction volumes after lockdown. Additionally, we observe that the dashed red line, representing the mean prediction error after lockdown, clearly is lower than the dashed green line, representing the mean prediction error before lockdown. Since the prediction error is constructed to compare sell prices before and after lockdown while at the same time controlling for composition and calendar effects, the observation that the mean prediction error is lower, i.e. larger in absolute value, after lockdown implies that sell prices were lower after lockdown. The interpretation of the reduction in spread between observed sell prices and predicted prices is that sell prices fell compared to the yardstick offered by the model. For completion, Fig. A.1(a) in the Appendix plots transaction volumes for Oslo in the pre- and post-intervention windows using three different widths of data windows. We see that the reduction in volume and prediction error is intact for in all three choices of widths. Notice also that we use windows in resolutions that are multiples of 7 days. We do this to avoid a weekday selection effect. By using 7-day periods, we control for intra-week price and volume patterns generated by the intra-week pattern in open houses (Røed Larsen, 2021).

Before we go on to explore the statistical significance of the reductions seen by visual inspection, we investigate whether such price movements are of magnitudes that could have happened every year. We do this to rule out the possibility that the observed reduction is a figment of the model, not truly reflective of the lockdown implemented on March 12. To this end, we perform placebo tests by estimating regressions of the hedonic model for 2014, 2017 and 2019 as well 2020. The results are displayed in Fig. 3. We choose the three years 2014, 2017, and 2019 in which the timing of Easter is similar to 2020.[6]

[5] We have experimented with different temporal markers, but the results are not materially affected by these choices. The month, weekday, and Easter dummies are the most important variables in this respect.

[6] We choose years in which the Easter holiday is not included in the 28-day period around March 12.

Table 3
Summary statistics. Pre-/post-intervention. Auction data, Oslo 2020. Auction data have been acquired from the realtor arm of Norway's largest bank, DNB. Pre- and post-intervention are 14-day periods before and after lockdown. The pre lockdown period includes the date of the lockdown, March 12, 2020. No. ad. clicks refers to the number of people who have visited the online advertisement for the property, No. showings is the number of open houses organizes, and No. viewers is the number of people who showed up at the showings. No. bidders is short notation for the mean number of bidders per auction. Similarly for No. bids which is short for the mean number of bids per auction. The distance sell price versus highest rejected bid is defined as the difference between the sell price and the highest rejected bid as a fraction of highest rejected bid multiplied by 100. Finally, we measure bidder behavior by calculating the percentage spread between the opening bid and the ask price. No. obs. is number of auctions. No. obs. ∗ is number of auctions in which a previous bid has been rejected at latest the day before acceptance.

Variable	Pre lockdown		Post lockdown	
	Mean	Std.	Mean	Std.
No. ad. clicks	5955.87	4537.23	3993.90	2174.17
No. showings	2.67	2.29	1.85	1.22
No. viewers	10.59	8.44	5.06	4.78
No. bidders	2.45	1.49	2.24	1.47
No. bids	8.32	6.63	8.19	7.06
No. bids per bidder	3.95	2.37	4.16	2.41
Seller confidence: Dist. sell price vs. rejected bid	1.69	4.07	0.52	2.06
Bidder behavior: Dist. opening bid vs. ask:	−5.39	5.09	−6.75	5.25
No. obs.	129		83	
No. obs.*	19		10	

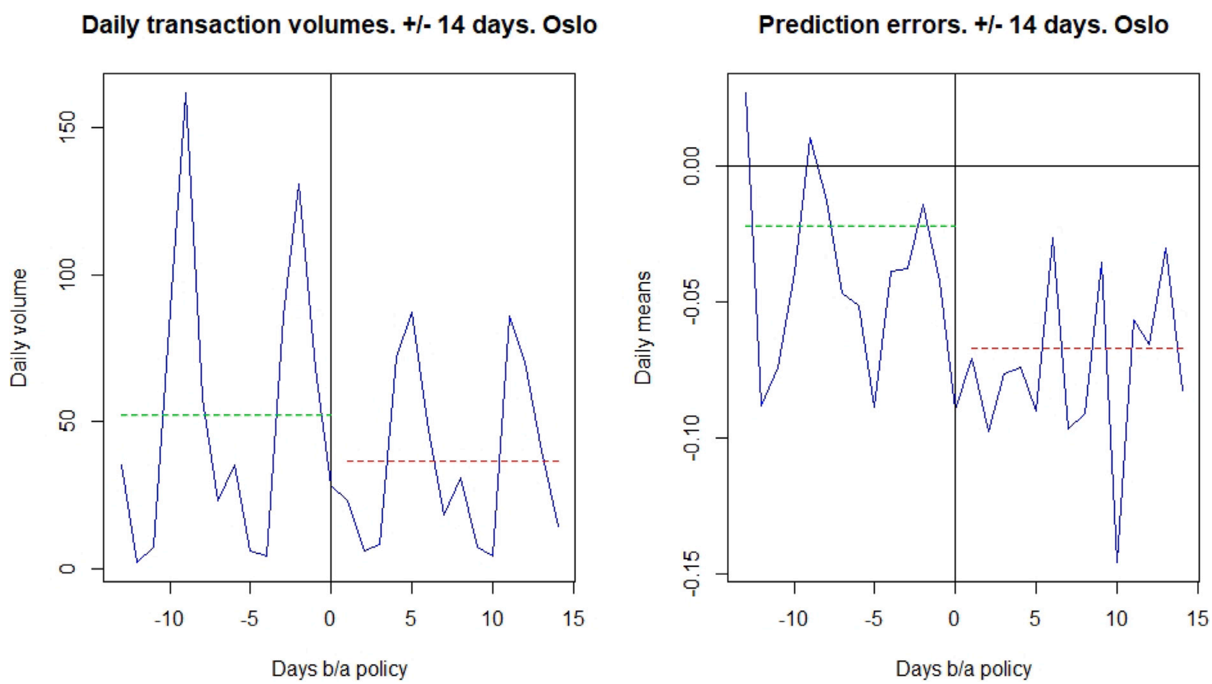


Fig. 2. Transaction volumes and mean daily price prediction errors before and after lockdown. Width in two week multiples. Oslo, 2020. The graphs depict transaction volumes and prediction errors for two periods, before and after the lockdown. The pre-intervention period includes T = 0, the day of the policy intervention, March 12, 2020. This is because 69.8 percent of bids are delivered before 2:00 PM, the time of the lockdown announcement. The sell-prediction spread is computed by subtracting the predicted price from the sell price and dividing by the predicted price. The hedonic time dummy model used to predict prices includes a second order polynomial in size; spatial FE; interaction apartment and second order size polynomial, lot size, ownership type, year, calendar month, weekday dummies, and Easter dummy. We also use dummies for week 8 and week 9 to capture the effects from the Winter school holiday season. The models are estimated using the relevant data time periods. These periods are different for the years 2014, 2017, 2019, and 2020 since we use data from 2 January 2010 until (not including) February 14 for the given year when we estimate each of the four models. The prediction period covers the 14-day period prior to and including March 12 and the 14-day period starting March 13 for each year (February 27–March 26, except in 2020 in which February 29 exists). Thus, the estimation time periods and prediction time periods do not overlap since we perform out-of-range predictions. For the years 2014, 2017, 2019, and 2020 the pairs of number of observations in the model estimation data set and the number of out-of-range predicted prices are, respectively, (75,056; 1535), (131,313; 1468), (168,384; 1631), and (188,430; 1246). Fig. A.1 in the Appendix compares these results by also showing 7 and 21 day windows for sensitivity analysis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In these three years, the model is estimated on data before (and not including) February 14 that year. Thus, the 2014-predictions are based on four years of data while the 2017-predictions and 2019-predictions are based on seven and nine years of data, respectively. None of the observed differences in prediction errors before and after March 12 in the years 2014, 2017, and 2019 are statistically significant. The difference in 2020, on the other hand, is statistically significant. The placebo test supports the notion that the observed difference is due to the lockdown and not spurious.

Across our sample, the prediction error for transactions in the hedonic model would be stationary with a mean of zero under the null hypothesis of no Covid-19 effect or lockdown effect. In order to test the null in the weeks around the lockdown, we use a simple regression model to look for signs as to how the housing market behaved before and after lockdown relative to the predictions of the hedonic model.

To this end, we use the following regression model to test whether the mean the prediction error to shifts around the lockdown

$$prederr_i = \beta_0 + \beta_1 D_{2-3wb,i} + \beta_2 D_{1wb,i} + \beta_3 D_{1wa,i} + \varepsilon_i \ , \tag{2}$$

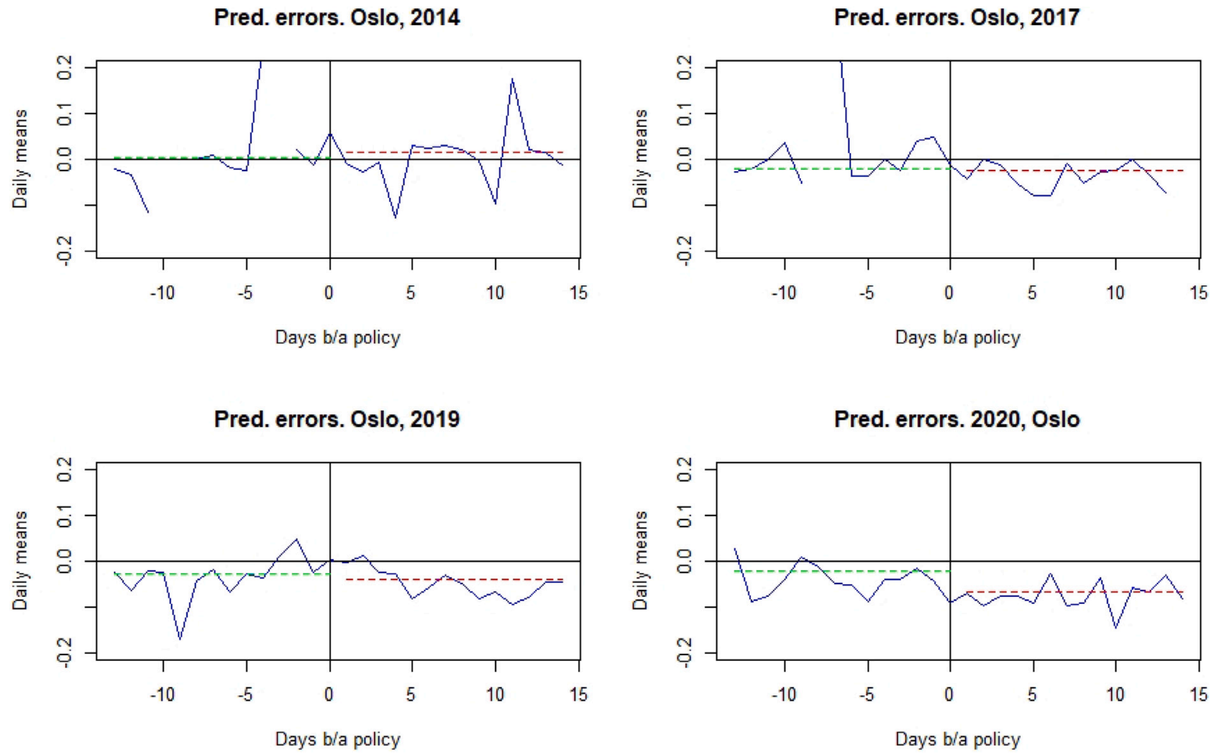


Fig. 3. Mean daily price prediction error. True lockdown and 3 placebos. Oslo, 2014, 2017, 2019, and 2020. The panel of plots shows the prediction errors in three placebo years in which Easter is outside of the data window. The hedonic model is estimated on data before (and not including) 14 February in each year. The predictions are for the 28 day period that covers 14 days before and after lockdown. For days without transactions we plot no prediction errors. Extreme prediction errors are due to days with few observations.

in which $prederr_i$ is the prediction error of transaction i (for a total of N = 1928 transactions in the period from 21 days before and including March 12 and the 21 days after March 12 2020). $D_{2-3wb,i}$ is a dummy variable equal to one if the transaction date belongs to the period before March 6 (i.e. two or three weeks before lockdown), $D_{1wb,i}$ is equal to one if the transaction date is between March 6 and March 12 (i.e. the week before lockdown), and $D_{1wa,i}$ is equal to one if the transaction date is between March 13 and March 19 (the first week of lockdown). Hence, the reference period will be week 2 and 3 after lockdown — from March 20 to April 2. ε_i is an error term and β_0 a constant term.[7]

We estimate (2) sequentially by adding one dummy variable at a time. The data include three weeks before lockdown and three weeks after lockdown. The results from the four models are shown in Table 4. In Model 1, which only estimates the constant term, we simply test whether the prediction error on average is zero. In Model 2, we test whether the two first weeks of our sample (one and two weeks before lockdown) are significantly different from the rest of the sample. We test whether the week before lockdown is significantly different from the lockdown period in Model 3. Finally, in Model 4, we test whether the prediction error for the weeks around lockdown is significantly different from the default (week 2 and 3 after lockdown) and thus each other.

The estimated models nested in (2) are summarized in Table 4. They show that the prediction error is significantly negative for the entire sample (from Model 1). This is expected since at least four of these six weeks are affected by Covid and the lockdown. Model 2 shows that the prediction error is significantly less negative in the first two weeks in our sample compared to the rest of the sample. The combination of the coefficients in Model 2 implies that the prediction error from February 20 to March 5 was close to zero on average. The implication is that our model says the housing market was neither overvalued nor undervalued by two to three weeks before the lockdown.

However, the coefficient for the week before lockdown in Model 3 suggests that house prices were systematically lower the week before lockdown compared to what our hedonic model says prices normally should be.

Table 4
Regressions of prediction error on week dummies. Oslo, 2020. Estimated standard errors are reported in parentheses below the estimated coefficients. The standard errors are estimated using 'vcovCL' function in R, which provides heteroskedasticity robust errors that are clustered on zip code. The levels of significance are *** p < 0.01 ** p < 0.05 * p < 0.1. The period termed '1 week before' includes T = 0, the day of the policy intervention, March 12 2020. This is because 69.8 percent of bids are delivered before 2:00 PM, the time of the lockdown announcement. The period termed '1 week after' starts on March 13 2020. The period that contains week 2 and 3 after lockdown constitutes the default for the full model (Model 4). The sell-prediction spread is computed by subtracting the predicted price from the sell price and dividing by the predicted price. The hedonic time dummy model used to predict prices includes a second order polynomial in size; spatial FE; interaction apartment and second order size polynomial, lot size, ownership type, year, calendar month, weekday dummies, and Easter dummy. We also use dummies for week 8 and week 9 to capture the effects from the Winter school holiday season. The models are estimated using data from before (and not including) February 14, 2020.

	Model 1	Model 2	Model 3	Model 4
Intercept	−0.043***	−0.060***	−0.070***	−0.068***
	(0.0065)	(0.0066)	(0.0068)	(0.0075)
2-3 weeks before		0.044***	0.053***	0.052***
		(0.0079)	(0.0085)	(0.0093)
1 week before			0.033***	0.031***
			(0.010)	(0.011)
1 week after				−0.0049
				(0.011)
R^2_{adj}	–	0.015	0.019	0.019
No. observations	1928	1928	1928	1928

[7] An alternative specification is to include the dummy variables in the hedonic model directly. This approach is equivalent in explanatory power, but we prefer using the spreads because they allow us to put the deviations on a percentage basis and to plot the results in a straightforward way.

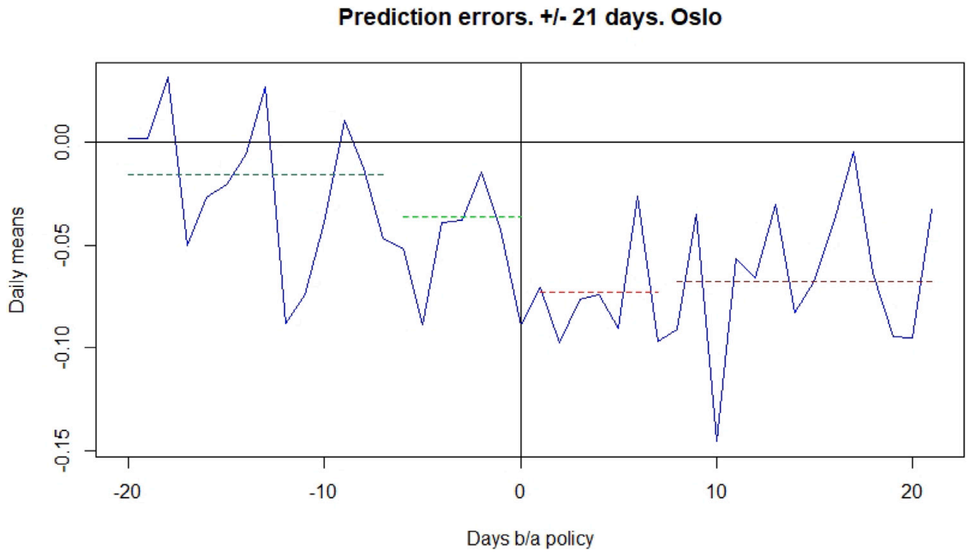


Fig. 4. Prediction errors and corresponding constant terms according to the estimates of (2) outlined in Table 4.

The constant terms combined with the estimated dummy variables in Model 4 imply an average prediction error of −0.016 for the first two weeks of our sample, −0.037 for the week before lockdown, −0.073 for the first week after lockdown and −0.068 for weeks 2–3 after lockdown (but no significant difference between the first week after lockdown and the next two weeks). Hence, the average prediction error is close to zero in the beginning of the sample, then drops the week before lockdown and then drops further after lockdown. For ease of interpretation, these regression results are plotted in Fig. 4 together with the daily means of prediction errors.

The results in Model 4 are key. The interpretation is that agents in the housing market displayed behavioral changes before lockdown. House prices were 1.6 percent lower than expected two weeks before lockdown. One week before lockdown, prices were 3.7 percent lower than expected, both substantially lower than in normalcy and lower than the week before. Then, the week after lockdown prices were reduced further, to 7.3 percent below normalcy. The interpretation is that about half of the reduction in sell prices were due to behavioral changes before lockdown.

In order to probe deeper into the dynamics between sellers and buyers, we now turn to results from data from bidding logs. We first look at the extensive margin of bidding by looking at number of bidders and number of bids per auction. To study the intensive margin of bidding, we use the two measures introduced in Section 2.4, namely seller confidence (the spread between the sell price and the highest rejected bid in days before the day of acceptance) and exploitative bidding (the percentage spread between an auction's opening bid and the ask price). We follow week-by-week results since day-by-day would be susceptible to intra-week effects.[8]

In order to estimate the potential effects in weeks before and after lockdown, we estimate the model:

$$X_i = \beta_0 + \beta_1 D_{2-3wb,i} + \beta_2 D_{1wb,i} + \beta_3 D_{1wa,i} + \varepsilon_i, \quad (3)$$

in which X_i is short notation for number of bidders, number of bids, number of bids per bidder, seller confidence or exploitative bids for sale i (for all sales in the period from 21 days up to March 12 and 14 days from March 12 2020). $D_{2-3wb,i}$ is a dummy variable equal to one if the transaction is carried out before March 6 (i.e. 2–3 weeks before lockdown), $D_{1wb,i}$ is equal to one if the transaction is carried out between March 6 and March 12 (i.e. the week before lockdown), and $D_{1wa,i}$ is equal to one if the transaction is carried out between March 13 and March 19 (the first week of lockdown). Hence, the reference period will be week 2 and 3 of the lockdown — from March 20 to April 2. ε_i is an error term and β_0 a constant term.

In Table 5, we see that the number of ad clicks drop substantially after lockdown. In the 2–3 weeks period before lockdown, there were more than 6400 ad clicks on average. After lockdown, this number drops to roughly 4000. The tendency is that the number of ad clicks start declining before lockdown, and one week before lockdown, there were a little more than 5600 ad clicks on average. There is also a clear tendency that fewer showings are organized in the week prior to lockdown, and it drops further after lockdown. While the number of viewers remain stable prior to lockdown, it drops substantially after lockdown. There is little change in number of bids, number of bidders, and number of bids per bidder in the two weeks prior to lockdown, and in the two weeks after the lockdown. The extensive margin of bidding therefore suggests little changes in bidding behavior, although there are signs that search-activity moderates.

Turning to the intensive margin, we see that seller confidence did not change prior to lockdown. There are, however, signs that there was a short-lived drop in seller confidence just after lockdown. However, exploitative bidding shows significant effects for all of the periods we are investigating. In the 2–3 weeks period prior to lockdown, the typical opening bid was 4.9 percent below the ask price. In the one week period prior to lockdown, the same number is 5.56 percent. In the week after lockdown, it drops further to 6.19 percent, and in the 2–3 weeks period after lockdown the opening bid is 7.78 percent below the ask price. We interpret these findings as indications that exploitative bids started to become more frequent before lockdown and was even more common after lockdown. This supports the notion that buyers attempted to take advantage of the situation.

3.2. Policy reversal and re-opening

Turning to the period around the re-opening, Fig. 5 shows mean daily sales volumes and mean daily prediction errors for the four periods before lockdown; after lockdown and before (and including) announcement; after lockdown and after announcement but before (and including) re-opening; and after re-opening. There seems to an effect of the re-opening by looking at the means. In fact, it appears that the re-opening completely reverses the lockdown effect on prices. The interpretation on sales volume, however, needs to be more cautious

[8] In Oslo, Monday and Tuesday are the days with most bids and most acceptances.

Table 5
Bidding data, Oslo 2020. The table tabulates bidding data for three weeks around re-opening. The 1st week before re-opening includes T = 39, i.e. April 20, the day of the re-opening, due to symmetry with the treatment of March 12. Auction data have been acquired from the realtor arm of Norway's largest bank, DNB. No. ad. clicks refers to the number of people who have visited the online advertisement for the property, No. showings is the number of open houses organizes, and No. viewers is the number of people who showed up at the showings. No. bidders is short notation for the mean number of bidders per auction. Similarly for No. bids which is short notation for the mean number of bids per auction. Confidence is defined as the difference between the sell price and the highest rejected bid as a fraction of highest rejected bid multiplied by 100. Finally, we include exploitative bids, i.e. the percentage spread between the opening bid and the ask price. "Observations" denotes number of auctions.

	No. Ad. Clicks	No. showings	No. viewers	No. bidders	No. bids	Bids per bidder	Confidence	Exploitative
Intercept	3986.74***	1.94***	4.46***	2.23***	8.05***	4.24***	3.40**	−7.78***
	(217.36)	(0.13)	(0.52)	(0.14)	(0.54)	(0.22)	(1.28)	(0.57)
2-3 weeks before	2423.71***	0.90***	6.96***	0.38**	0.64	−0.32	−1.44	2.88***
	(474.00)	(0.29)	(0.97)	(0.18)	(0.79)	(0.29)	(1.74)	(0.73)
One week before	1642.65***	0.52**	6.20***	0.26	0.49	−0.38	−1.66	2.22***
	(575.66)	(0.26)	(1.16)	(0.23)	(0.97)	(0.35)	(1.80)	(0.82)
One week after	39.94	−0.00	1.34	0.22	0.38	−0.29	−2.62*	1.59*
	(399.68)	(0.26)	(1.07)	(0.33)	(1.37)	(0.40)	(1.55)	(0.93)
Observations	304	323	323	323	323	323	46	323
R^2_{adj}	0.0742	0.0283	0.151	0.00231	−0.00767	−0.00430	−0.0320	0.0438

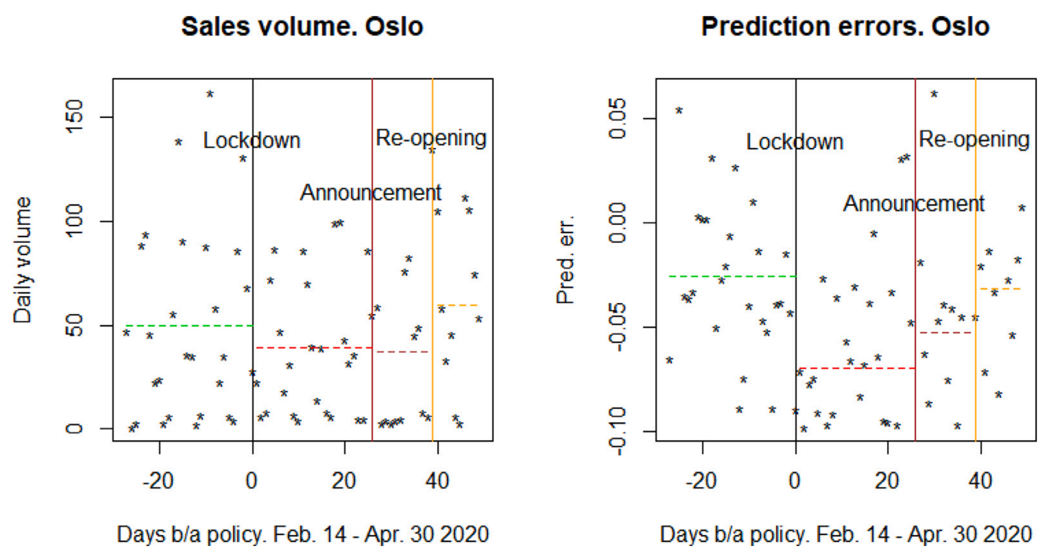


Fig. 5. Sales volumes and prediction errors. Oslo, 2020. In the plot, we require that daily observations are based on at least two transactions and that mean daily prediction error in absolute values is smaller than 0.1. All transactions are, however, included in the computations of period means. The period before lockdown runs from T = −27 and includes T = 0. The lockdown period runs from T = 1 to T = 39. The re-opening period starts at T = 40. On April 7 (T = 26), there was an announcement of the coming re-opening.

since April typically is a month with a high number of transactions after Easter.

The date for re-opening was announced on April 7. Such announcements often have an effect on their own, and we find evidence consistent with this notion since the mean prediction error in the 7-day period before and including April 7 is −0.069 while the mean prediction error in the subsequent 7-day period is −0.052. The difference is statistically significant with a p-value of 0.055, thus the announcement is associated with a positive effect.

In order to test for effects before and after the re-opening date, we perform tests in the same manner as in the previous section. We test effects on the prediction error by estimating

$$prederr_i = \beta_0 + \beta_1 D_{1wb,i} + \beta_2 D_{1wa,i} + \varepsilon_i \ , \tag{4}$$

in which $prederr_i$ is the prediction error of transaction i (for a total of N = 898 transactions in the period from 14 days up to April 20 and the 7 days from April 20 2020). $D_{1wb,i}$ is a dummy variable equal to one if the transaction is carried out the week before April 20, and $D_{1wa,i}$ is equal to one if the transaction is carried out between April 20 and 26 (the first week after reopening). Hence, the reference period represents two weeks before reopening (April 7 to 13), since we only include data until the end of April and thereby are unable to analyze the second week after re-opening. ε_i is an error term and β_0 a constant term. Table 6 summarizes the results from estimating (4) sequentially by starting with only the intercept term and then including one and two dummy variables.

The estimated models for the reopening period, summarized in Table 6, show that the prediction errors are significantly negative for all of the models, but that none of the estimated dummy variables are significant. Thus, the prediction errors are closer to zero for this period than around lockdown, suggesting that the housing market was affected by Covid-19 to a larger extent in the weeks around the lockdown than the weeks around re-opening. This is consistent with the pattern seen in Fig. 5 in that the by the time of re-opening, house prices were close to normal. The absence of a structural break around the re-opening date may also be an effect of the pre-announcement of the re-opening date such that the event was less of a shock to the housing market.

We also test for changes around the re-opening data using bidding data. As for the lockdown period, we estimate

$$X_i = \beta_0 + \beta_1 D_{1wb,i} + \beta_2 D_{1wa,i} + \varepsilon_i, \tag{5}$$

in which X_i is short notation for number of bidders, number of bids, number of bids per bidder, seller confidence or exploitative bids for sale i (for all sales in the period from 21 days up to April 20 and 7 days from April 20 2020). $D_{1wb,i}$ is equal to one if the transaction is carried out between April 14 and 20 (i.e. the week before re-opening), and $D_{1wa,i}$ is equal to one if the transaction is carried out between April 21 and 27 (the first week after re-opening). Hence, the reference period will be

Table 6
Regressions of prediction error on week dummies. Oslo, 2020. Estimated standard errors reported in parentheses below the estimated coefficients. The standard errors are estimated using 'vcovCL' function in R, which provides heteroskedasticity robust errors that are clustered on zip code. The levels of significance are *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$. The period termed '1 week before' includes T = 39, i.e. April 20, due to symmetry with the treatment of March 12. The period termed '1 week after' starts on April 21 2020. The sell-prediction spread is computed by subtracting the predicted price from the sell price and dividing by the predicted price. The hedonic time dummy model used to predict prices includes a second order polynomial in size; spatial FE; interaction apartment and second order size polynomial, lot size, ownership type, year, calendar month, weekday dummies, and Easter dummy. We also use dummies for week 8 and week 9 to capture the effects from the Winter school holiday season. The models are estimated using data from before (and not including) February 14, 2020.

	Model 1	Model 2	Model 3
Intercept	−0.048***	−0.040***	−0.057***
	(0.0079)	(0.010)	(0.015)
One week before		−0.018	−0.0013
		(0.011)	(0.016)
One week after			0.023
			(0.018)
R^2_{adj}	–	0.0015	0.0022
No. observations	898	898	898

two weeks before re-opening — from April 7. ε_i is an error term and β_0 a constant term. Table 7 summarizes the results from estimating (5) sequentially by starting with only the intercept term and then including one and two dummy variables.

Similar to the lockdown, there is little change in number of bidders and number of bids placed in each auction across periods as seen in Table 7. Both the lockdown and the re-opening therefore seems to have little impact on the extensive margin of bidding behavior. However, there is a positive effect on the average number of bids per bidder increasing from 3.57 to 4.38 the week before re-opening. There is no change in number of ad clicks, number of showings, or number of viewers around the time of the reopening. All these measures remain approximately at post-lockdown levels.

There are no differences in the distance between the sell price and the highest rejected bid in this re-opening period. It is, however, evident that exploitative bidding falls markedly after the policy is reversed. There is no evidence that exploitative bidding started falling prior to the re-opening.

3.3. Social mobility and sentiment

Below we triangulate our main findings with evidence based on social mobility data and economic sentiment.

First, Fig. 6 shows how key social mobility statistics evolved during the period we analyze. The figure reports abnormal traffic in Oslo, using data from 144 traffic stations as well as a metric that measures the tendency of people to stay home (provided by Google).

The traffic statistics have a clear downward trend starting already three weeks prior to the lockdown. After the re-opening, however, the traffic patterns gradually returned to, and even exceeded, the baseline. The social mobility data from Google show a somewhat different pattern. There are very small deviations from baseline prior to the lockdown, followed by a large jump at the lockdown date and then a gradual return to baseline. Thus, in line with the results from the housing market, these social mobility statistics indicate that not only did households adhere to the lockdown policies implemented by the government, but also that behavioral changes likely affected mobility patterns prior to the policy interventions.

To further explore to what extent behavioral changes in the housing market are associated with changes in general market expectations, we make use of a unique daily Norwegian business cycle sentiment index and daily changes in the asset market. The sentiment index builds on the work by Thorsrud (2020), and is constructed based on daily newspaper coverage. As such, it is tailored to measure the information households potentially have about economic developments. Changes in this index capture how news affects the general economic outlook on a daily basis. In contrast, daily changes in the asset market capture more directly how investors and professional market participants evaluate the state of the economy and the future outlook.

As seen from Fig. 7 the sentiment index and the (normalized) prediction errors track each other, especially before lockdown, at which time both series clearly trend downwards. In the week(s) prior to re-opening, we also observe that the sentiment seems to increase gradually. We do not find an association between house price changes and changes in stock market prices. We include the figure for comparison purposes.

Table 8 formalizes the relationship between sentiment, stock market developments, and prediction errors in the housing market using a simple linear regression model. In line with the visual impression above, the correlation between sentiment changes and abnormal price movements is positive and significant, while changes in the stock market do not significantly affect the housing market during this period. Moreover, even though the model is very simplistic, the adjusted R^2 suggests that over 5 percent of the variation in prices are associated with variation in sentiment.

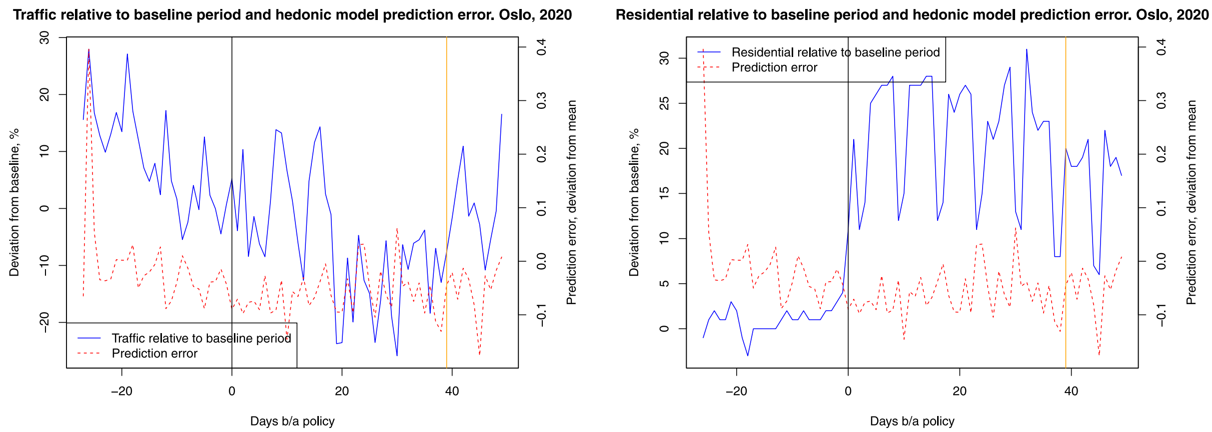
These results support the findings in the previous analysis. Market developments in the housing market during the early Covid-19 period are partly driven by behavioral changes, and these behavioral changes are also visible in other statistics measuring social mobility and economic sentiment. We observe an association between policies and announcements on the one hand and house prices and sentiment on the other hand.

4. Concluding remarks and policy implications

The Covid-19 pandemic sparked a debate on how to balance policy interventions aimed at stopping the spread of the virus against negative

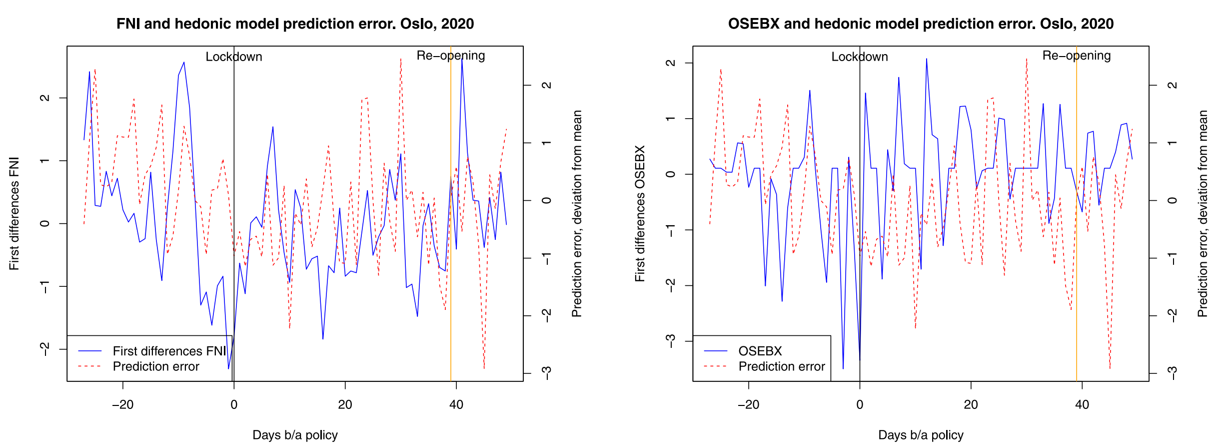
Table 7
Bidding data, Oslo 2020. The table tabulates bidding data for three weeks around re-opening. The 1st week before re-opening includes T = 39, i.e. April 20, the day of the re-opening, due to symmetry with the treatment of March 12. Auction data have been acquired from the realtor arm of Norway's largest bank, DNB. No. ad. clicks refers to the number of people who have visited the online advertisement for the property, No. showings is the number of open houses organizes, and No. viewers is the number of people who showed up at the showings. No. bidders is short notation for the mean number of bidders per auction. Similarly for No. bids which is short notation for the mean number of bids per auction. Confidence is defined as the difference between the sell price and the highest rejected bid as a fraction of highest rejected bid multiplied by 100. Finally, we include exploitative bids, i.e. the percentage spread between the opening bid and the ask price. "Observations" denotes number of auctions.

	No. Ad. Clicks	No. showings	No. viewers	No. bidders	No. bids	Bids per bidder	Confidence	Exploitative
Intercept	4884.19***	1.90***	4.00***	2.52***	7.97***	3.57***	1.37	−8.22***
	(409.85)	(0.16)	(1.32)	(0.23)	(0.98)	(0.27)	(1.61)	(0.90)
One week before	492.52	0.08	−0.09	−0.11	1.03	0.81**	3.06	0.46
	(502.44)	(0.21)	(1.46)	(0.28)	(1.15)	(0.36)	(1.85)	(0.98)
One week after	219.19	0.31	1.33	−0.40	−1.29	−0.05	−1.44	1.93*
	(495.04)	(0.24)	(1.47)	(0.29)	(1.16)	(0.36)	(2.64)	(1.02)
Observations	189	193	193	193	193	193	28	193
R^2_{adj}	−0.00589	−0.000857	0.000961	0.00332	0.0202	0.0270	0.0524	0.0153



(a) Traffic (b) Immobility

Fig. 6. Social mobility and immobility. The period before lockdown runs from T = −27 and includes T = 0. The lockdown period runs from T = 1 to T = 39. The re-opening period starts at T = 40. Fig. 6(a) graphs the sum of the number of vehicles passing 144 registration points in Oslo municipality each day relative to baseline period. The baseline is calculated based on the median traffic volume for each day of the week in the period from 3 January to 6 February, 2020, corresponding to the baseline period used in the Google mobility project (Google LLC, 2020). The graph then reports the percentage deviation to the corresponding baseline day of the week for each day after 6 February, 2020. Data are collected using the Norwegian Public Roads Administration?s Traffic Data API. Fig. 6(b) graphs immobility measured as individuals' tendency to stay home using Google residential data. The Google mobility project (Google LLC, 2020) provides data from users that have enabled position tracking for their Google account. If so, the GPS in the cell phones yield data for a sample of Google users, which in turn allow Google to use these GPS data to calculate changes in time spent at home. For each day from 15 February, the change in mobility is compared to the baseline period (3 January to 6 February, 2020 as we also use when calculating the baseline period for traffic volume), for the corresponding day of the week.



(a) Sentiment (b) Stock market

Fig. 7. Sentiment and stock market changes. The period before lockdown runs from T = −27 and includes T = 0. The lockdown period runs from T = 1 to T = 39. The re-opening period starts at T = 40. For visual clarity, all data series are normalized. Fig. 7(a) graphs sentiment changes together with prediction errors in the housing market. The sentiment index is produced by Retriever and Centre for Applied Macroeconomics and Commodity Prices at BI Norwegian Business School (CAMP), and builds on research by Thorsrud (2020). Fig. 7(b) graphs changes in the stock exchange index, measured using the OSEBX index at the Oslo Stock Exchange, together with prediction errors in the housing market.

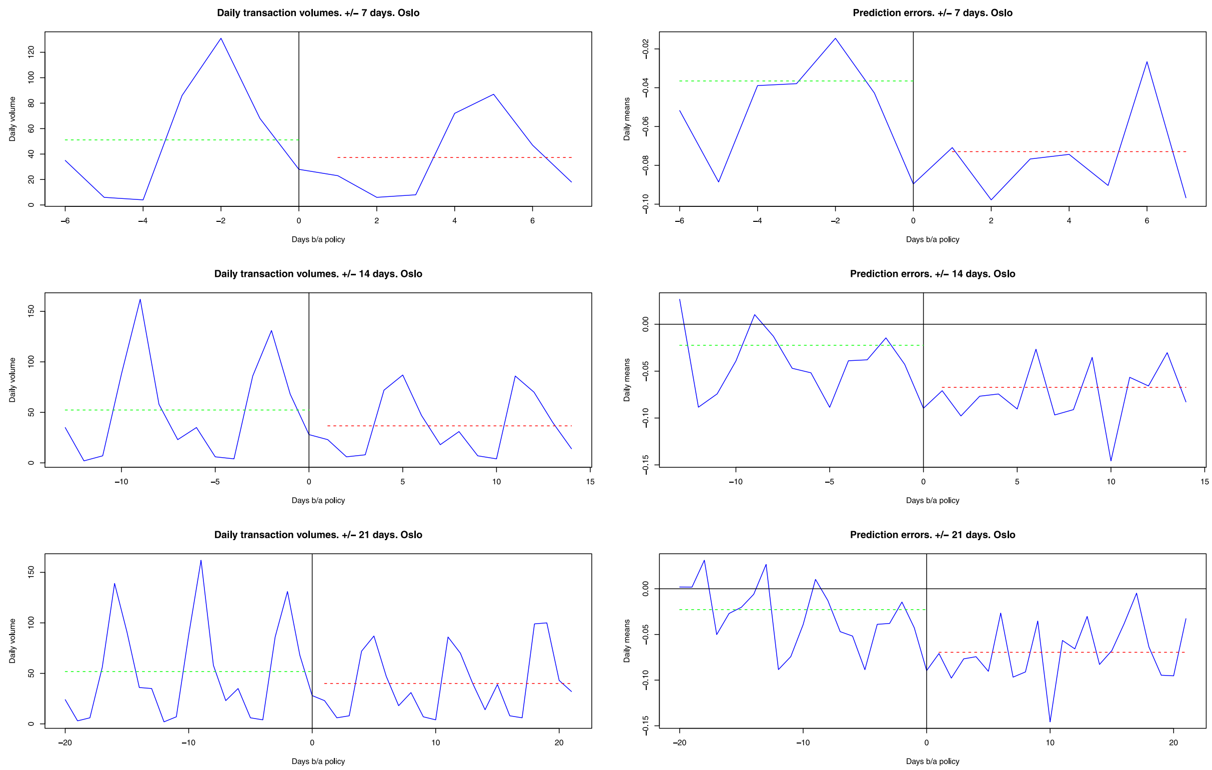
economic outcomes. In this article, we use unique Norwegian day-by-day transaction and bid-log data in order to examine how market participants reacted to the spreading news of Covid-19 in early March, 2020, the lockdown on March 12, and the re-opening on April 20.

We build our analysis around a hedonic time-dummy model, controlling for housing attributes, location, and temporal features using dummies for year, calendar month, Easter, weekdays, and week numbers, and construct counter-factuals based on the out-of-sample predictions errors from this model during the period we analyze.

Our key finding is that behavior in the housing market changed before lockdown. This may be a useful finding for policymakers and inform economic debate on the lockdown effects. Our results are consistent with the position that it was the virus that reduced economic activity. While the lockdown further depressed prices, we find that prices stabilized after the lockdown, which is consistent with the position that the lockdown was part of the solution, not the problem. In short, people appear to respond to the news of Covid-19, not only to the policies against Covid-19.

Thus, our paper offer an economic lesson. That lesson is that people voluntarily changed behavior before the lockdown policy. It follows that without governmental intervention it is probable that behavioral changes in themselves could have affected the economy. However, we do not find similar changes in the stock-market.

The lockdown did lead to lower seller confidence and more exploitative bidding. The re-opening reversed the lockdown effect on prices. For transaction data, the results of the lockdown are particularly striking. While mean daily transaction volume in the week before March 12 was 51 sales, it was 37 after lockdown. According to our estimates, half of



(a) Transaction volume (b) Prices

Fig. A.1. Figs. A.1(a) and A.1(b) report transaction volumes and mean daily price prediction errors before and after lockdown. Width in week multiples. Oslo, 2020. The graphs depict transaction volumes and prediction errors for two periods, before and after the lockdown. We vary the width using resolutions of 7, 14, and 21 days. The pre-intervention period includes T = 0, the day of the policy intervention, March 12, 2020. This is because 69.8 percent of bids are delivered before 2:00 PM, the time of the lockdown announcement. The sell-prediction spread is computed by subtracting the predicted price from the sell price and dividing by the predicted price. The hedonic time dummy model used to predict prices includes a second order polynomial in size; spatial FE; interaction apartment and second order size polynomial, lot size, ownership type, year, calendar month, weekday dummies, and Easter dummy. We also use dummies for week 8 and week 9 to capture the effects from the Winter school holiday season. The models are estimated using data from before (and not including) February 14, 2020. The metric is a difference-in-means metric. Its distribution can be approximated using the t-distribution.

Table 8
House price developments, sentiment, and the stock market. The sample starts on 14 February and ends on 30 April. Estimated model: $Prediction\ Error_t = a + b(\Delta Sentiment_t\ Index) + c\Delta(Stock\ Exch.\ Index_t) + \epsilon_t$, in which Δ is the difference operator. The levels of significance are *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$ and standard errors are reported in parentheses below the coefficient estimates. See Fig. 7 for further details.

	Prediction error
Intercept	−0.043***
	(0.005)
Diff. Sentiment	0.174***
	(0.072)
Diff Oslo stock exchange	−0.0003
	(0.0003)
R^2_{adj}	0.052
No. observations	77

the total fall in prices observed in the week after the lockdown occurred before the lockdown.

These conclusions are robust to a number of alternative modeling choices. Placebo regressions demonstrate that it is unlikely that these results have been obtained by chance. Moreover, our findings are supported by evidence provided by other high-frequent indicators of social mobility and daily news sentiment. In particular, daily traffic and social mobility data show that policy interventions were actually followed by the public, while changes in news sentiment correlates well with the abnormal price movements we observe during this period. These effects are also in line with changes prior to the lockdown. Interestingly, changes in stock market prices do not seem to carry the same type of information, suggesting that households and professional market participants evaluated the situation differently.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Price developments illustrated by multiple time frame windows

See Fig. A.1.

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