WORKING PAPER SERIES

2020 | 3

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Behavioral changes and policy effects during Covid-19:[*]

Evidence from day-by-day sales and bid-by-bid auction logs in the housing market

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September 16, 2020

Abstract

We exploit unique Norwegian day-by-day transaction and bid-by-bid auction data in order to examine how market participants reacted to the spreading news of Covid-19 in early March 2020, the lock-down on March 12, and the re-opening on April 20. We find that behavior changed voluntarily before the lock-down, and we find effects on the housing market from both the lock-down and the re-opening. In particular, there exists a discontinuity on the date of the lock-down in transaction volumes, sell-prediction spreads, aggressive bidding behavior, and seller confidence. However, when we compare observed price developments with our estimated counter-factual price developments, we find that roughly half of the total fall in prices had occurred when the lock-down was implemented. The re-opening completely reverses the lock-down effect on prices. We also show that voluntary behavioural changes, as well as lock-down 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.

Keywords: *Auctions; Bids; Covid-19; Discontinuity; Housing Market; Policy Intervention*

JEL Codes: *D91; R21; R31*

[*]The authors are grateful to DNB Eiendom and Eiendomsverdi for auction and transaction data.
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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 lock-down 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 lock-down 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 lock-down of Norway on March 12? 2) How large were reductions in transaction volumes, sell prices, and bidding activity in the days immediately following the lock-down? 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 lock-down on March 12. The lock-down itself is also associated with 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 lock-down on March 12. These results indicate both a voluntary behavior effect before lock-down and an additional policy effect after lock-down. After the re-opening on April 20, transaction volumes and sell prices increased substantially. Moreover, we find that the tendency among bidders to extend aggressive bids (less than 90 percent of ask price) increases sharply after the lock-down. Sellers, on the other hand, displayed a higher tendency to accept lower bids after the lock-down. 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 lock-down and re-opening effects, are clearly visible in social mobility data, indicating that market participants indeed followed policy guidelines. Moreover, changes in daily news sentiment correlates with abnormal price movements during this period.

These findings are important for at least four reasons. First, they are important for policy. After lock-down, several commentators claimed that policy adversely affected the economy. Although true, 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 Covid-19 second 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, 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), Leamer (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 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 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 lock-down, parents kept kindergarten children and school pupils at home and refrained from usual leisure activities, and companies issued statements in which employees were encouraged to work from home. The Norwegian government ordered a lock-down 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 may be 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.

Results from the analysis just before and just after the lock-down have the clearest causal interpretation. The reason why is that the behavioral changes before the lock-down cannot have been caused by policy changes that had not yet been implemented. The discontinuity in market effects on the lock-down date may plausibly be attributed to the lock-down. We

[1] The Norwegian GDP for the year 2017 in market value is 3,300 billion NOK; see http://www.ssb.no. The firm Eiendomsverdi computed the market value of the Norwegian housing stock in September 2017 to be 8,000 billion NOK (contact eiendomsverdi.no).

substantiate this claim by showing that in placebo years differences before and after March 12 are statistically insignificant; only in 2020 are the difference statistically significant. However, in the interim period between the lock-down 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 lock-down 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 minute-by-minute bidding logs in auction data in addition to a daily sentiment index, traffic data, and Google mobility data. The transaction data include the date on which the highest bid was accepted. Since bids and acceptances of bids are legally binding in Norway, 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 auction data 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 inspect bidding-behavior with high temporal resolution just before and right after policy announcements, including the possibility of examining whether or not certain strategic bids are made by prospective buyers and whether or not such strategic bids are accepted by the sellers.

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 (2020)), from February 14 to April 30, 2020, and compare predicted prices with observed sell prices. 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. By looking at number of bids and number of bidders, we study behavior at the extensive margin. 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 aggressive bidding measure based on the frequency of opening bids below 0.9 of 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.

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. (2020), Atkeson (2020), Baker et al. (2020), Caballero and Simsek (2020), Guerrieri et al. (2020), 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 (2020)). 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. (2020) 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. (2020), 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 and anticipation effects. Second, we dig into both buyer and seller behavior before, during, and after lock-down.

The novelty of our study lies in the application of timely high frequency 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 Data, institutional background, 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 a seller wants to sell his unit, he places an online advertisement on Finn.no. In this advertisement, he includes photos, a thorough description, an ask price, and an announcement of a date for an open house. Prospective buyers search the platform Finn.no, and make a short-list of which open houses to visit.

The auction takes place shortly after the open house, and the bidding is done digitally. The realtor continuously communicates with the seller and all bidders, actual and prospective. 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 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. The time-on-market (TOM) is low, and in the capital Oslo, TOM is typically less than four weeks and often 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]

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 Figure 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 Nor-

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

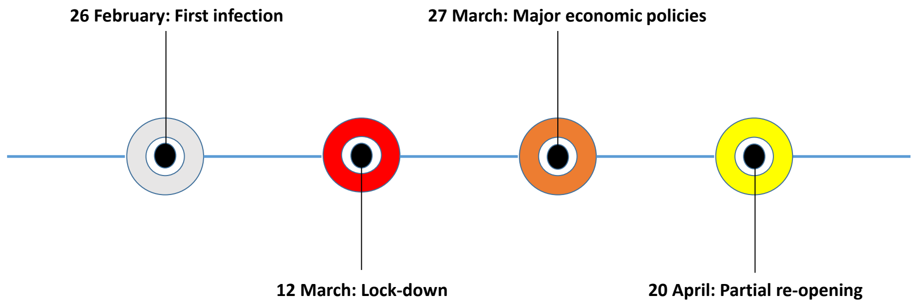


Figure 1: Four key dates in the Covid-19 development in Norway, 2020. A full documentation of all dates and all policies would exhaust the space available. Online documentation exists at the Norwegian Ministry of Finance and the Norwegian Prime Minister's office at `regjeringen.no`. Health data and documentation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

wegian municipalities would implement local school shut-downs. Also, there were reports of nervousness in the population and that parents had kept pupils at home. The day before, March 11, the Danish Prime Minister had announced that Denmark would implement a lock-down. It is not unlikely that the actions taken in several Norwegian municipalities were linked to the Danish policies, as Norway and Denmark share a long history and strong cultural bonds. In the afternoon of March 12, on 2:00 PM, the Norwegian Prime Minister held a press conference in which a Norwegian lock-down 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 lock-down, 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 folio 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 Methods for banks and realtors, in addition to constructing the Norwegian house price statistics for Real Estate Norway.[3] 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 spans 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 onwards 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 all data.

In Table 2, we present summary statistics for transactions in the 14-day period consisting of the 13 days prior to the lock-down date March 12 and the lock-down date (the pre-intervention period) and the 14 days post intervention for Oslo. 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

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

	Min	25	Median	Mean	75	Max
			Oslo			
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		Mar 24 2015			Apr 30 2020
No. obs.			192,106			
Prct. share	Apartments		89.1			
Prct. share	Detached houses		3.8			

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.

		Pre Lockdown	Post Lockdown	
Variable	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	

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.

and post-intervention is smaller on a percentage basis. By employing a hedonic model, we control for these composition effects.

2.4 Auction data

We have acquired auction data from one of the the largest real estate agencies in Norway, DNB Eiendom. The data cover the period from January 1 to April 30, 2020.

The auction data comprise detailed information on every single auction that led to a sale in 2020, and that was handled by an agent at DNB Eiendom, over the sample period. 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. 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 bidding data are used to construct two measures capturing 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 frequency of opening bids that are less than 90 percent of ask price, and use this as a measure of aggressive bidding.

Table 3 summarizes the bidding data partitioned into pre-intervention and post-intervention. From Table 3, we observe that 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. However, there is a large difference between pre-intervention and post-intervention in several key measures. First, in the pre-intervention period the distance between the sell price and the highest rejected bid in days prior to the acceptance date is 2.49. This means that, on average, the sell price is two and a half percent higher than the highest rejected bid (in days prior to, but not on the same day). After lock-down it was 0.8 percent. Our interpretation is that seller confidence is affected by the policy intervention. Moreover, before lock-down 18 percent of auctions had an opening bid that was very low, i.e. at least ten percent lower than the ask price. This frequency was 27 percent after lock-down. This aggressive bidding indicates 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

Variable	Pre lock-down Mean	Std.	Post lock-down Mean	Std.
No. bidders	2.47	1.48	2.30	1.47
No. bids	7.75	6.79	7.70	6.57
No. bids per bidder	3.10	1.73	3.33	1.78
Seller confidence: Dist. sell price vs. rejected bid	2.49	2.48	0.78	1.36
Aggressive bidding: Perc. with op. bid < 90% ask price	17.92		27.14	
No. obs.	106		70	
No. obs.*	16		8	

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 lock-down. The pre lock-down period includes the date of the lock-down, March 12, 2020. 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. Percent with opening bid below 90 % of ask price is the number of auctions with opening bid with a bid below 0.9 of ask price divided by the total number of auctions multiplied by 100. 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.

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 (2019), and is given by:

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

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 and out-of-range 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 these, the residual, is divided by the predicted price and termed the prediction error, measuring the percentage deviation between observed and predicted price. 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. 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 divide the difference in means by the square root of the sum of the two second order moments divided by their respective sample sizes. Thus, we estimate the variances using observed second order moments for each sample. Then, we approximate the distribution of the difference in means using the t-distribution.[4] We use the same metric to compare means in transaction volumes.

3 Results

In the following, results from the lock-down are first analyzed in detail using both transaction and auction data as well as placebo tests. Next, a similar analysis is conducted for the reopening period. Finally, results for the whole period are evaluated against data on sentiment and social mobility.

[4] Rice., J. A. (1995): Mathematical statistics and data analysis, Belmont, CA: Duxbury, p. 395.

3.1 The lock-down

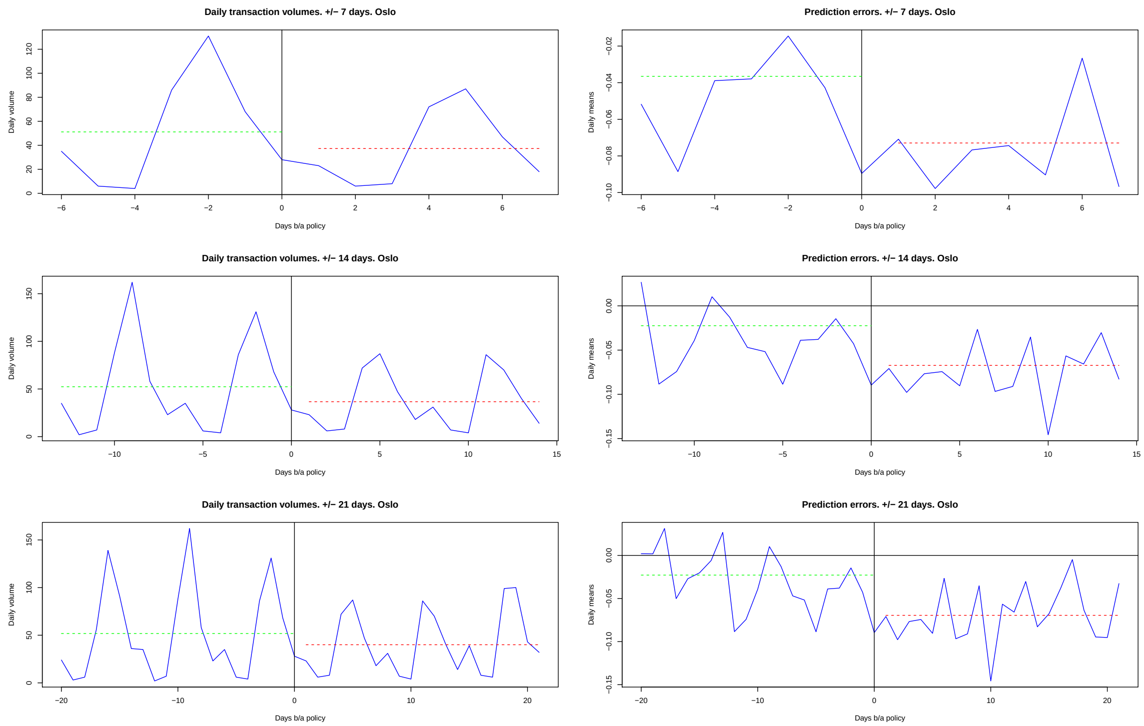
Figure 2a plots transaction volumes for Oslo in the pre- and post-intervention windows using three different widths of data windows. In order to control for intra-week price and volume patterns generated by the intra-week pattern in open houses (Røed Larsen, 2020), we use resolutions of multiples of 7 days. The green and red lines represent means over transaction volumes.

Transaction volumes show a clear structural break on the date of the lock-down. In the pre-intervention 7-day-period the mean transaction volume is 51 transactions per day while it is 37 in the 7-day post-intervention period. Table 4 shows that the difference is statistically significant. The table also shows that a lower resolution obtained by increasing the width of the data window to 14 and 21 days does not change the impression of a clear structural break. All the means of transaction volumes are statistically significantly higher in the pre-intervention period compared to the post-intervention period, regardless of bandwidth.

Figure 2b presents price developments in the pre-intervention period versus the post-intervention period, using different multiples of weeks in the width of the data window. Price developments are represented by the price prediction error, i.e. the daily mean difference between predicted prices from a hedonic time dummy model versus observed sell prices across units (for each day).

The mean sell-predicted spread, i.e. the mean difference between observed sell prices and predicted prices relative to predicted prices, for the 7-day pre-intervention period is -0.037.[5] This implies that prices were 3.7 percent lower in the seven days leading up to the lock-down compared to what the hedonic time dummy model tells us was to be expected had the housing market behaved in March 2020, as it had in the previous 10 years from 2010. This finding is indicative of market participants making behavioral changes ahead of the policy-intervention. The spread falls to -0.073 in the 7-day post-intervention period. The difference between the pre and post lock-down period is statistically significant, as shown in

[5]This is not a mean of 7 daily means, but a mean across transactions in the 7-day period.



(a) Transaction volume (b) Prices

Figure 2: Figure 2a and 2b report transaction volumes and mean daily price prediction errors before and after lock-down. Width in week multiples. Oslo, 2020. The graphs depict transaction volumes and prediction errors for two periods, before and after the lock-down. 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 lock-down 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 4, and is indicative of an additional effect of the lock-down that re-enforces the effect from the voluntary behavioral changes. We observe that the result is robust to varying the resolution by increasing the bandwidth with multiples of weeks.

As shown in Figure 3, which reports the results from placebo regressions, these unusual price movements are unlikely to have happened by chance. In the lower right panel of

Var.	Per.1	Cut-off	Per. 2	$Mean_1$	$Mean_2$	n_1	n_2	Std_1	Std_2	Metric
Volumes	- 7 days	12 Mar	+ 7 days	51.1	37.3	358	261	46.4	32.1	4.4
Volumes	- 14 days	12 Mar	+ 14 days	52.4	36.6	733	513	49.6	30.7	6.9
Volumes	- 21 days	12 Mar	+ 21 days	51.8	40.0	1,088	840	48.3	33.0	6.4
Prices	- 7 days	12 Mar	+ 7 days	-0.037	-0.073	358	261	0.18	0.14	2.8
Prices	- 14 days	12 Mar	+ 14 days	-0.022	-0.067	733	513	0.18	0.15	4.7
Prices	- 21 days	12 Mar	+ 21 days	-0.023	-0.070	1,088	840	0.18	0.15	6.1

Table 4: Mean daily transaction volumes and price prediction errors before and after lock-down. Widths in week multiples. Oslo, 2020. The table tabulates transaction volumes and prediction errors for two periods, before and after the lock-down. 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 lock-down 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, and day of week dummies, and Easter dummy. We also use dummies for week 8 and week 9 to capture the Winter school holiday season. The models are estimated using data from before (and not including) February 14, 2020.

the figure, we show the differences between the estimated counter-factual developments of prices compared to actual developments of prices in 2020. The three other plots are the same estimations done in placebo years. We chose years in which the Easter holiday is not included in the 28-day period around March 12. Even though we have controlled for Easter in the hedonic model, the transaction volumes are low in Easter and the best comparison for the year 2020 are thus the three years 2014, 2017, and 2019. 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. We see that the difference in means is substantial in 2020, but not in the placebo years, lending support to our counter-factual exercise. While 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 is.

While the results above clearly indicate a shift in the mean around the lock-down, visual inspection of the prices in Figure 2 suggest a downward-sloping trend starting at least two weeks prior to the lock-down. Panel b of figure 4 shows the result of fitting two non-

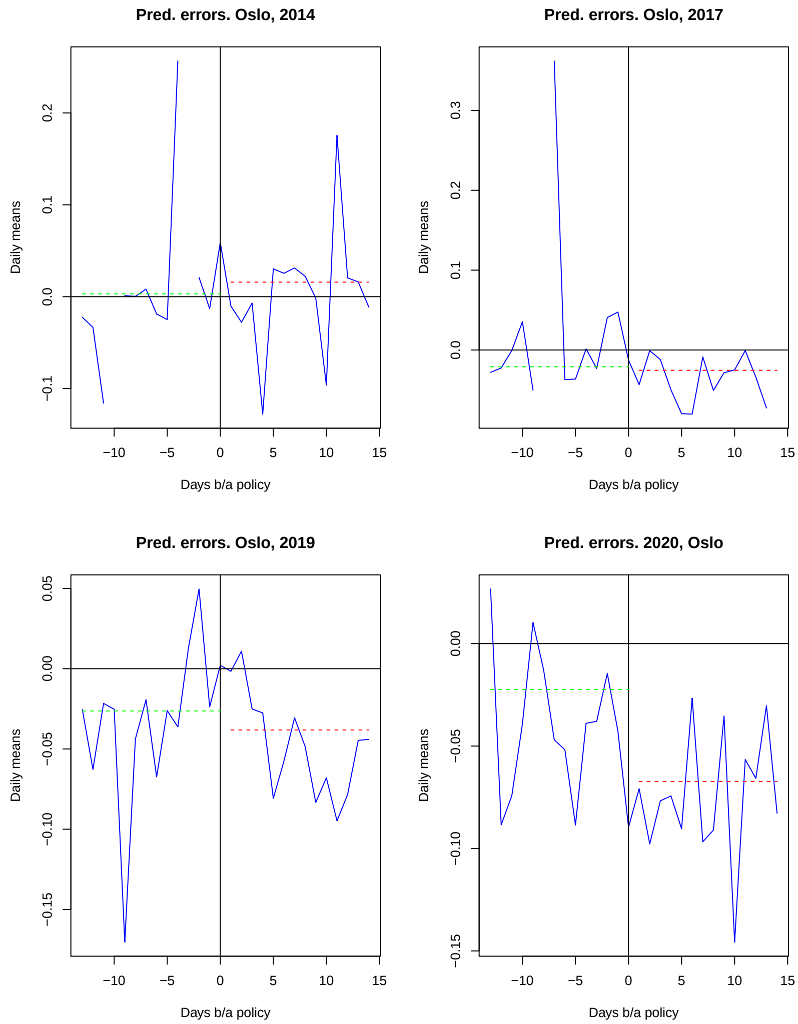
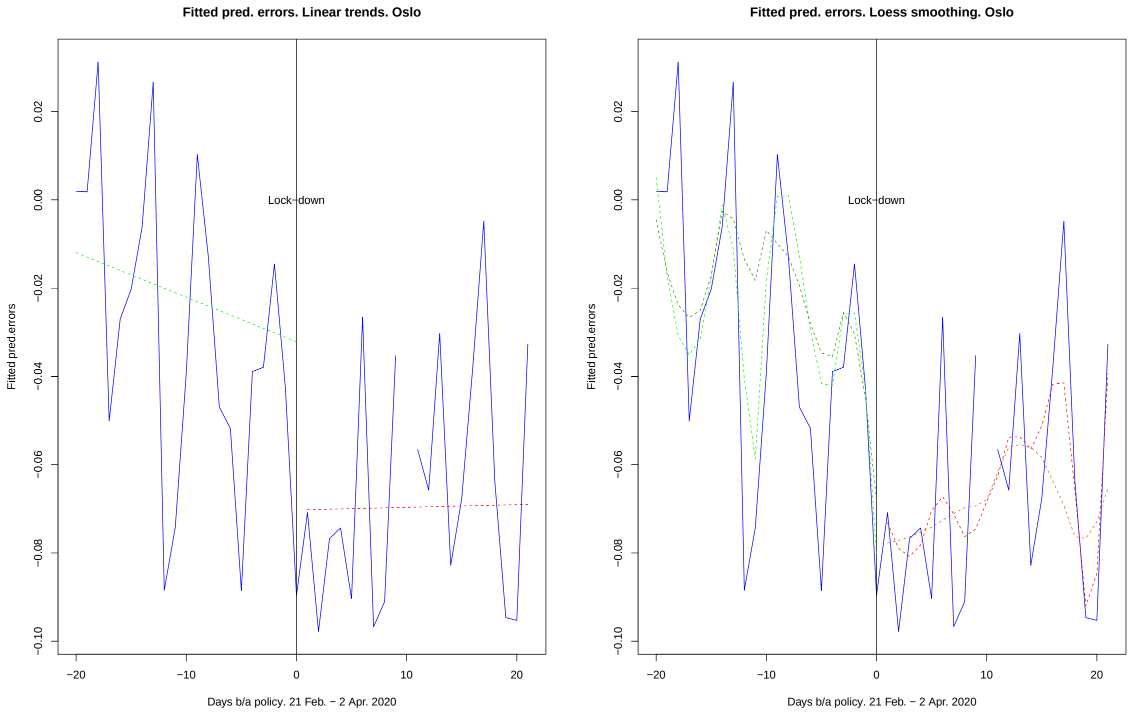


Figure 3: Mean daily price prediction error. True lock-down and 3 placebos. Oslo, 2014, 2017, 2019, and 2020. The panel of plots shows the prediction errors in three placebo years in which Easter is outside of the data window. The hedonic model is estimated on data before (and not including) 14 February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

parametric local regressions, one for the period before the lock-down and one for the period after, using loess-smoothing parameters of 0.35 and 0.55. The figure supports the notion of a structural break around the date of the lock-down in that the fitted (red) line bottoms out. The figure also supports the idea that market participants had already started to act upon negative news before the lock-down in that the non-parametric trend for the period before the lock-down (the green line) is displaying a declining trend. A similar finding is obtained



(a) Linear (b) Non-parametric

Figure 4: Figure 4a shows two fitted linear trends in number of days after period start. The linear trends are computed using the micro observations on each transactions, not the daily means, which are represented by the blue line. Thus, a few extreme daily means are not given much weight since they are computed on the basis of few transactions that day. One example is T = 10, a point that represents a mean spread based on four transactions. We remove T = 10 from the blue line in the graph in order to facilitate sharper focus. It is, however, included in the computations of the green and red lines. Figure 4b shows non-parametric local regression trends. The graph shows two separate (for the period before and after the lock-down) non-parametric trends in number of days after period start. We use the loess-function in R with smoothing parameters equal to 0.35 and 0.55. Oslo, 2020.

by fitting a simple linear trend to each window, which we plot in Panel a. The linear trends also shows the discontinuity on the lock-down and the stability of prices in the three weeks following the lock-down.

In order to probe deeper into the dynamics between sellers and buyers, we now turn to results from the auction data. 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 aggressive bidding (the frequency of auctions with an opening bid that is lower than 90 percent of the ask price).

We follow week-by-week results since day-by-day would be susceptible to intra-week effects.[6] In Table 5, we see that there is little change in number of bids, number of bidders, and number of bids per bidder in the two weeks prior to lock-down, and in the two weeks after the lock-down. The extensive margin of bidding therefore suggests little changes in bidding behavior. Turning to the intensive margin, our seller confidence measure is 3.03 in the first week, i.e. the week that starts with the day 14 days before lock-down. On average, an accepted bid is three percent higher than the highest rejected bid (in days prior to the day of the acceptance). Then, one week before lock-down, this metric falls to 1.59 percent, a reduction that indicates behavioral changes in sellers' tendency to accept lower bids and thus behave as if they are more impatient or at least do not have the confidence to wait for higher bids. During the first week after lock-down, this seller confidence measure has fallen to 0.96 percent. Then, two weeks after lock-down it is even lower, 0.60 percent. We interpret these results as showing that seller confidence changed before lock-down and fell after lock-down.

Our aggressive bidding measure is at 13 percent two weeks before lock-down and at 22 percent one week before. This indicates that buyers appear to have changed behavior prior to the lock-down. The measure was slightly lower in the week right after lock-down, 18 percent, but much higher two weeks after lock-down, 35 percent. We interpret these findings as showing that aggressive bids started to become more frequent before lock-down and was higher after lock-down. This supports the notion that buyers attempted to take advantage of the situation.

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

Variable	Two weeks prior	One week prior	One week after	Two weeks after
No. bidders	2.36	2.55	2.38	2.23
No. bids	7.30	8.10	7.47	7.91
Bids per bidder	3.09	3.11	3.08	3.56
Seller confidence: Dist. sell price vs highest rejected bid	3.03	1.59	0.96	0.60
Aggressive bidding: Opening bid < 90 % ask price	13.04	21.67	18.18	35.14
No. obs.	46	60	33	37
No. obs.*	10	6	4	4

Table 5: Means per week. 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 lock-down are 14-day periods before and after lock-down. The pre lock-down period includes the date of the lock-down, March 12, 2020. 'No. bidders' is short notation for the mean number of bidders per auction. Similarly for 'No. bids' which is number of bids per actions. The variable 'distance sell price versus highest rejected bid' is defined as the difference between the sell price and the highest rejected bid in days prior to the day of acceptance, as a fraction of highest rejected bid multiplied by 100. The variable 'opening bid below 90 % of ask price' is the number of auctions with opening bid with a bid below 0.9 of ask price divided by the total number of auctions multiplied by 100. 'No. obs.' is number of transactions. 'No. obs.∗' is number of auctions in which a previous bid has been rejected at latest the day before acceptance.

3.2 Policy reversal and re-opening

Turning to the period around the re-opening, Figure 5 reports mean daily sales volumes and mean daily prediction errors for the three periods before lock-down, after lock-down, and after re-opening. We see that there is an effect of the re-opening. In fact, it appears that the re-opening completely reverses the lock-down effect on prices. The interpretation on sales volume, however, needs to be more cautious since April typically is a month with a high number of transactions after Easter.

Table 6 summarizes mean daily transaction volumes and price prediction errors before and after re-opening. Comparing means from the week after re-opening to the means in the week prior to lock-down (see Table 4), there are only minor differences in transaction volumes. It must be noticed that the Easter of 2020 is included in the two weeks prior to re-opening, which could explain why transaction volumes are low in this week, and high in the week after.

There is little difference in the mean sell-predicted spread between the 7-day period two

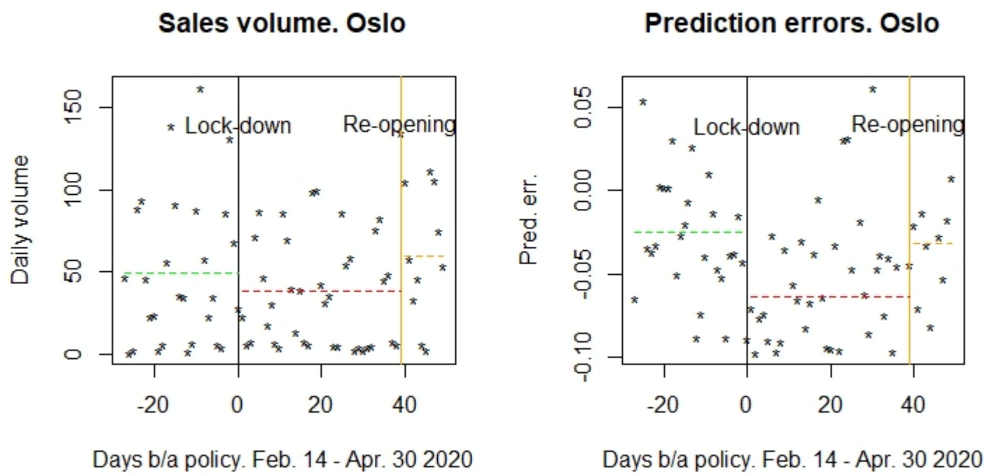


Figure 5: Sales volumes and prediction errors. Oslo, 2020. In the plot, we require that daily observations are based on at least two transactions and that mean daily prediction error in absolute values is smaller than 0.1. All transactions are, however, included in the computations of period means.The period before lock-down runs from T=-27 and includes T=0. The lock-down period runs from T=1 to T=39. The re-opening period starts at T=40.

weeks before and the 7-day period one week before the re-opening of the Norwegian economy. Thus, we find less evidence of an anticipation effect in relation to the policy reversal. This could partly be related to the way in which the hedonic model is constructed, since it presupposes the usual negative Easter-effect on prices, which may have been less relevant in 2020, since people were staying at home instead of travelling. Comparing the 7-day period prior to the re-opening to the 7-day period after the re-opening, it is evident that the sell-predicted spread gets narrower. This suggests that the re-opening had a positive effect on house prices. For the 7-day period following the policy reversal this spread is -0.034. Even though this is almost the same as the spread in the week before lock-down, -0.037, it still implies that prices were 3.3 percent lower in the 7-day period after policy is reversed than what is expected based on the hedonic time dummy model. We say this with caution as the uncertainty of the counter-factual increases the longer the extrapolation is.

Table 7 summarizes the bidding data for the 7-day period 2 weeks before re-opening, the 7-day period one week before re-opening, and the 7-day period following the re-opening.

Variable	Period	Reference date	Length	No. obs.	Mean	St.dev.
Volumes	2nd week before	Apr. 20	7 days	133	19.0	25.0
Volumes	1st week before	Apr. 20	7 days	402	57.4	45.3
Volumes	1st week after	Apr. 20	7 days	363	51.9	43.5
Prices	2nd week before	Apr. 20	7 days	133	-0.0567	0.163
Prices	1st week before	Apr. 20	7 days	402	-0.0580	0.160
Prices	1st week after	Apr. 20	7 days	363	-0.0339	0.194

Table 6: Mean daily transaction volumes and price prediction errors before and after re-opening. Widths in week multiples. Oslo, 2020. The table tabulates transaction volumes and prediction errors for three weeks around re-opening. The 1st week before re-opening includes T = 39, i.e. 20 April, the day of the re-opening, due to symmetry with the treatment of March 12. 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, and weekday dummies, and Easter dummy. We also use dummies for week 8 and week 9 to capture the Winter school holiday season. The models are estimated using data from before 14 (and not including) February 2020.

Similar to the lock-down, there is little change in number of bidders and number of bids placed in each auction across periods. Both the lock-down and the re-opening therefore seems to have little impact on the extensive margin of bidding behavior.

There are, however, substantial differences in the distance between the sell price and the highest rejected bid before and after re-opening. This suggests that seller confidence was restored after the re-opening of the Norwegian economy. The results are also suggestive of an anticipation effect, as the seller confidence measure increases substantially between the 7-day period two weeks before re-opening and the 7-day period one week before re-opening. However, again it is important to have in mind that the 7-day period two weeks prior to the re-opening includes Easter. It is also evident that aggressive bidding falls markedly after the policy is reversed, suggesting less aggressive behavior from buyers. In the 7 days preceding the policy reversal, the opening bid was at least ten percent below the ask price in 36 percent of the auctions, while this measure falls to a little less than 14 percent after the re-opening. There is no evidence that aggressive bidding started falling prior to the re-opening.

In short, the results in sections 3.1 and 3.2 document that behavioral changes accounted for a substantial part of the housing market movements in the period surrounding the lock-

Variable	Two weeks prior	One week prior	One week after
No. bidders	2.45	2.30	2.00
No. bids	7.17	8.06	5.88
No. bids per bidder	2.76	3.55	2.84
Seller confidence: Dist. sell price vs. rejected bid*	0.38	2.63	3.79
Aggressive bidding: Perc. with op. bid < 90% ask price	33.33	36.05	13.79
No. obs.	33	86	58
No obs.*	3	10	2

Table 7: Means per week. Pre-/post policy reversal. Auction data, Oslo 2020. The table tabulates auction 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. bidders' is short notation for the mean number of bidders per auction. Similarly for 'No. bids', which is number of bids per actions. The variable 'distance sell price versus highest rejected bid' is defined as the difference between the sell price and the highest rejected bid in days prior to the day of acceptance, as a fraction of highest rejected bid multiplied by 100. The variable 'opening bid below 90 % of ask price' is the number of auctions with opening bid with a bid below 0.9 of ask price divided by the total number of auction multiplied by 100. 'No. obs.' is number of transactions. 'No. obs.∗' is number of auctions in which a previous bid has been rejected at latest the day before acceptance.

down. In fact, our estimates suggest that roughly half of the total fall in prices observed in the week after the look-down had occurred already in the week prior to the lock-down, and that the re-opening completely reverses the lock-down effect on prices. However, there is less evidence of behavioral changes affecting price developments in the period shortly 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, Figure 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 lock-down. After the re-opening, however, the traffic patterns gradually returned to, and

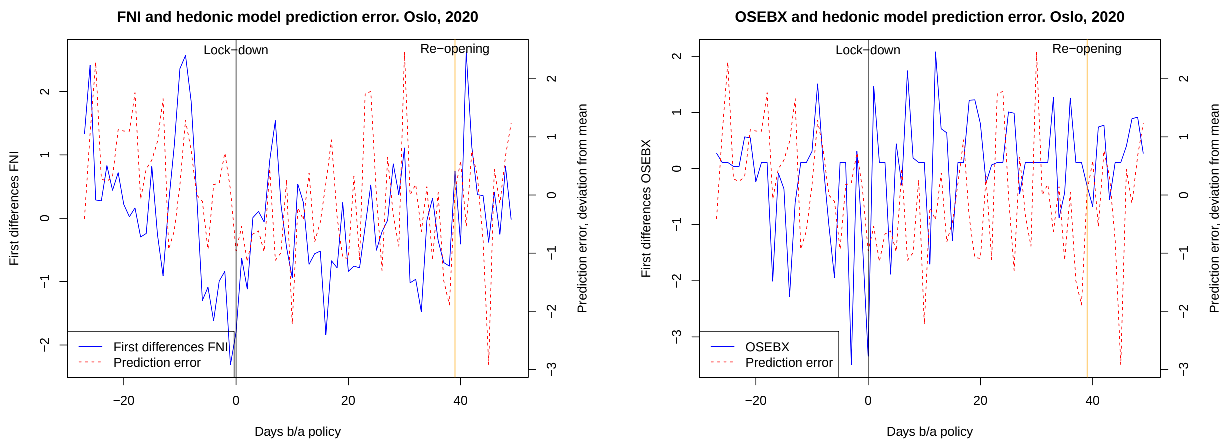
(a) Traffic

(b) Immobility

Figure 6: Social mobility and immobility. The period before lock-down runs from T=-27 and includes T=0. The lock-down period runs from T=1 to T=39. The re-opening period starts at T=40. Figure 6a graphs the sum of the number of vehicles passing 144 registration points in Oslo municipality each day relative to baseline. The baseline is calculated based on the median traffic volume for each day of the week in the period from January 3 to February 6, 2020. The graph then reports the percentage deviation to the corresponding baseline day of the week for each day after February 6, 2020. Data are collected using the Norwegian Public Roads Administration's Traffic Data API. Figure 6b graphs immobility measured as people's 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 allows Google to use these GPS data to calculate changes in time spent at home. For each day from February 15, the change in mobility is compared to the baseline period, for the corresponding day of the week, from January 3 to February 6, 2020.

even increased above, the baseline. The social mobility data from Google show a somewhat different pattern. There are very small deviations from baseline prior to the lock-down, followed by a large jump at the lock-down date and then a gradual return to baseline. Thus, in line with the results from the housing market, these social mobility statistics indicate that households actually adhered to the lock-down 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



(a) Sentiment (b) Stock market

Figure 7: Sentiment and stock market changes. The period before lock-down runs from T=-27 and includes T=0. The lock-down period runs from T=1 to T=39. The re-opening period starts at T=40. For visual clarity, all data series are normalized. Figure 7a 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). Figure 7b 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.

builds on the work by Thorsrud (2020), and is constructed based on daily newspaper coverage. As such, it is tailored at measuring the information households potentially have about economic developments, and 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 Figure 7 the sentiment index and the (normalized) prediction errors track each other, especially before lock-down, where both series clearly trend downwards. In the week(s) prior to re-opening, we also observe that the sentiment seems to increase gradually. Interestingly, even though the changes in the stock exchange index display some of the same trends, the association with prediction errors in the housing market is much less clear.

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

$Prediction\ Error_t = a + b(\Delta Sentiment_t\ Index) + c\Delta(Stock\ Exch.\ Index_t) + \epsilon_t$			
Variable	Estimated coef.	St. err.	P-value
Intercept	-0.0434	0.0052	2.6e-12
Diff. Sentiment	0.174	0.072	0.018
Diff. Oslo stock exchange	-0.000341	0.00028	0.24
No. obs.		77	
Root mean sq. err.		0.0432	
Adj. R^2		.0524	
F-statistic		0.0509	

Table 8: House price developments, sentiment, and the stock market. The sample starts on 14 February and ends on 30 April. The Δ is the difference operator. See Figure 7 for further details.

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-squared statistic suggest 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 in large part driven by behavioral changes, and these behavioral changes are also visible in other statistics measuring social mobility and economic sentiment. At the same time, market participants seem to have followed governmental policies, such as the lock-down, and the effect of these policies have an independent effect on both house prices and sentiment.

4 Concluding remarks and policy implications

The Covid-19 pandemic has sparked an ongoing debate on how to balance policy interventions aimed at stopping the spread of the virus against negative economic outcomes. In this article, we use unique Norwegian day-by-day transaction and bid-by-bid auction data in order to examine how market participants reacted to the spreading news of Covid-19 in early March, 2020, the lock-down 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 analyse.

Our findings suggest that the lock-down depressed prices. The lock-down also led to lower seller confidence and more aggressive bidding. The re-opening completely reversed the lock-down effect on prices. For transaction data, the results of the lock-down are particularly striking. While mean daily transaction volume in the week before March 12 was 51 sales, it was 37 after lock-down. Hence, behavioral changes occurring also before the lock-down likely matter a lot. According to our estimates, half of the total fall in prices observed in the week after the look-down occurred before the lock-down.

These conclusions are robust to a number of alternative modelling 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 lock-down. 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.

One key finding has important policy implications. In the debate following the lock-down, the predominant view was that policy intervention adversely affected the economy. We find that even without any change in policy, the economy would have been adversely affected, due to voluntary adjustments in behavior. People responded to the news of Covid-19, not only to the policies against Covid-19.

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Acknowledgements:
Housing Lab is partly funded by the Norwegian Ministry of Finance and the Norwegian Ministry of Modernisation and Municipalities. Housing Lab also receives financial support from Krogsveen and Sparebank1-Gruppen. We are greatful for the financial support. All views expressed in our papers are the sole responsibility of Housing Lab, and does not necessarily represent the views of our sponsors. The authors are grateful to DNB Eiendom and Eiendomsverdi for auction and transaction data.

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