

Can Ratings Mitigate Consumer Inattention? Evidence From the Swedish Housing Market

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Abstract

I study the effects of ratings designed to capture the financial risk associated with apartment ownership in Sweden. I find a discontinuous impact around rating thresholds on sales prices and real estate agents' pricing decisions, but only after ratings started being displayed in online listings. This is not driven by changes in the number of bidders in apartment auctions. However, the magnitude of the rating effect is larger for sales administered by high- relative to low-quality real estate agents. My results suggest that ratings conveying financial information to consumers must ensure a high degree of salience to be effective. However, financial intermediaries remain likely to play a role in the transmission of such information.

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1 Introduction

Consumers often fail to understand, or even pay attention to, important information in many financial decision-making settings. These constraints may lead consumers to make sub-optimal choices at substantial cost when stakes are high (Campbell 2006; Handel and Schwartzstein 2018). Understanding how to improve the transmission of information to consumers is, therefore, an important problem. The effectiveness of such efforts requires an understanding of which constraints are binding: consumers may fundamentally lack access to financial information, or fail to consider it in absence of salient cues. Accordingly, it has proven difficult to design interventions that deliver meaningful results at scale (Beshears et al. 2018). I address this by investigating the effects of market-wide ratings, incorporating financial information, on consumer behavior and market-level outcomes in both low- and high-salience settings.

I study this in the context of the Swedish housing market, where apartment properties are organized as co-operatives (co-ops) owned jointly by its residents; when purchasing an apartment, the buyer purchases a share in the co-op that owns it. This model of ownership exists in many countries, and approximately 10% of Europeans live in such co-ops (Cameron et al. 2012). Since these co-ops can (and do) take on debt that their members are personally liable for, their financial status becomes a highly important factor to consider when purchasing an apartment.¹ Despite their importance, previous studies find that co-op debt (as well as other hidden costs, such as taxes) is poorly reflected in apartment prices (Hjalmarsson and Hjalmarsson 2009; Almenberg and Karapetyan 2014; Elinder and Persson 2017; Agarwal and Karapetyan 2022), and 60% of homeowners are unaware of the debt level of their co-op (SBAB 2025). The Swedish case provides a particularly interesting setting to study, because several market features that might plausibly improve information transmission are already in effect: real estate agents are mandated by law to provide information, and co-ops produce publicly available annual reports that are physically handed out to prospective buyers during public viewings.

This paper studies a mechanism designed specifically to improve the transmission of such information to consumers. Since late 2015, a private company (*Allabrf*) has produced letter-based, color-coded ratings that capture the financial status of apartment co-ops in Sweden, based on data from publicly available annual reports. These ratings were, at first, freely available to consumers on a searchable website. Their salience increased substantially in 2018, when they started being shown in listings on what is by far the largest platform for apartment listings in Sweden (*Hemnet*). Importantly, these ratings are not tied to any regulation or used by banks to make credit assessments in mortgage lending. As such, they provide an opportunity to study i) the effect of ratings solely as

¹When the construction of an apartment building is finalized, a co-op is formed and decides the degree to which the purchase of the building (from the developer) should be financed by debt, and how much should be paid by the initial group of buyers. Different financing decisions result in large differences in initial co-op debt, for which future members will be personally liable. Hence, higher co-op debt implies a lower net value of the asset which should result in lower apartment prices. Over time, however, differences in co-op debt may also reflect differences in further investments (such as exterior renovations).

a mechanism to provide and signal information and ii) their impact on market outcomes in low- and high-salience regimes.

The rating system is based on six continuous, financial variables that are based on raw data from co-op annual reports.² A co-op obtains a particular rating by passing a cutoff in an index score based on these variables. The ratings range from *C* to *A++*, but almost all (~ 99%) co-ops obtain one of the three middle ratings which I will focus on in this paper: *B* in yellow color, *A* or *A+* in green. All else equal, better ratings should translate into higher sales prices by reflecting lower liabilities associated with the co-op (in the form of debt) but also greater financial prudence (e.g. sensitivity to future interest changes and balance between expenses and revenues).

I estimate the effect of obtaining a particular rating by exploiting the plausibly exogenous variation in rating assignment of co-ops that are close to a particular cutoff. I use data on apartment sales in the three largest metropolitan areas of Sweden between late 2015 and 2020, combined with unique and proprietary data from the company producing the ratings. The main sample contains ~ 115,000 apartment sales, covering about half of the market for apartments over the sample period.

I discuss a set of hypotheses related to the staggered implementation of the rating system. If consumers demand information on co-op finances but are fundamentally unable to understand or obtain it, then the introduction of ratings (an information shock) should affect prices immediately upon their release. The appearance of ratings in online listings (a salience shock) should only matter if consumers are inattentive to co-op finances in absence of salient cues (as found in, e.g., [Agarwal and Karapetyan 2022](#)), or rely on ratings as convenient heuristics in their search process, such as by filtering out co-ops with poor finances. In the latter scenario, we should expect poorly rated co-ops to attract fewer bidders.

I document six empirical results. I first show that obtaining an *A* as opposed to a *B* leads to a 2.5% increase in subsequent sales prices. This is a sizeable effect: at the sample mean, it translates to ~ 1,300 SEK per square meter, or ~ 125 USD. Further, I show that the finances of co-ops rated *A* or *A+* are more similar compared to those rated *B*, and I find no evidence that obtaining an *A+* vs. an *A* (both displayed in green) has any impact on prices.

My second finding is that the effect around the *A/B* cutoff is almost entirely concentrated in time periods after October 2018, when the ratings started to be shown in online apartment listings. This change greatly increased the salience of the rating system, while all of its other features remained unchanged. The effect that I observe had already emerged within one year of the implementation of this high-salience regime. Hence, it appears unlikely to be driven by e.g. a secular trend in the awareness of the rating system.

Third, I find that the effect on sales prices is matched by a corresponding effect on the listing price, which refers to the price set by the real estate agent (conditional on seller approval) to be shown in

²These are co-op debt, membership fees, EBITDA, revenues from other sources than its members (e.g. commercial property), operating expenses, and sensitivity to interest rate changes.

the apartment listing. Hence, the observed effect of ratings arises already at the stage during which the agent makes his or her assessment of the market value of the apartment.

Fourth, I find that better ratings have no impact on the number of unique bidders in apartment auctions. This holds both before and after the introduction of ratings in online listings. This result, I will argue, provides evidence against a mechanism in which ratings serve purely as a time-saving heuristic used by consumers in the process of searching for apartments.

Fifth, I document that sales administered by high-quality real estate agents (as captured by experience and seller reviews) exhibit a significantly larger impact of ratings on prices. This difference appears unchanged by the introduction of ratings in online listings, and underscores the importance of financial intermediaries in information transmission *even* when such information is made both available and salient.

Sixth, I present suggestive evidence that consumers became more sensitized to important but overlooked features of co-op finances after the ratings became pervasive in the market. To show this, I investigate the degree to which co-op debt is reflected in sales prices separately for sales before and after the ratings started to be shown in *Hemnet* listings. I find that the influence of co-op debt in sales prices increased substantially after this increase in salience, and that this is only partly explained by the ratings themselves. While suggestive, this is in line with the hypothesis that ratings nudge consumers to care more about the underlying factors that the ratings are (coarsely) designed to capture.

A back-of-the-envelope calculation suggests that the effect of ratings on sales prices that I document corresponds to a large share of the price gap between *A*- vs. *B*-rated co-ops that would be expected if co-op debt was reflected in sales prices at a one-to-one rate. More generally, these results indicate that making financial information freely available, even in a simple format, does not affect market prices unless combined with a high degree of salience. However, even when made salient to buyers, real estate agent characteristics still predict the influence of rating information on prices. A possible explanation for this is that real estate agents are able to influence the degree to which ratings are taken into account by prospective buyers (e.g. downplaying or underscoring their importance). As such, policies that successfully improve the transmission of financial information to consumers may not necessarily be able to simultaneously reduce the reliance on intermediaries.

This study contributes to both the literature on consumer inattention to financial information and the literature on ratings. The finding that households do not understand or have access to financial information, and/or make mistakes given information that is in fact available, generalizes to a wide range of settings such as investments (Calvet et al. 2009), retirement savings (Madrian and Shea 2001), mortgage refinancing (Andersen et al. 2020), housing purchases (Hjalmarsson and Hjalmarsson 2009; Almenberg and Karapetyan 2014; Repetto and Solís 2019; Andersen et al. 2022), taxes (Chetty et al. 2009) and real estate taxes in particular (Elinder and Persson 2017; Gindelsky et al. 2023). At the same time, ordinal rankings based on publicly available information have been shown to influence behavior in a broad range of settings, including school ratings in education (Figlio and

Lucas 2004; Sauder and Lancaster 2006), review-based ratings in consumer markets (Luca 2011), and credit ratings in financial markets (Kliger and Sarig 2000; Bernstein et al. 2023). I contribute to these lines of research by distinguishing between the availability and salience of ratings: features that are typically studied as a bundled treatment.³ Even in one of the largest purchasing decisions that consumers face—buying a home—freely available ratings designed to capture important financial information had little impact on market prices before being made highly salient. This indicates that the salience component of ratings is a highly important driver of their success in affecting consumer behavior.

A related strand of research studies the role of intermediaries in shaping consumer decisions. This work emphasizes their informational role, showing that intermediaries can help interpret complex information but may also distort or selectively present information when their incentives diverge from those of their clients (Levitt and Syverson 2008; Inderst and Ottaviani 2012; Mullainathan et al. 2012). In my setting, real estate agents are legally obliged to provide all relevant information, including on co-op finances, related to the apartment being sold to prospective buyers. Despite this, I find that the extent of the rating effect on prices varies significantly between high- and low-quality real estate agents—even after ratings were made salient in online listings. These patterns suggest that while salience plays a key role, intermediaries also shape how rating information is incorporated into prices.

This study also relates to a broader literature on interventions aimed at reducing consumer mistakes in financial decisions. Research has examined a variety of mechanisms, including simplification of choice sets (Keim and Mitchell 2016), provision of default options or nudges (Madrian and Shea 2001; Banerjee et al. 2025), financial education (Hastings et al. 2013), and changes in the presentation or salience of existing information (Chetty et al. 2009). In a closely related study, Agarwal and Karapetyan (2022) find that the disclosure of co-op debt in online apartment listings in Norway had a large impact on pricing. My results reinforce the interpretation that salience, rather than the mere availability of information, is the driving force behind the effectiveness of such interventions.

2 Institutional setting

2.1 The Swedish housing market

Almost all apartments in Sweden are sold through auctions organized by real estate agents. Unlike in many other settings, only one agent is involved in the sale process. This agent, hired and paid by the seller, is legally mandated to act in the best interest of both the seller and the buyer, following a set of best practices outlined by law (FMI 2023). These involve informing prospective buyers about

³For example, Andrabi et al. (2017) produce school report cards containing ordinal rankings based on average test scores, and deliver these to parents. Whether such report cards would impact market outcomes had they only been made available at, e.g., a searchable webpage remains an open question.

the property and making the costs associated with owning it explicit. However, exactly which information, and how it should be presented to prospective buyers, is not explicitly specified. The Swedish Estate Agents Inspectorate oversees compliance with these practices, and agents must complete a two-year degree to obtain a license to operate legally. Agents typically charge fees based on a fixed percentage (usually around 1.5% of the sale price) or a fixed sum plus a commission percentage above a negotiated threshold (Österling 2016).

The agent manages almost all practical and legal aspects of the sales process. Once hired, the agent arranges a photography session and gathers information about the apartment and the co-op that owns it. After creating advertisement materials, the agent publishes listings on the agency's website and *Hemnet.se*, the largest search engine for housing sales in Sweden. Only licensed agents can post listings at *Hemnet*. These listings include a listing price, advertisement materials (photographs, descriptions, etc.), the monthly fee paid to the co-op, and a map showing the apartment's location.⁴

The listing price is a strategic variable for real estate agents, with lower prices believed to attract more potential buyers (Österling 2016; Repetto and Solís 2019). However, agents are legally prohibited from setting "overly misleading" listing prices, as part of their mandate to act in the best interests of both buyers and sellers. While this is not precisely defined, court cases have established that a downward deviation from the sale price of 10% is acceptable, 18% to provide grounds for an official warning, and 30% to be misleading (FMI 2019a). Beyond legal constraints, agents may avoid misleading pricing due to potential reputational damage, as this practice is generally viewed negatively in the industry.

It is also important to note that the listing price may itself influence the sales price. In a scenario where real estate agents have more information about the apartment being sold than prospective buyers – which seems plausible – the listing price may be viewed as reflecting unobserved characteristics, and thus enter consumers' valuations. As such, setting a low listing price may not always be strategically optimal on part of real estate agents. The data shows a very close correlation between listing and sales prices over time. The average premium is 9%, with a standard deviation of 8-9%. The premium (i.e. difference between sales and listing price) decreased after prices slumped in 2017-18, and so did its dispersion (Figure A.1 in the Online Appendix).⁵

After publishing the listings, the agent hosts public viewings of the apartment. During these viewings, the most recent co-op annual report is made available in print, along with a brochure containing photographs and information about the apartment. The sales price is determined in the form of anonymous, ascending price auctions where bids are typically published in real time at the agency website.⁶ In most cases, the listing price serves as the starting point for the auction. The seller is

⁴The monthly fee is paid to the co-op that owns the property and serves as the primary source of funding for collective expenses, such as renovations and debt repayments.

⁵A possible explanation is that The Swedish Estate Agents Inspectorate received an increasing number of formal complaints on agents setting excessively low listing prices in the preceding years, suggesting a mounting pressure against such behavior among consumers (FMI 2019b).

⁶While the most common practice is ascending price auctions with open bids, nothing prevents buyers to post secret bids directly to the seller via the agent, which happens quite frequently.

never obliged to accept a bid, and may choose to not sell the apartment at all even after an auction is finished. When a buyer has posted a bid that the seller accepts, both parties meet with the agent to sign the contract. The agent is in charge of preparing all such material.

While agents coordinate the monetary transaction between the parties' banks, prospective buyers must secure financing independently. Typically, a significant portion of the sale price (around 70% on average) is financed through mortgage loans ([Finansinspektionen 2021](#)). Most of the time, buyers pre-negotiate a loan amount with their bank before starting their search for an apartment, such that the final size of the issued loan does not need to be negotiated when a deal has been struck with a seller. However, the bank is legally allowed to pull back their loan offer before the deal is closed, and typically performs a quick check on the financial health of the co-op before signing off. It is rare for banks to reject issuing a loan based on this check, and importantly, they do not base lending decisions on the ratings studied in this paper. To confirm this, I contacted all major Swedish banks, which collectively cover nearly 100% of the mortgage market. All banks stated that they use their own internal evaluation practices that do not involve the ratings focused on in this paper.

2.2 Housing co-ops in Sweden (BRFs)

Having purchased an apartment in Sweden, the buyer acquires a share in the co-op (formally an economic association) that owns the apartment building. With this share comes a legally established right to use the purchased apartment. This system of co-owning apartment buildings together with neighbors via *Bostadsrättsföreningar* (roughly translated as “housing co-ops” and typically abbreviated as BRFs) dates back to 1930, when a law establishing the BRF as a legal entity was passed. As of today, virtually all non-rental apartment buildings are owned by co-ops.

Initial differences in co-op finances arise already at their inception. Once an apartment building is constructed, a co-op is formed and purchases the building from the developer. The way in which this purchase is financed varies; the co-op can take on large amounts of debt, and by doing so offer the newly produced apartments to the market at a lower price. Vice versa, the co-op can choose to keep debt low, and instead sell the new apartments at a higher price.

Any renovations that concerns parts of the property that is not interior to the individual apartments are under responsibility of the co-op. Co-ops typically finance such investments by cash reserves or taking on additional debt. Further, the co-op maintains collective running expenses for things such as water and often (but not always) heating. Other expenses include e.g. cleaning, trash disposal and interest payments on loans. The main source of income for co-ops is a monthly fee paid by its members. This fee can vary substantially between different co-ops depending on their financial situation, and constitutes a significant part of apartment-owners' expenses alongside interest rate payments and amortization. In 2017, an average 65% of expenses consisted of this co-op fee ([Statistiska centralbyrån 2017](#)). Other sources of income can include commercial rental activity to e.g. businesses at the street floor of the building. On average, though, such additional revenues

constitute only around 5% of co-op revenues. Co-ops are mandated by law to produce audited annual reports, that describe their activities over the last fiscal year and provide a comprehensive picture of their financial situation. These annual reports are typically posted on the website of the co-op.

Apartment owners are personally liable for a share of the total debt of their co-op. This share is proportional to the size of the apartment. As such, the net price of acquiring an apartment is equal to the sum of its sales price and its associated co-op debt. Theoretically, and in absence of differences in taxation of co-op and private loans, this should imply a *ceteris paribus* relationship between co-op debts and sales prices equal to negative one. In practice, interest payments on private loans are tax deductible up to 30%, making trading off co-op debt with additional private debt more attractive. However, while previous studies find a negative relationship between co-op debt and sales prices for similar apartments, it is far weaker than what theory would predict. This has been attributed to consumers' being biased towards salient sources of debt (private loans) while overlooking less salient sources (co-op debt) (Hjalmarsson and Hjalmarsson 2009; Almenberg and Karapetyan 2014).⁷

The monthly fee that the co-op charges is, on the other hand, widely known to be a very important factor to consider when purchasing an apartment. It is also the only feature of co-op finances that is highly salient, and shown in e.g. online listings. However, assessing the financial situation of the co-op beyond just the current fee remains very important. The level of monthly fees are far from a sufficient statistic for co-op debt: even within deciles of the monthly fee, there is *considerable* variation in co-op debt (see Figure A.2 in the Online Appendix). While some co-ops may currently run high fees in order to finance debt repayments, which allows for a lower fee in the future, other co-ops may do the opposite – this is entirely up to the members of the co-op, i.e. the people living in the building.

2.3 The rating system

The company *Allabrf* launched its co-op rating system in September 2015 in order to improve the transmission of information on co-op finances to consumers in the housing market. The data used to produce these ratings comes entirely from co-op annual reports. However, there exists no public source for e.g. key statistics from these reports. One of the main tasks of *Allabrf* is therefore to digitize these records and compile them in a database. *Allabrf* aims to produce new ratings for all co-ops in Sweden annually, and co-ops cannot opt out from being rated.⁸

The algorithm generating these ratings is proprietary, and was developed by *Allabrf* in collaboration with experts on housing co-ops. It is meant to give a comprehensive summary of the 'financial health' of a co-op: poorly rated co-ops have expenses that eventually will require higher fees from its

⁷This theoretical prediction is underpinned by the assumption that two *otherwise identical* co-ops are being compared. In practice, and as previously discussed, differences in observed co-op debt may also reflect differences in investments. In Almenberg and Karapetyan (2014), this is addressed by restricting the comparison to newly constructed apartment buildings that are unlikely to have made substantial investments (such as renovations) yet.

⁸Despite the ambition to rate *all* co-ops in Sweden every year, exceptions occur. In some cases, annual reports might be hard to access particularly for small co-ops, or in other cases difficult to digitize.

members to be sustained. Likewise, highly rated co-ops may have the possibility to reduce fees. This is borne out in the data: on average, fee changes between any two consecutive years is negatively correlated with higher ratings (Table A.1 in the Online Appendix).⁹

The ratings are based on six continuous parameters, all defined per square meter of the owned property, with weights in parentheses: debt level (30%), membership fee (20%), cash flows [EBITDA] (20%), revenue from other sources than fees (10%), operating expenses (10%) and sensitivity to interest rate changes (10%). In each of these areas, the co-op receives a “sub-rating” (from worst to best: *C, B, A, A+, A++*) determined by whether or not the corresponding continuous parameter exceeds a given threshold. In order to construct the overall rating (which is the one I focus on in this study), these sub-ratings are encoded as integers between 1 and 5 and summed, with weights given above, to form an overall index score. The co-op receives an overall rating on the same scale from *A++* to *C* based on this index. The cutoffs in the index score are sharp at 1.5, 2.5, 3.5 and 4.5, respectively.

It is important to consider what these letter-graded ratings do and do not represent. The ratings are assigned at evenly spaced points along the index score distribution. However, this does not mean that the ratings are evenly spaced on some continuum of underlying co-op finances: the index score is merely a construct based on these data. In fact, there is a larger difference between co-ops rated *B* and *A* than *A* and *A+* along some dimensions (EBITDA, revenues from commercial activity) but not others (debt, interest payments; see Table 1). Further, the ratings do not capture valuable investments that co-ops might make, which may potentially be financed by debt. Hence, co-ops with higher levels of debt (and thereby, on average, poorer ratings) may not necessarily be less valuable from the perspective of buyers. Fortunately, I do have access to data on capital depreciation which allows me to investigate differences in investments across co-ops. This suggests that ratings *A* and *A+* are significantly “closer” to each other than *B*’s (see Section 6.2).

The rating system underwent several important changes in February 2019. First, the cutoffs for four out of the six sub-ratings were changed: operating expenses and membership fees were adjusted for inflation, while the cutoffs for debt levels and cash flows were revamped entirely. Second, the subcategory intended to capture sensitivity to interest rate changes was overhauled. Prior to the update, it was measured by raw interest payments, while the new parameter captures how many percent membership fees must increase in order to keep the balance sheet stable following a rate increase of 1%. Finally, the new rating system mandates that a co-op that does not own the plot of land that it sits on cannot obtain an overall rating above *A*.¹⁰ These changes led to the distribution of ratings being shifted to the left, i.e. in the direction of poorer ratings.

⁹The rating system does not take into consideration physical aspects of the building that the co-op owns. Hence, a co-op that recently made large renovations (a valuable amenity) may receive a poor rating by taking on debt. This is, however, partly addressed by the inclusion of controls for construction year in the main analysis, which absorbs some of the variation in renovation needs. Further, directly controlling for co-ops’ capital depreciation does not change the results.

¹⁰Co-ops can either own the plot of land that the apartment building sits on or lease it from the municipality. The leasing fees are often re-negotiated every 10 years but increase quite predictably. It is more common to own than to lease – in my sample, around 80% of co-ops owns their land.

The overall rating produced by *Allabrf* is shown in two main ways. First, it is publicly available via their website (simply by typing the co-op name in a search box at the front page) and has been so since the launch in September 2015. Second, and importantly, since October 2018 this rating is also shown in ads at *Hemnet*, the (by far) largest portal for housing listings in Sweden (Figure 1 shows an example listing). An interpretation of these ratings is not provided by *Allabrf*, but their color scheme gives clear hints: *C*'s are shown in bright red, *B*'s in yellow, and *A*'s and beyond in the same shade of green (Figure 2). The sub-ratings and further detailed information (such as parameter values underlying the ratings) are only shown to paying customers in the form of a report card (Figure 3). The cost of purchasing a report about a single co-op is around 99 SEK (\$10), but free access to all reports is available at a monthly membership fee of 349 SEK (\$35).

Previous literature has highlighted the importance of considering the business model (and thereby incentives) of both rating producers (Baghai and Becker 2018) and rated entities (Makofske 2020). In addition to providing paid reports to consumers, *Allabrf* has increasingly started to provide consultation and administration services to co-ops in order to expand their business model. While this may in theory provide incentives to give more favorable ratings to certain co-ops, it is unlikely to be the case in practice. This is because the rating system is purely algorithmic, and hence does not provide room for qualitative (and potentially biased) judgment. Further, the annual reports underlying the ratings are mandated by law to be audited by an external agent, which limits the possibility of falsely and/or misleadingly representing co-op finances in order to obtain a better rating.

3 Data

3.1 Apartment sales and co-op ratings

I use data on *Allabrf* ratings, as well as the underlying annual report data, based on annual reports from the fiscal years of 2014 through 2019 for roughly 10,000 unique co-ops in the three largest metropolitan areas of Sweden (Stockholm, Malmö and Gothenburg). The most important variables from this data source are the overall ratings and the running variable (referred to as the index score) that determines them. The index score ranges from 1 to 5 by steps of 0.1. This discreteness is an artifact of the mode of aggregation; for details, see the previous section. In conjunction with the rating system update in February 2019, *Allabrf* replaced also the outdated, historical ratings in their records. However, with help from *Allabrf*, I was able to recreate the rating system that was active prior to February 2019.

Apartment sales data are available from 2014 through 2020 ($N \approx 220,000$) in the same metropolitan areas from the housing ad website *Booli*. Except for listing and sales prices, this data set includes additional information about apartment-specific characteristics such as size, location and the date of sale. In addition to this, I have access to some real estate agent information such as consumer review count and ratings via the website *Hittamäklare.se*, which functions as an agent search engine

and is run by *Booli*. In the final sample, I drop sales with sales prices outside of the 1st and 99th percentile of the distribution, respectively, since the tails of this distribution are quite long.¹¹ While this sample restriction improves precision slightly, it has virtually no impact on the results overall (see Online Appendix B for robustness to sample restrictions)

The two data sets described above are merged on basis of the co-op organization number, date of sale of apartments, and the date at which a particular *Allabrf* rating was created. In particular, a rating for a particular co-op is defined to be “active” between the date of its creation and the date at which the subsequent rating was created. If no subsequent rating is available, I define the rating as being active for a year. I make this restriction to avoid basing my analysis on ratings that are regarded as “outdated” by consumers. Other choices, such as allowing a shorter or longer period after creation, give virtually identical results (see Online Appendix B). An apartment sale is matched to the rating of its co-op which was active at the date of sale. It should be noted that *Allabrf* produces new ratings throughout the year. This is due in part to the fact that co-ops do not release annual reports at a given date, but more importantly that *Allabrf* often has to collect and digitize annual reports manually.

In the matched sample, I restrict myself to sales between 2016 and 2020. The *Allabrf* rating system was launched to the public in September 2015, so earlier periods are not of interest, and later periods are difficult to analyze as I only have access to ratings based on annual reports up until 2019. Over these five years, the matched sample covers ~116,000 sales in just under 7,000 unique co-ops (with ~18,000 unique co-op/fiscal year cells). This covers around half of all sales in the metropolitan areas of Sweden during the period ([Statistiska centralbyrån 2021](#)), with coverage improving slightly over the sample years.¹²

For a smaller sample of 5,853 sales in Stockholm, I also have access to information on number of bidders obtained from *Länsförsäkringar Fastighetsförmedling*, one of the largest real estate agencies in Sweden. This data is used in an auxiliary analysis on the mechanisms behind the main results (Section 5.2).

3.2 Descriptive statistics

Table 1 provides summary statistics of apartment sales and co-op characteristics, pooled across years but grouped by the rating of the co-op. Apartments in co-ops obtaining high grades are generally more expensive per square meter than those in low-rated co-ops, despite being slightly larger which is typically associated with lower square meter prices. However, this is not without exceptions

¹¹This is due both to misreporting on part of *Booli*, where examples found include the addition/omission of a zero to the sales price, but more generally to the fact that housing is a very heterogeneous good: the market covers both suburban apartments of fifteen square meters without a kitchen, to penthouses in prime locations.

¹²I was unable to match around 30% of the available sales data to a co-op, which is due to multiple factors. First, neither *Booli* nor *Allabrf* has perfect coverage of their respective markets (around 75% each on average, but for *Allabrf* less in the beginning of the sample period when the rating system had recently launched) which leads to an imperfect match when the coverage does not coincide. Second, for quite a few cases, the rating was not updated for a relatively long time. Since I exclude sales where the rating is more than one year old, this also leads to a drop in sample size.

(such as co-ops rated A+ rather than A) and the differences are relatively small. Differences in prices become much more pronounced when conditioning on building age and city (Table A.2 in the Online Appendix); residualized on these factors, prices increase monotonically with ratings, but the difference between A and A+ remains small.

Apartments in strongly rated co-ops appear to be easier to sell – the average number of days that housing ads are running is almost 20% lower for top versus bottom rated co-op apartments. Turning to other characteristics, we see that the annual report variables (debt, fees, other revenues, OPEX, EBITDA and interest payments) vary monotonically with ratings in the anticipated directions. Also, higher rated associations (A+ and A++) are much more likely to own their land, which is to a large extent driven by this being a requirement for higher ratings under the updated rating system in 2019, but not entirely – top rated co-ops were more likely to own their land under the old system as well.

4 Empirical strategy

4.1 Hypotheses

In order to fix ideas, I briefly discuss the ‘treatments’ that the staggered implementation of the rating system gives rise to. The ratings should be viewed as providing a bundle of information about co-op finances. Some of this information is already available to consumers and fairly easy to interpret, such as co-op fees which are shown in online listings. Other parts of the bundle, such as EBITDA and sensitivity to interest rate changes, is unlikely to be easy to obtain or well understood by consumers. As such, the emergence of ratings partly constitutes an information shock to consumers. Note that information, here, can be interpreted broadly: ratings do convey data on co-op finances, but also coarse information on the ordinal ranking of co-ops. This information shock arrived in 2016, when the system was launched and ratings became freely available through a searchable, independent website. After 2018, they were also shown in online listings. I refer to this as a salience shock, and these periods as the low- and high-salience regimes.¹³ Further, the overhaul of the rating system in 2019 constitutes a shock to the way in which ratings are assigned to co-ops.

This is summarized as a timeline in Figure 4. The primary source of variation that I will use in this paper comes from comparing co-ops close to the rating thresholds. The second source is the staggered implementation of the rating system outlined here. This allows me to interpret and distinguish between different mechanisms behind the effect of ratings on sales prices.

I will consider three main mechanisms. First, consumers may demand but lack the knowledge or ability to obtain the information that the ratings convey. This is consistent with a large body of

¹³A subtle point is that the introduction of ratings in online listings actually did slightly more than simply introducing salience; it introduced salience of information *early in the search process* of prospective buyers. This is a substantive change insofar as buyers, in status quo, did not acquire information from annual reports or other sources already when searching for apartments online – which seems plausible. Potential impacts of ratings, and their salience, on the buyer search process is discussed in further detail in Section 5.2.

research finding that consumers often do not understand and/or are misinformed about financial information (Beshears et al. 2018). I hypothesize that when this information becomes available in a simple format, in the form of ratings, consumers rely on them to value different apartments. Under this hypothesis, ratings should affect prices already from 2016 when the ratings launched.¹⁴

In a second scenario, consumers may in fact be able to gather all necessary information about co-op finances, subject to a time or effort cost. At the stage of searching for potential apartments, however, this cost becomes prohibitively high, in which case ratings act a convenient heuristic. In this case, prices may well be affected by e.g. poor ratings leading to fewer prospective buyers and thereby bidders – the sales price in an ascending price auction is, under reasonable assumptions, increasing in the number of bidders. Since most consumers search for apartments via the *Hemnet* platform, this heuristic became particularly convenient from 2018. Hence, under this hypothesis, ratings should i) affect prices to a greater extent after 2018 and ii) also affect the number of bidders in apartment auctions.

Third, consumers may ultimately be unaware that co-op finances are important to consider when making apartment purchases, an inattention that may plausibly be affected by making these characteristics more salient (as found in Agarwal and Karapetyan 2022).¹⁵ In this case, salience of information – regardless of whether that information was previously available for free in an accessible format – may itself have an impact on consumer valuations. Under this hypothesis, ratings should affect prices only after 2018 when they entered the online listings.

Finally, I will be using the change to the rating system that occurred in 2019 as an alternative strategy to identify the impact of better vs. worse ratings in my main estimation framework. This is discussed in detail in Section 4.4.

4.2 Identification of rating effects

In this section I outline the main identification strategy used in this paper. The aim is to estimate the causal effect of a co-op obtaining one rating versus another on the sales prices of apartments belonging to it, holding constant the underlying information that ratings are designed to capture.

The score determining the rating of a particular co-op is, as previously discussed, discrete and fairly coarse, ranging from 1 to 5 by steps of 0.1. Hence, there are 9 discrete bins between the rating B (at cutoff 2.5) and A (at 3.5). A consequence of this coarseness, is that discontinuities in underlying

¹⁴An important point, here, is that the incorporation of ratings in *Hemnet* listings may also have given them credibility. This is unlikely to have been an important consideration, for two reasons. First, *Allabrf* was already well known and received substantial media coverage before 2018, with company representatives frequently appearing in media to comment on housing market trends (Hellekant 2015; Kellberg 2015; Spängs 2015). Second, the description of the rating system explicitly states that the ratings are based on an algorithm that assigns ratings based on a set of clearly defined variables. Given this, the role of credibility is likely less central than, say, recommendations based on subjective expert judgement on a case-by-case basis.

¹⁵I will remain agnostic regarding which class of models of consumer behavior that best capture such an inattention.

variables such as co-op debt and fees are likely to occur at *each* step of the running variable.¹⁶ Since co-op debt and fees are typically correlated with prices directly (insofar as consumers take such factors into account) and indirectly (since e.g. older co-ops tend to have lower debt and fees), this presents a problem. I address this by adopting a covariate-adjusted design, where the running variable enters as a piece-wise linear function and a set of covariates are included.¹⁷

The baseline specification I use is given by

$$\begin{aligned} \ln(\text{Price})_{sbt} = & \beta_1 \mathbb{1}(\text{index}_{bt} \geq c_r) + \beta_2(\text{index}_{bt}) + \beta_3(\text{index}_{bt} \times \mathbb{1}(\text{index}_{bt} \geq c_r)) \\ & + \alpha_y + \alpha_a + \alpha_c + \Gamma X_{bt} + \epsilon_{sbt} \end{aligned} \quad (1)$$

where $\ln(\text{Price})_{sbt}$ is the log sales price of sale s of an apartment belonging to co-op b at date t . index_{bt} is the value of the running variable for co-op b at time t , and c_r is the relevant cutoff between two ratings. Hence, the running variable enters linearly and is allowed to have different slopes on each side of the cutoffs: allowing for a more flexible fit does not appreciably change the results (Online Appendix C). For ease of exposition, the running variable is transformed to be 0 at the cutoff in each regression, ensuring that the treatment effect at the cutoff may be read off the β_1 coefficient directly. The α terms denote fixed effects at the levels of sales year (y), locality (a) and deciles of construction year (c).¹⁸ Finally, X_{bt} includes the level of debts and membership fees of co-op b at time t . Finally, X_{bt} also includes the living area of the apartment to improve precision. Standard errors are clustered at the co-op level in the baseline regressions.

The main specification uses the widest possible bandwidth around each cutoff, and hence includes all observations that achieved either of the two ratings that a particular cutoff separates. However, as robustness, I will also show results under multiple alternative choices of bandwidth: these are entirely in line with the main estimates.

An important feature of the rating system is that the *vast* majority of co-ops obtain the ratings B , A or $A+$. Figure A.3 in the Online Appendix shows the pooled distribution of co-op ratings prior to and after the update in February 2019, referred to as the old and new rating systems respectively. In both cases, less than 2% of co-ops obtain the top or bottom ratings of C or $A++$, and around 60% of the distribution is centered at the modal rating A . Due to this, I will not analyze the effect of obtaining the top and bottom ratings.

¹⁶In Table A.3 in the Online Appendix, I test for differences in co-op debt and fees between each two consecutive bins of the running variable (e.g. 1.6 vs. 1.5, 1.7 vs. 1.6, and so on). The differences are indeed statistically significant at the 5% level in one third of the cases – substantially more than expected due to chance alone – and the magnitudes are non-negligible.

¹⁷This approach is very similar to that of Repetto and Solís (2019), which studies left-digit bias among consumers in the Swedish housing market. The main results are larger – and likely inflated due to the discontinuities in debt and fees as discussed – when excluding these controls, but very robust under several alternative variations of included covariates (Online Appendix D).

¹⁸In my data, localities are defined by *Booli* and meant to capture different neighborhoods. In Stockholm, for example, there are 66 unique localities. The median number of flats sold in any given locality and year is 150.

4.3 Balance of fixed and observable characteristics

Equation (1) will, in general, be invalid if unobserved determinants of apartment prices change discontinuously at the cutoffs even conditional on the included covariates. This is fundamentally an untestable assumption. However, there is little reason *a priori* to believe that the cutoffs defined by the *Allabrf* rating algorithm, that is also proprietary and therefore not known to the public, would be subject to active manipulation such as strategic behavior of consumers, co-ops or real estate agents. However, as previously discussed, the coarse nature of the running variable may still give rise to discontinuities in underlying co-op finances throughout its distribution.

To address this, I estimate the main specification given by equation (1) using several predetermined co-op and apartment characteristics as outcomes. In this case, predetermined characteristics come in two forms: those that are fixed (such as structural features of the apartment building, e.g. number of floors), and those determined prior to the introduction of the *Allabrf* rating system (such as average sales prices in e.g. 2014).

Table 2 shows the results from this exercise. First, the average square meter price in a co-op based on prices before the launch of co-op appears to be well balanced around both cutoffs of interest. This is important: as prices in a given co-op correlate heavily over time, this outcome should pick up most of the unobserved confounders that we are worried about. Second, for a subset of co-ops I have access to annual report data as far back as 2014, for which all financial outcomes underpinning the rating system appear well balanced. Further, while the most important features of the apartment building are controlled for in the main specification (such as neighborhood and construction year), it is also reassuring that the number of floors and centrality of the apartment are also balanced around the cutoffs.¹⁹ This balance on observables holds when restricting the bandwidth around each cutoff (Table A.5 in the Online Appendix).

4.4 Further threats to identification

Although important observable characteristics of co-ops and apartments appear to be well balanced around the cutoffs conditional on the included covariates, as shown in the previous section, we might still be worried about threats to identification stemming from unobservables. In this section, I separately address the risk of heaping in and manipulation of the running variable.

Figure 5 shows histograms of the running variable (i.e. the index score) separately by year. As described in Section 2.3, the new rating system of February 2019 caps the rating of co-ops that leases their land at A (~25% of co-ops). In practise, this is done by capping their index score at 3,

¹⁹In Table A.4 in the Online Appendix, I perform the same balancing exercise when excluding all of the covariates in the main specification given by Equation (1). In line with the discussion of Section 4, co-op finances in 2014 are indeed imbalanced around the cutoffs. So are, in fact, also the number of floors in the building, which is likely an artifact of larger buildings in general having less debt and fees per square meter. Hence, the included covariates are necessary to ensure balance in these predetermined characteristics. Accordingly, the main results are larger and highly statistically significant – but likely inflated – when excluding these covariates (see Online Appendix D)

which explains the large spike in the density observed at this value in 2019 and 2020. As this spike contains disproportionately strong co-ops, it is a source of potential bias.²⁰ I address this in three different ways: by 1) conditioning on co-op land ownership status explicitly, 2) dropping observations with an index score of exactly 3 at dates after February 2019 (i.e. under the new rating system) or 3) restricting the sample only to co-ops that own their land and are thereby unaffected by this cap. Adopting either approach does not change results (Online Appendix E). In the main results, I opt for the first approach and always include a dummy for co-op land ownership status in the regressions unless explicitly stated otherwise.

Further, one should also be worried about more subtle signs of heaping in the distribution around the cutoffs. In particular, there are signs of such heaping around the *B* to *A* cutoff in 2016 and 2017. While the effect on prices that I find at this cutoff is concentrated in the latter years, suggesting that non-random heaping is not driving my results, it is still important to address. I do so by adopting two donut approaches that drops observations 1) exactly at or 2) within ± 0.1 index points of the cutoffs. The main results are robust to both of these specifications (Online Appendix F). To the extent that heaping occurs around the cutoffs, then, it appears to reflect noise rather than problematic correlations with underlying confounders.

Since *Allabrf* is practically the sole actor conveying the financial information of co-ops to the broader public, and does so in a very visible manner, it is not unreasonable to believe that there exists incentives on part of co-ops to manipulate their ratings. However, there is little reason to believe that this is a problem in practice. While co-ops could possibly affect their reported financial situation both by adjusting fundamentals (paying off debt, raising fees) and performing creative accounting exercises, the *Allabrf* rating algorithm is proprietary and not known by neither the public nor co-ops. Given this, it is difficult to see how co-ops would be able to manipulate their score to e.g. pass a given threshold.

However, the weighting of the different subcategories is public information. Hence, it might still be possible for co-ops to improve their rating by e.g. running larger deficits (cash flow has a weight of 10% in the overall rating) in order to pay off debts (debt level is weighted more heavily at 30%). While potentially far-fetched, I am able to address this source of possible manipulation by exploiting the variation coming from the update of the *Allabrf* rating system in February 2019. In particular, I run the main specification given by equation (1) while restricting the sample to apartments sold after the rating system update (12 February 2019), as well as conditioning on the rating the co-op *would have had* under the old rating system. We may call this the “simulated rating”.²¹ Since the specifics of the rating update were not anticipated, this approach ensures that the results are not being driven by unobserved differences among co-ops that might have attempted to manipulate their

²⁰It contains for example those that would have gotten the top rating in the old system, but does not own their land and hence gets capped at a score of 3

²¹I am borrowing this term from Rouse et al. (2013), which uses a similar approach when studying the impact of school accountability ratings.

way to a higher rating in the old system. The specification I run here is given by equation (2):

$$\begin{aligned} \ln(\text{Price})_{sbt} = & \beta_1 \mathbb{1}(\text{index}_{bt} \geq c_r) + \beta_2(\text{index}_{bt}) + \beta_3(\text{index}_{bt} \times \mathbb{1}(\text{index}_{bt} \geq c_r)) + \\ & + \alpha_y + \alpha_a + \alpha_c + \Gamma X_{bt} + \sum_{r \in R} \delta_r \times \mathbb{1}(\text{SimulatedRating}_{bt} = r) + \epsilon_{sbt} \end{aligned} \quad (2)$$

For t after 12 February 2019, where $\text{SimulatedRating}_{bt}$ refers to the rating r that co-op b would have had at time t under the old rating system. Adopting this approach gives even larger effects compared the main specification (Online Appendix G), but this increase is mostly explained by effect sizes being larger in later years also in the main analysis. Hence, the main results are robust to adopting this approach as a safeguard against manipulation.

As a final check on robustness, I successfully replicate the patterns of the main results using the simplest possible difference-in-differences approach of comparing sales prices at different points in time for co-ops that switch ratings (Online Appendix H). This lends further evidence to the main results not being driven by underlying differences in co-op characteristics.

5 Results

In this section, I first establish the existence of an effect on apartment prices. I show that it is driven entirely by a corresponding effect on the listing price, set by real estate agents, in time periods after the ratings became highly salient to consumers. I proceed by showing that ratings had little impact on the number of bidders in apartment auctions. Thereafter, I investigate the role of real estate agents in explaining the extent to which co-op ratings affect prices. Finally, I provide suggestive evidence that the ratings directed attention to co-op finances in a way that is not fully explained by the information provided by the ratings themselves.

5.1 Effects on apartment prices

Figure 6 shows piece-wise linear plots on sales and listing apartment prices for the cutoffs at B to A and A to $A+$, respectively, using the main specification in equation (1). Both sales and listing prices increase only weakly in the running variable, which is to be expected since I am conditioning on both co-op debt and fees, two of the most salient features of underlying co-op financials. However, at the cutoff between A and B there is a clear discontinuity in both outcomes amounting to an effect of just below 2%. This effect is sizeable: at the sample mean, it translates to an impact on sales prices of around 67,000 SEK, or just over 6,000 USD. Given the striking similarity between the effects on sales and listing prices, the impact of ratings seem to be entirely priced in already at the stage during which agents set listing prices.

Point estimates from the baseline specifications are shown in the first two columns of Table 3. The effects of going from B to A on sales and listing prices are equal to 1.8% and 1.6%, respectively,

statistically significant at the 5% level ($p = 0.012$ and $p = 0.019$). These effects do not disappear when the bandwidth around the cutoff is restricted in several steps, but rather increase slightly and remain stable and highly statistically significant around 2% (Table A.6 in the Online Appendix), which provides evidence against the results being driven by functional form misspecification. There is no discernible effect of going from the rating *A* to *A+* in neither listing nor sales prices, which I will discuss in greater detail in Section 6.2.

In the last hypothesis discussed in Section 4.1, the effectiveness of ratings hinges on their salience to consumers. An event that greatly increased the salience of the ratings was their introduction on the *Hemnet* platform, by far the largest search engine for housing listings in Sweden. This is clearly reflected in the data: the last four columns of Table 3 shows the results of estimating the main specification separately on sales realized one year before versus one year after the date at which the *Allabrf* and *Hemnet* collaboration started. In the year before this change the effect on sales prices was modest at best, estimated to just below 1% but not statistically significant at any conventional level. However, in the year following it, the point estimate increases to 2.6% (corresponding to 80,000 SEK, or 8,000 USD, at the sample mean) and is much more precise ($p = 0.012$). These patterns are very similar for listing prices. Figure 7 shows the equivalent estimations visually. In line with the regression results, the discontinuity at the *A* vs. *B* cutoff is much clearer after the ratings were introduced in online listings. It should be noted that, in the main specification, I cannot formally reject equality of the *A/B*-discontinuity before and after the *Hemnet* collaboration started ($p = 0.188$). When using tighter bandwidths around the cutoffs, though, this difference becomes more pronounced (Table A.7 in the Online Appendix) and significant at conventional levels ($p = 0.042$ and $p = 0.014$).

One surprising aspect of the discontinuity between ratings *B* and *A* is that the entire effect appears to arise already in the listing price, set by real estate agents. In particular, for all levels of the running variable, the sales price is simply the listing price plus a (constant) level shift, which is consistent with consumers treating the co-op financial outcomes as essentially priced in by the real estate agent.²² This finding is, however, entirely consistent with real estate agents being both fully rational and informed – under the belief that *consumers* attach value to the *Allabrf* ratings, it may well be rational for real estate agents to incorporate them in pricing decisions. I will return to the role of real estate agents in explaining the effect of ratings on prices in Section 5.3.

Another approach to scrutinize the effect of the *Hemnet* salience shock, is to compare sales prices of co-ops with different ratings over time. The validity of this approach relies on e.g. *A*- and *B*-rated apartments having similar trends in prices leading up to October 2018, when ratings started being shown in listings. Figure 8 shows monthly sales prices, residualized on the vector of controls used in the main analysis, of apartments with different ratings one year before and after the *Hemnet* change. When comparing *A*- and *B*-rated co-ops, price trends largely appear to move in parallel up until close to the *Hemnet* collaboration, after which they diverge sharply by a magnitude of approximately $2p.p.$,

²²Even unconditional on covariates, the markup (i.e. the sales minus listing price) is remarkably bell-shaped (Figure A.4 in the Online Appendix), with the exception of an expected spike at zero (a typical situation in which the sales and listing prices coincide is where there is only one bidder in the auction), with a mean of 9%.

similar to what was found in the main analysis. The divergence starting already in September – rather than October, when the *Hemnet* collaboration formally launched – is due to the fact that in my data, the date of sale is in many cases recorded as the listing publication date when the actual sales date is unknown. Since a typical sales process takes 2–4 weeks, many sales recorded in September actually took place in October.²³ I see no divergence in prices of co-ops rated A+, relative to A, which is in line with the results from the main analysis.

If ratings and their salience affect consumer valuations and real estate agents’ pricing decisions, we might also expect them to influence sellers. A potential seller may delay listing their apartment if they anticipate an improvement in their co-op’s rating. Moreover, even if new ratings are entirely unexpected, they should still factor into the selling decision due to their documented impact on sales prices. I investigate this in Online Appendix I, by comparing changes in number of sales in co-ops that switch ratings over time. In a small window around rating assignment (30 days), co-ops obtaining an A relative to a B experience an increase in number of sales equal to 14% of the sample mean (0.24 sales). This effect dissipates as I increase the window around rating assignment. This likely reflects the fact that people ultimately have other reasons to move than financial gains, making ratings unlikely to affect timing over longer periods of time. Finally, in line with the previous results, I find no effects of ratings on this timing decision 1) before ratings were introduced at the *Hemnet* platform and 2) when moving from an A to an A+.

5.2 Number of bidders in apartment auctions

The main results of the previous section suggest that consumers are willing to pay a premium for better ratings. This result emerges only after ratings became highly salient in apartment listings. Relating to the discussion in Section 4.1, this is consistent with an hypothesis where ratings serve as a convenient heuristic – or filtering tool – for consumers when browsing apartments online.

Even if consumers may fundamentally be able to gather and understand information in co-op annual reports, it likely incurs some time and effort costs. When stakes are high, it seems reasonable to pay such costs. However, when browsing tens or even hundreds of apartments online, consumers may well find it beneficial to first screen listings according some heuristic, and then gather information on a smaller set of objects (by attending public viewings and reading annual reports). Ratings may then serve as a convenient heuristic for consumers specifically during this part of the process, allowing them to e.g. avoid poor co-ops. In this case, prices may be affected by poor ratings leading to fewer prospective buyers and thereby bidders, since the sales price in an ascending price auction is, under reasonable assumptions, increasing in the number of bidders.²⁴

²³Unfortunately, since I only have access to one date per sale, I am unable to quantify the extent of this measurement error. The main results are entirely robust to excluding sales recorded within 30 days of the *Hemnet* collaboration, whose treatment status with respect to the change in salience is unclear (see Table A.8 in the Online Appendix).

²⁴This argument is made in [Repetto and Solís \(2019\)](#), which finds that apartments priced just below multiples of a million attract more bidders.

To investigate this hypothesis, I leverage the smaller sample containing information about number of bidders obtained from the real estate agency *Länsförsäkringar Fastighetsförmedling*.²⁵ In Table 4, I first estimate the main regression on sales and listing prices and verify that the main effect is present also in this limited sample. In fact, the effect is highly statistically significant and even larger than in the main sample, amounting to around 5.8%. Turning to the last three columns, however, I do not find evidence for any impact on the number of bidders, neither in the full sample, nor when restricting the sample period to after the *Hemnet* collaboration. The same is true when focusing only on sales in which there were more than one bidder.²⁶ Despite the relatively small sample size, I can reject positive effect sizes greater than 0.06 bidders in the full sample. This amounts to only a few percentage points relative to a sample mean of just below 2.5 bidders per auction. As such, I find no evidence that the observed effect on sales prices presented in Section 5.1 is mediated by a change in the number of bidders.

5.3 The role of real estate agents

The main results presented in Section 5.1 suggest that the effect of ratings on prices emerge already when real estate agents set listing prices. This, in turn, raises the question of whether the rating effect varies with agent characteristics. While real estate agents are required to provide information on the apartment co-op when administering a sale, this responsibility is not codified in a set of actual practices and may vary from simply providing an annual report upon request, to incorporating the co-op's finances in the sales pitch and marketing material.²⁷ Given this discretion in terms of highlighting co-op finances in the sale, it is plausible that more skilled or experienced real estate agents may emphasize the ratings when advantageous, and downplay their importance when not, ultimately leading to a stronger transmission of ratings on prices.

In this section, I investigate the role of real estate agents in explaining the strength of the effects of ratings on sales and listing prices. In particular, I have access to a set of measures of agent experience and popularity among sellers which I combine into a standardized index. I then compare the effect of ratings on prices among agents that are more or less experienced and popular among sellers, as a proxy for their quality (as seen from the seller's perspective).

First, I compute the number of previous sales administered by the agent up until a given sale. Second, I have access to consumer ratings (on a scale from 1 to 5) and recommendations of real estate agents from the website *Hittamäklare.se* (translated as "Find a realtor", where sellers can browse, hire and rate real estate agents), which is run by the same company from which I have

²⁵The distribution of unique bidders in this sample has a mode at one, decreasing monotonically as the number increases (Figure A.5 in the Online Appendix). Given the long left tail of this distribution, I exclude sales exceeding the 99th percentile of unique bidders (> 9) in all regressions, but results are very similar when including the full sample as well.

²⁶A de-facto bidding process often takes place even in cases where there is only one participating bidder. This is because sellers may reject any bid at any time if they are not satisfied, leading to an auction "against the seller".

²⁷For example, in the cases where it applies, real estate agents often emphasize co-ops' exceptionally low debt levels or membership fees in their listing descriptions.

access to sales data (*Booli*).²⁸ To rule out the possibility that agent sorting is endogenous with respect to the ratings themselves (e.g. experienced agents being more likely to take on sales in strongly rated co-ops), I estimate the main specification in (1) using these measures of agent quality as outcomes, and present results in Table A.9 in the Online Appendix. Here, the effect of obtaining an *A* rather than a *B* actually has a negative sign in all three outcomes, indicating that real estate agents selling *A*-rated apartments are actually slightly worse along these quality proxies. However, the estimates are generally statistically insignificant and their magnitudes are very small relative to sample means, and should likely be interpreted as zeros. Hence, I find no evidence of differential selection of high- vs. low-quality real estate agents close to the rating cutoffs.

I combine these three measures – number of past sales, recommendations, and agent ratings – using principal component analysis (PCA). All measures load positively onto the first eigenvector of this decomposition, suggesting that experienced agents also tend to be highly rated and recommended by other sellers. Finally, I divide agents into groups based on whether they are above or below the median of this index separately for each year in my sample. In Table A.10 in the Online Appendix, I show that above-median agents sell slightly more expensive properties (6*p.p.*) on average, than below-median agents. They also generate a larger premium of sales over listing prices (0.7*p.p.*), a difference which persists when controlling for the full set of apartment and co-op characteristics used in the main analysis.

In Table 5, I estimate the main specification of ratings on listing and sales prices separately for sales administered by above- and below-median agents, in terms of the agent quality index. I perform this exercise both before and after the *Allabrf* ratings started being shown in apartment listings. I find a fairly stark difference in the effect of obtaining an *A* vs. a *B* among these different sets of real estate agents: in sales administered by an above-median agent, obtaining an *A* vs. a *B* leads to an increase in both listing and sales prices of around 2*p.p.* even *before* ratings were made salient in apartment listings. The corresponding effect among below-median agents is close to zero. This provides suggestive evidence that high-quality agents – from the perspective of the seller – are able to strengthen the effect of ratings on prices, possibly by emphasizing their importance when advantageous.²⁹

One might expect that this role of real estate agents in explaining the effect of ratings on prices may have deteriorated once ratings became salient to consumers. In particular, such a change may have limited agents’ possibility of selectively highlighting the ratings to previously unaware, prospective buyers. However, I find no evidence for this hypothesis: the incorporation of ratings into apartment listings seems to have produced a uniform, upward shift in the impact of an *A* vs. a *B* on prices for both types of agents.

²⁸All three measures correlate positively with markups (percentage deviation between sales and listing price), so to the extent that agent quality actually matters for prices, these measures seem to pick up some of that effect. Studies looking at cases when agents sell their own homes show that they, on average, *do* have the ability to increase sales prices (Levitt and Syverson 2008) – however, whether they deploy these “skills” also when selling the homes of others (as in this case), or how much such skills vary across agents, remain open questions.

²⁹However, I find no such effect at the *A+* vs. *A* margin, which I discuss in further length in Section 6.2.

These findings raise the question of how to disentangle the direct role of salience from the contribution of intermediary effort. To structure this argument, denote the contribution of agents to the rating effect at the A vs. B cutoff as $e^t(s)$, where $t \in \{high, low\}$ denotes agent type, and $s \in \{0, 1\}$ indicates the salience regimes (i.e., before and after the introduction of ratings in the online listings). I refer to this as agent effort. Further, let δ be the impact of salience on the rating effect. In Table 5, I cannot reject the hypothesis that the *Hemnet* change led to a uniform shift in the rating effect for both types of agents, such that:

$$\begin{aligned} e^{low}(0) &\approx 0 \\ e^{high}(0) &\approx 1.8 \\ e^{low}(1) + \delta &\approx 1.8 \\ e^{high}(1) + \delta &\approx 3.6 \end{aligned}$$

Two points follow. First, the difference in agent effort remains constant across salience regimes ($e^{high}(s) - e^{low}(s) \approx 1.8$). This excludes “multiplier effects” in effort, where high-quality agents became relatively more effective at separating between A and B -rated apartments once the ratings became salient. Such an effect would, all else equal, make the difference between high- and low-quality agents diverge. The same argument can be made in the opposite direction: agent effort did not become less important, in which case a convergence would be expected.

Second, the observed 1.8 percentage point increase after the *Hemnet* change could reflect either a direct buyer response (δ) or a uniform increase in agent effort across both types. In the latter case, both types of agents must have increased their effort identically. I cannot distinguish between these mechanisms. What is clear, however, is that agent heterogeneity continues to matter even in a regime of high salience.

5.4 Consumer attention to co-op debt

To conclude, I revisit the question of how co-op debt is reflected in sales prices before and after the introduction of ratings in online listings. [Almenberg and Karapetyan \(2014\)](#) studies the capitalization of co-op debt in sales prices, and finds a far smaller importance of debt than theory would predict. This is attributed to consumers exhibiting a bias towards more salient sources of financial risk. Further, [Agarwal and Karapetyan \(2022\)](#) finds that making this information more salient brings debt capitalization closer to the rational prediction.

I present suggestive evidence that the introduction of ratings in the market for apartments was associated with an increase in the correlation between sales prices and co-op debt. Further, most of the increase remains when conditioning on the ratings themselves, suggesting that it is not mechanical (which, given that ratings have been shown to affect prices while simultaneously capturing co-op debt, would have been plausible).

The pattern motivating this analysis is shown in Figure 9. The figure shows point estimates on deciles of co-op debt on sales prices (both per square meter) from a regression that conditions on month and co-op fixed effects, before and after the introduction of ratings in *Hemnet* listings.³⁰ Intuitively, this specification captures the effect on prices of changes in debt within a given co-op. In addition to differences in financing decisions, however, such variation in debt also reflects investments made by the co-op that increases its value. I therefore condition on co-op capital depreciation to hold the value of such investments constant in all regressions, which is proposed in [Almenberg and Karapetyan \(2014\)](#) but not adopted due to lack of data. The figure shows that debt changes not explained by valuable investments went from not impacting prices at all, to exhibiting a clear negative association after the ratings were introduced at *Hemnet*.

Table 6 shows point estimates from similar regressions of debt levels, entering linearly, on prices. Due to differences in tax deductibility, market efficiency would require more than a one-to-one relationship between debt and prices when holding quality constant and, thereby, a coefficient on debt smaller than -1 (as discussed in Section 2.2). Here, quality is assumed to be captured by the co-op fixed effect. I find that the point estimate on co-op debt decreases from just below zero to a highly significant -0.182 after the *Hemnet* collaboration.³¹ The latter is smaller but in the same ballpark as the effect found in [Almenberg and Karapetyan \(2014\)](#) (-0.19 to -0.3 depending on specification).

The last column of Table 6 shows that the increased sensitivity to co-op debt is only partly explained by the *Allabrf* ratings themselves: conditioning on these increases the point estimate by around 30% to -0.127 . While resulting in a massive drop in precision, restricting the sample to include only sales within one year of the *Hemnet* collaboration gives very similar patterns (Table A.11 in the Online Appendix). The results presented here suggest that the capitalization of co-op debt in sales prices did indeed increase after the *Allabrf* rating system became salient to consumers, and that this is not entirely explained by the direct impact of ratings on prices documented in Section 5.1. An explanation for this, is that the ratings serve as a nudge to consumers about the importance of co-op finances, which in turn directs consumer attention to features of it that are relatively easy to observe – such as co-op debt.³²

Despite this documented change in capitalization corresponding to the introduction of the ratings in online listings, the magnitude of capitalization remains very low; in the pre-period, it is virtually zero. A possible explanation could be that I am only leveraging variation *within* co-ops over time, ignoring variation between co-ops which may stem from differences in initial financing decisions

³⁰Since both prices and debt are given in monetary units, previous literature typically runs such regressions in levels rather than logarithms. To allow for comparisons, I follow this convention.

³¹However, given the imprecision of the pre-period estimate, I cannot formally reject equality of the coefficient on debt before and after the *Hemnet* collaboration at conventional significance levels ($p = 0.184$). Therefore, some caution is warranted here and this analysis should be seen as suggestive.

³²Under the hypothesis that the *salience* of the ratings drive this increase in the capitalization of debt in prices, we should see no impact around the launch of *Allabrf* in September 2015. At this time, the ratings were not shown in apartment listings. I verify this in Table A.12 in the Online Appendix, using the same two-way fixed effects strategy as described above. Both one year before and after the launch in 2015, I find no negative relationship between debt and prices.

(for a discussion on sources of co-op debt differences, see Section 2.2). In a simpler model, shown graphically in Figure A.6 in the Online Appendix, I investigate the relationship between debt and prices conditioning only on capital depreciation and construction year (as proxies for investments and renovation needs). Before the *Hemnet* change, I find a correlation of -0.21 , which is very close to that of [Almenberg and Karapetyan \(2014\)](#). After the change, this correlation reduces to -0.43 . While the levels differ, the change is very similar to that found previously (Table 6).

6 Discussion

6.1 How large is the effect of ratings on prices?

In the main analysis of this paper, I found that obtaining an *A* versus a *B* increases sales prices by 2.5% after the ratings were introduced in online listings. Since the explicit aim of the rating system is to help consumers take co-op finances into account, it is informative to consider to which degree this might have been successful. However, such an exercise requires an idea of how much value consumers *should* attach to the information that the ratings reflect. In absence of a fully specified model, this is difficult to answer. I will therefore provide back-of-the-envelope calculations that can be seen as rough estimates of the correction in prices that the ratings lead to.

If consumers are perfectly informed about co-op finances and take them into account in their purchasing decision in an optimal way, any discontinuous response around the rating cutoffs would lead to *less* correct pricing. Under validity of the RD design, rating assignment is as good as random at the cutoffs, and thus reflect no difference in co-op fundamentals. However, the assumption of full information and perfect rationality is highly implausible in this setting.³³ It seems more likely that the ratings provide new information about the difference in finances among co-ops in some vicinity of the rating cutoffs, where it is difficult for consumers to tell them apart. The appropriateness of the rating effect can therefore be approximated by comparing it to the actual differences in co-op finances in various bandwidths around the rating cutoffs.

In this exercise, I will focus on the difference in co-op debt per square meter between *A*- and *B*-rated co-ops. This difference is likely a lower bound of the average price gap that we would expect between such co-ops, holding quality constant, for two reasons. First, other features of co-op finances also improve when moving from a *B* to an *A*, such as revenues from commercial property. However, these are more difficult to price and will therefore be disregarded here.³⁴ Second, due to tax deductibility favoring personal loans, consumers should be willing to trade off co-op debt at *more* than a one-to-one rate. For the sake of simplicity, I ignore this and assume a conservative rate of substitutability equal to one.

³³For instance, in a recent survey 60% of homeowners reported not knowing the level of debts in their own co-op, despite 70% reporting to have read the annual report ([SBAB 2025](#)).

³⁴The difference in debt may also reflect differences in investments made by *A*- and *B*-rated co-ops, which prospective buyers may value. As will be expanded upon in Section 6.2, this is unlikely to account for the observed gap in co-op debt between *A*- and *B*-rated co-ops.

Table 7 shows average differences in co-op debt per square meter within different bandwidths of the *A* vs. *B* rating cutoff. If consumers are entirely unable to distinguish between co-ops rated *A* and *B* in absence of the ratings, the rating effect should (at least) reflect a difference in debt equal to 2379 SEK (\$230). At the sample mean, the effect of around 2.5% corresponds to 1300 SEK (\$125) per square meter. Hence, the rating effect would imply a price correction of around 55%. Assuming a more sophisticated consumer, that relies on ratings for information only within tighter bandwidths around the cutoff, would increase the degree of price correction to 79% and 104%, respectively. In the latter case, the rating effect is large enough to slightly overcorrect prices, which is potentially worrying.

How large is the risk of overcorrection in practice? It is difficult to form a strong prior on how well consumers understand differences between co-ops near the rating cutoffs. However, the visual RD evidence in Figures 6 and 7 suggests that information is limited in the absence of ratings. Specifically, the relationship between prices and the co-op index score is only weakly positive—and in some cases flat—within each rating category. While this relationship is only correlational, it casts some doubt on the notion that consumers are able to meaningfully price relative differences in co-op finances in absence of the ratings. In that case, the risk of ratings overcorrecting prices would be fairly limited.

6.2 Co-op investments and the A+ vs. A margin

It should be noted that the argument presented in the previous section can also be applied to co-ops rated A+ versus A. In fact, the average difference in debt between such co-ops amount to around 3700 SEK (\$350). As previously shown, though, there is virtually no price difference between co-ops rated A+ relative to those rated A (Table 1), and I find no rating effect at the A+ vs. A cutoff (Table 3), which is potentially puzzling.

However, directly comparing co-ops solely on the basis of debt might be misleading. High co-op debt, and thereby poor ratings, may not solely be a result of the initial decision on financing taken by the first co-op members, but also investments in amenities perceived as valuable by prospective buyers (a liability mirrored by an increase in the value of the asset).³⁵ For instance, a co-op may take on additional debt in order to finance e.g. a new roof, which raises the value of the building. The result that consumers appear to value A's over B's, but not A+'s over A's, could be rationalizable if these ratings reflect valuable investments to different degrees.³⁶

While I do not have direct data on the investments that co-ops make, I do observe their capital depreciation. When a co-op makes a large, debt-financed investment, their depreciation typically increases which thereby provides a proxy for such investments. In Figure A.7 in the Online Appendix,

³⁵As discussed in Section 2.2, initial differences in co-op finances arise already when the co-op is formed, depending on how the purchase of the apartment building from the developer is financed.

³⁶Note that this argument does not apply to the results of the main analysis. Under validity of the RD assumptions, co-ops *at the margin* between two ratings are as good as randomly assigned a particular rating. Hence, their underlying finances, as well as the physical characteristics of their buildings, are balanced. Such considerations enter when making an assessment of how ratings “should” be priced, not at the relevant margins but on average.

I plot the average capital depreciation and debt against the co-op index score that determines rating assignment. As suspected, co-ops with higher ratings tend to have significantly lower levels of debt, but also lower investments as captured by capital depreciation. This relationship is approximately linear for co-ops rated *A* or *A+*. However, while debt continues to increase when we move to co-ops rated *B*, capital depreciation does not. Relative to *A*-rated co-ops, those rated *A+* have lower debt but also lower investment levels, while *B*-rated co-ops carry higher debt but do not exhibit correspondingly high levels of investment.

A possible interpretation here is that the ratings *A* and *A+* mainly represent differences in co-op finances driven by differential timing of debt-financed investments, which leaves the net value of the underlying asset unchanged. On the contrary, the higher levels of debt in *B*-rated co-ops may to a larger extent be driven by differences in initial financing decisions, where higher debt solely represents a liability. This would explain why there is a significant price difference between a *B* and an *A*, but none between *A* and *A+*.

Another way of framing this, is that the ratings *A+*, *A* and *B* should not be seen as evenly spaced points on a continuum of underlying co-op finances; the analysis above suggests that the ‘distance’ – in terms of net asset value – from a *B* to an *A* is greater than that of an *A* to an *A+*. In fact, this is to some extent signaled by the common color used for ratings *A* and above, and their separation by plus signs rather than new letters. If prospective buyers perceive the rating system as signaling these distances, this would explain the existence of a rating effect at the *B*-to-*A* cutoff, but none at the *A*-to-*A+* cutoff.³⁷

However, the idea that consumers understand the ‘distances’ between the different ratings is only one of several (and not mutually exclusive) explanations for the difference in effects at the two rating margins. It could also be explained by consumers caring only about the perceived tail risk of buying into “particularly poor” co-ops, as reflected by the rating *B*. Further, credit constraints may start to bind when co-op debt is sufficiently low: even if consumers *would* be willing to pay more for such co-ops, they are unable to do so since regulations prevent them from taking on more private debt.³⁸

6.3 The roles of information, salience and real estate agents

The ratings studied in this paper provide information on co-op finances that most consumers would otherwise be unlikely to obtain. Although the underlying information is available in annual reports, much of it is challenging for non-experts to understand. However, based on the hypotheses developed in Section 4.1 and the subsequent empirical findings, providing straightforward and accessible information seems to be a necessary but insufficient condition for ratings to influence consumer

³⁷Somewhat relatedly, [Bazley et al. \(2021\)](#) shows that colors may also play a psychological role in financial decision-making. In their case, losses displayed in red (relative to black) impacts experiment participants’ risk preferences and trading behavior. The color-coding in my setting may well contribute to the different results that I find at the two rating cutoffs.

³⁸In Sweden, banks require 15% of the sales price in cash as down payment, and typically limit loan sizes to around five times of annual pre-tax income.

behavior. If consumers were solely lacking information, increasing the salience of ratings would not have enhanced their effectiveness. Moreover, if consumers used (salient) ratings only as heuristics in their search process, we would expect ratings to impact the number of bidders in apartment auctions.

Instead, I conclude that the findings support a hypothesis where consumers fail to consider financial information, and that making this information highly salient – as well as presenting it at a very early stage of the decision process – could serve as a remedy. This interpretation aligns with previous studies ([Almenberg and Karapetyan 2014](#); [Agarwal and Karapetyan 2022](#)), to which I contribute by distinguishing between the roles of providing new information, and making that information salient.

However, I find that real estate agents likely also play a role in the transmission of the information that ratings provide. While the salience shock boosted the effect of ratings on prices across the board, there remains a sizable difference in this effect between different types of real estate agents – both before and after the shock. Hence, the view that information – and the salience thereof – may reduce the influence of financial intermediaries is, in this case, not supported.

My results directly provides lessons for policymakers aiming to improve the transmission of financial information to consumers. In particular, it casts doubt on the effectiveness of policies that only make such information *available* to consumers, whether in its raw form or even in a simplified format. Such policies are likely to go unnoticed by consumers unless accompanied by efforts to ensure a high degree of salience, early in the decision-making process, for the information provided.³⁹ However, my results cast doubt on the efficacy of such policies in making consumers less reliant on financial intermediaries.

7 Conclusion

In Sweden, apartment buildings are organized as co-ops, where each apartment owner shares financial responsibility for the building with their neighbors. As a result, the financial stability of the co-op becomes an important consideration for individuals looking to purchase an apartment. However, previous studies have found that important aspects of co-op finances are undercapitalized in apartment prices ([Hjalmarsson and Hjalmarsson 2009](#); [Almenberg and Karapetyan 2014](#)). This paper investigates the effect of a rating system developed by the company *Allabrf* in late 2015, designed to provide a comprehensive summary of the financial status of co-ops. I use a combination of proprietary data on the rating system and records of apartment sales and compare prices in apartments close to rating thresholds.

My findings show that obtaining a better rating positively and substantially affects sales prices. Despite being free and accessible through a searchable website, this effect arises only after the

³⁹I am fundamentally unable to disentangle the impact of salience per se, and moving information to the beginning of consumers' decision-making process (i.e. when they search for apartments online). One could, for example, imagine a policy where real estate agents had to display ratings when administering public viewings. This would introduce salience at a later point during the process, which my analysis is not suited to address. Studies focusing on the timing of information acquisition could be a promising avenue for future research.

ratings became highly salient in apartment listings, and is not driven by changes in number of bidders. However, the magnitude of the impact of ratings on prices varies substantially across high- and low-quality real estate agents, a difference that appears unaffected by the change in salience. I do find suggestive evidence that the ratings nudged consumers to consider co-op finances over and above what is predicted by the informational content of the ratings themselves, pointing to both real estate agents and consumers playing a role in the transmission of ratings on prices.

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8 Figures

Figure 1: Screenshot of *Hemnet.se* apartment listing

skandia: ICA Banken SBAB!

✓ Visa alla banker

Om BRF Vitbetan 27

Antal Lägenheter	40	Föreningens betyg (2020) Högsta betyg A++ innebär en mycket god ekonomi. Lägsta betyg C betyder att föreningen har ekonomiska svårigheter. C B A A+ A++ Köp BRF-analys på allabrf.se
Registreringsår	1998	
Status	Äkta förening	

[Läs mer om föreningen hos allabrf.se](#)

Källa: All information om bostadsrättsföreningen kommer från allabrf.se. [Rapportera fel](#)

Karta & restider

Ungefär 450 m till havet

Gatuvy Flygfoto **Karta** Större karta

Södermalm KATARINA-SOFIA KVARTERET NÄTTUGGLAN Sofia kyrka Danviken


Notes: Screenshot taken 2022-04-11 from *Hemnet.se*. The shown section heading translates to "About BRF Vitbetan 27", and it is situated just below the top section of the listing which primarily shows photographs and summary information about the apartment. The *Allabrf* ratings are displayed under the heading "Föreningens betyg (2020)", which translates to "Co-op rating (2020)".

Figure 2: Screenshot of *Allabrf* rating color scheme



Notes: Screenshot taken 2022-04-11 from *Allabrf.se*, which shows the rating scale and its colors. This style of presentation is used throughout on the website, as well as in online listings at *Hemnet.se* (see Figure 1 for an example listing).

Figure 3: Screenshot of paid *Allabrf* rating report



allabrf.se

HSB BRF Norrängen i Huskvarna (726000-3509)

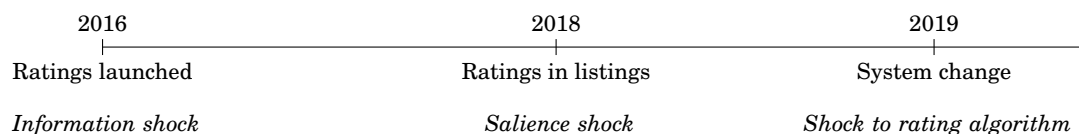
2019-02-18

Sida 2 / 7

SAMMANFATTNING		A+		A+	
NYCKELTAL	VIKT	2017		2016	
		Betyg	Värde	Betyg	Värde
Belåning <small>Föreningslån per kvm</small>	30%	A+	2 007 kr	A+	2 057 kr
Avgiftsnivå <small>Årsavgift per kvm</small>	20%	A	577 kr	A	577 kr
Kassaflöde <small>Kassaflöde per kvm</small>	20%	A	143 kr	A+	159 kr
Hysesintäkter och övriga intäkter <small>Hyses- och övriga intäkter i % av totala intäkter</small>	10%	B	5.1%	C	4.0%
Rörelsekostnader <small>Rörelsekostnader per kvm</small>	10%	A+	410 kr	A+	373 kr
Räntekänslighet <small>Föreningens räntekänslighet i %</small>	10%	A++	3.5%	A++	3.6%

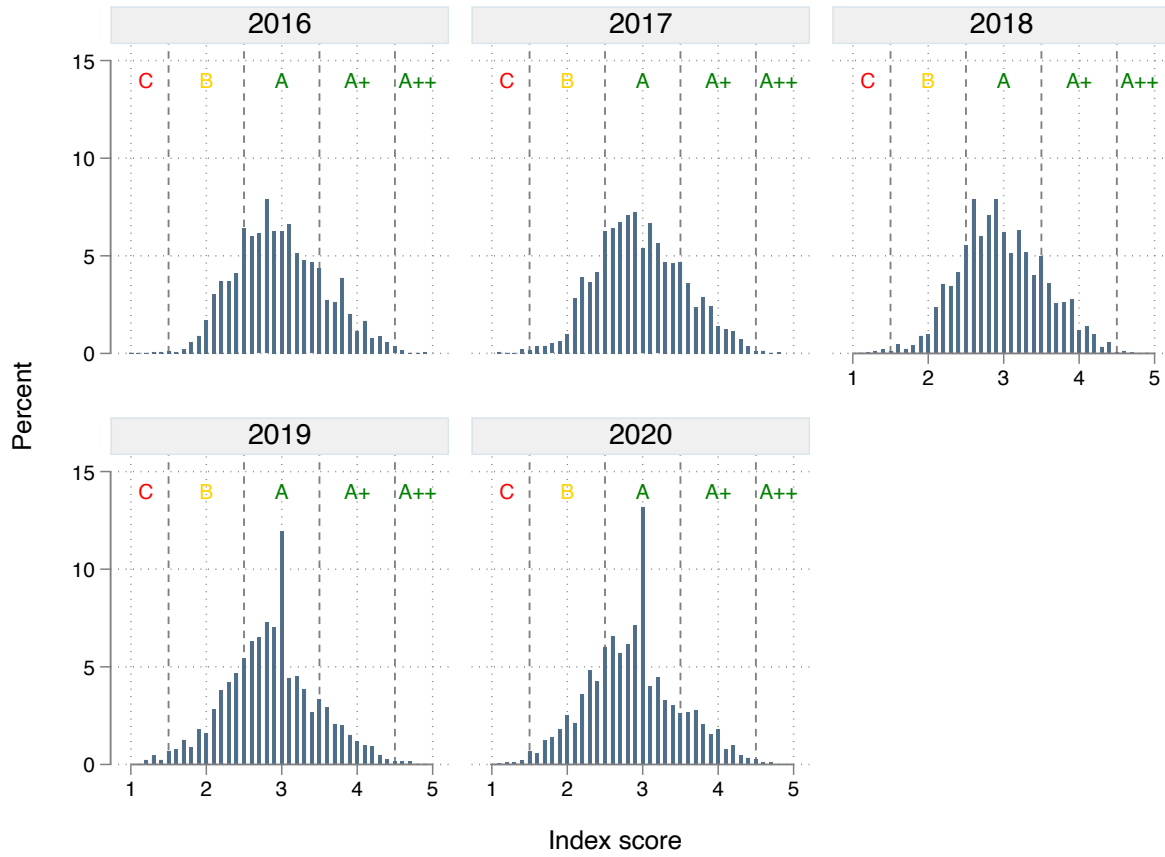
Notes: Example report card from *Allabrf.se*, available to paying customers. The cost of a report card for one co-op is 99 SEK (\$10), but access to all co-ops is available at a monthly membership fee of 349 SEK (\$35). The overall ratings are shown at the top of the report, with sub-ratings by year below. The categories in order are debt, fees, cash flows, rental and other sources of revenue, operating expenses and sensitivity to interest rate changes.

Figure 4: Implementation of the rating system



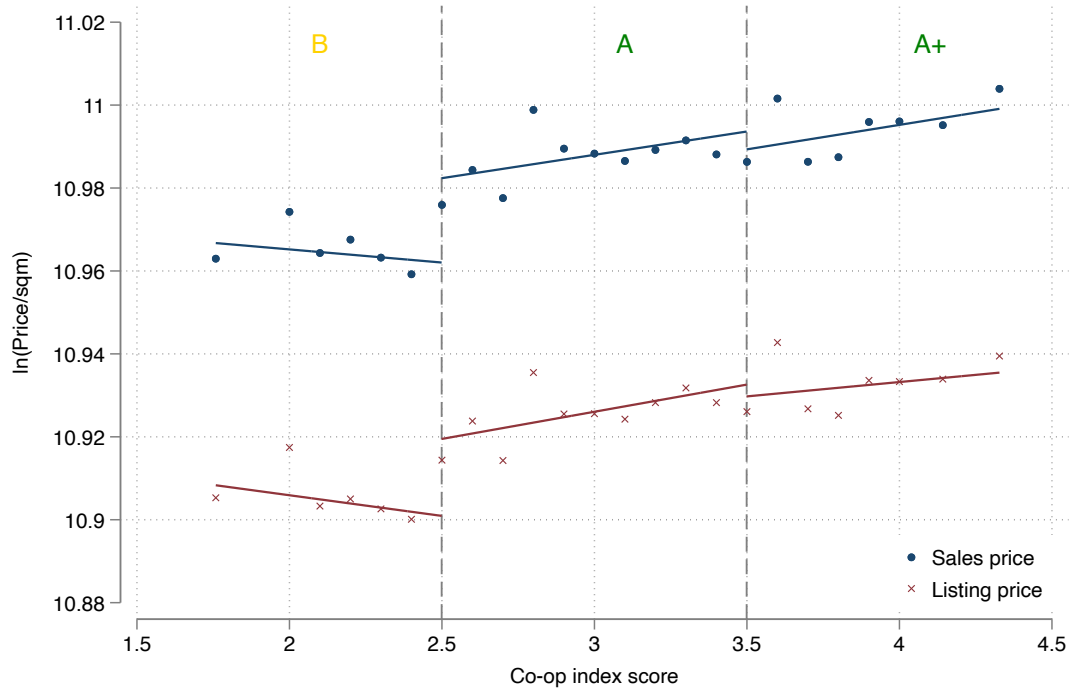
Notes: This figure provides a stylized timeline of important changes to the *Allabrf* rating system over the study period.

Figure 5: Histograms of the running variable by year



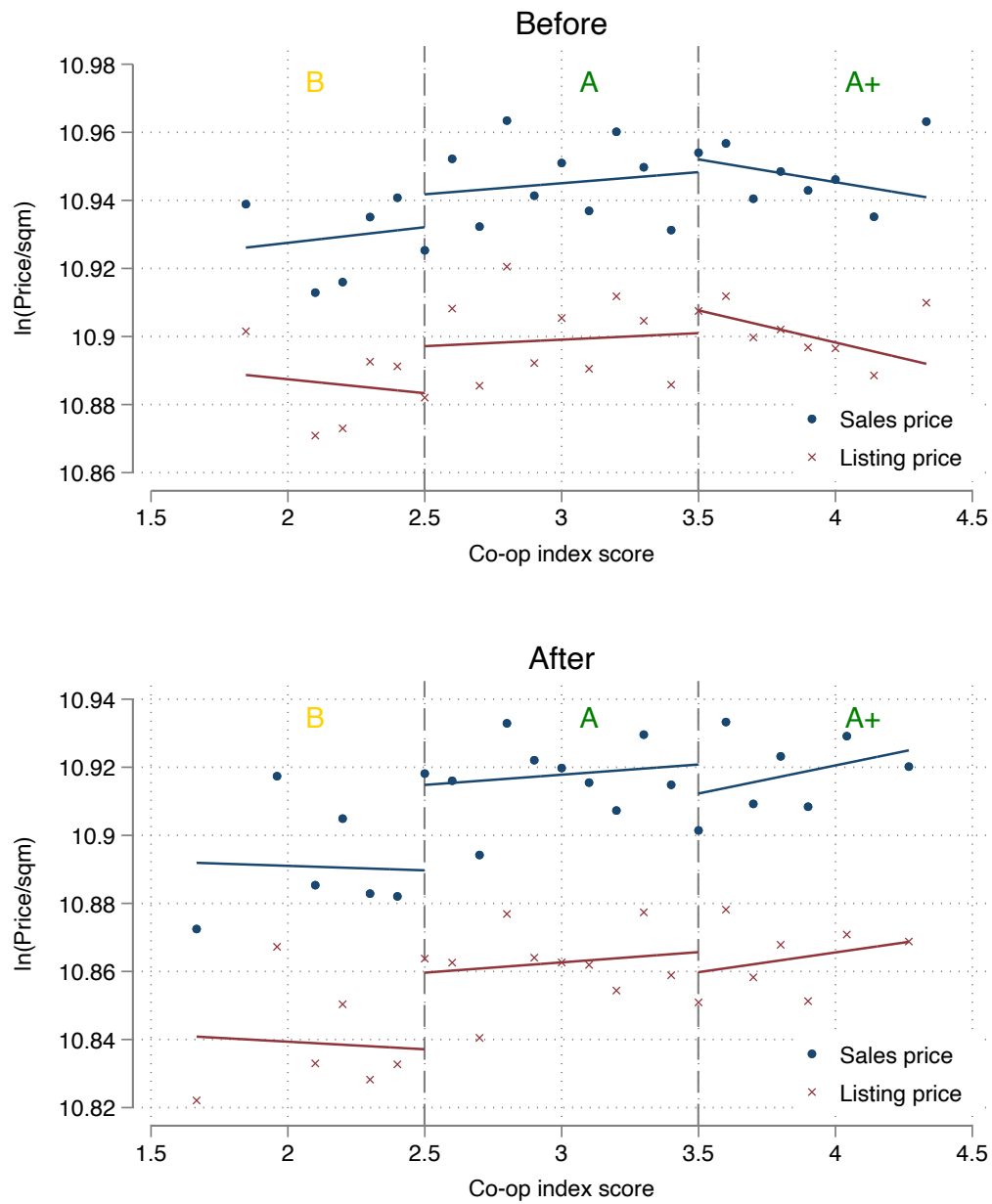
Notes: The figures show the distributions of co-op index scores (the running variable determining the co-op ratings) by year. Each bar corresponds to the percent of co-ops with a particular value of the running variable (ranging from 1 to 5 by steps of 0.1) in a given year. The red, vertical lines indicate rating cutoffs; a co-op obtains a rating if it has an index score at or above the corresponding cutoff, but below the next. In the new rating system introduced in 2019, the index score of co-ops that did not own their land was capped to 3, which explains the large spike in the density at this value for the last two subfigures. This issue is addressed in Section 4.4. Other sources of heaping at the cutoffs is addressed by adopting a “donut” approach in Appendix F.

Figure 6: Pooled effects of ratings on log apartment sales and listing prices



Notes: This figure shows piece-wise linear fits of the co-op index score on log apartment listing/sales prices per square meter pooled over all sales years between 2016 and 2020. The data is residualized on year-of-sale, building construction year decile, and locality (e.g. neighborhood) fixed effects, as well as a dummy for the co-op land ownership status and linear controls for co-op debt, membership fees and living area. Points denote averages in each equally sized bin of the *residualized* co-op index score; hence, they do not correspond to the actual index score values. For point estimates and inference, see Table 3.

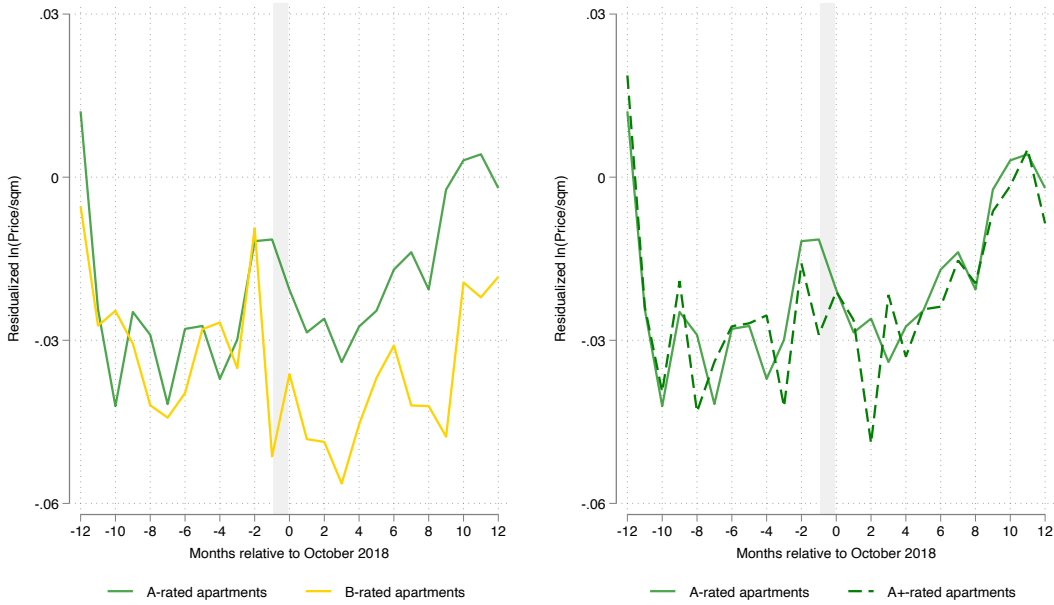
Figure 7: Effects of ratings on log apartment prices one year before and after 6 October 2018 (*Hemnet* collaboration)



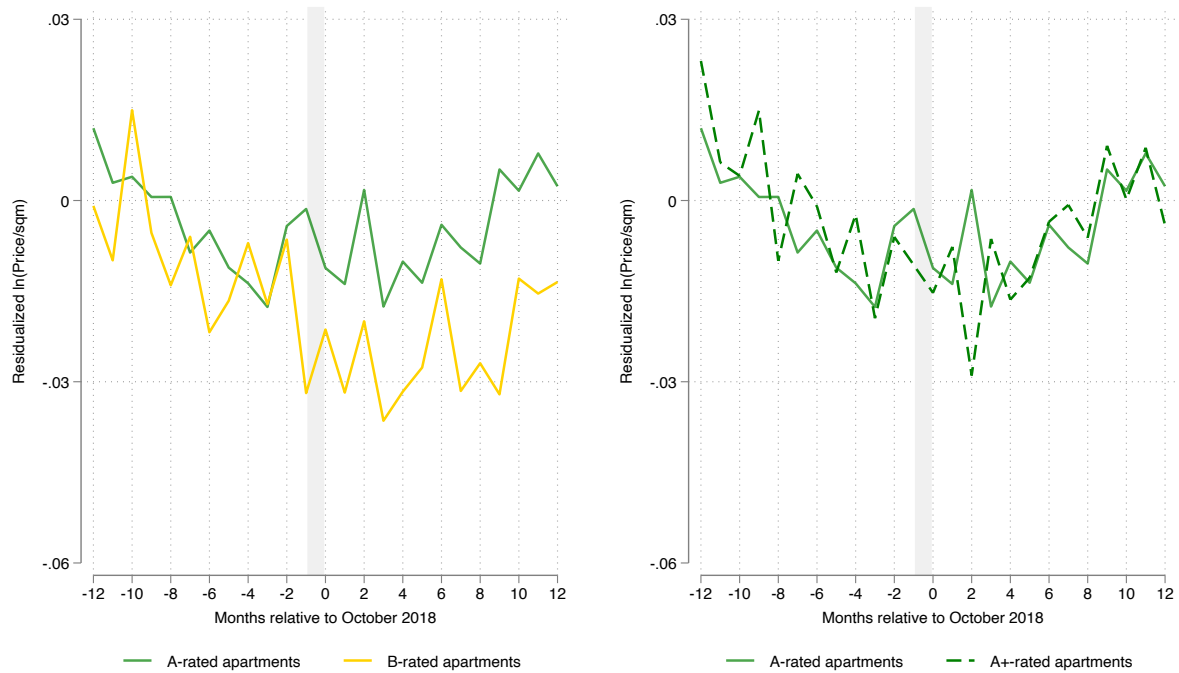
Notes: This figure shows piece-wise linear fits of the co-op index score on log apartment listing/sales prices per square meter for sales realized one year prior to (the top panel) or one year after 6 October 2018 (the bottom panel) when *Hemnet* started showing the *Allabrf* ratings in their housing ads. The data is residualized on year-of-sale, building construction year decile, and locality (e.g. neighborhood) fixed effects, as well as a dummy for the co-op land ownership status and linear controls for co-op debt, membership fees and living area. Points denote averages in each equally sized bin of the *residualized* co-op index score; hence, they do not correspond to the actual index score values. For point estimates and inference, see Table 3. The lower level of prices, as compared to pooled results in Figure 6, is due to prices falling in 2018 and 2019.

Figure 8: Price trends of co-ops with different ratings

(a) Sales prices

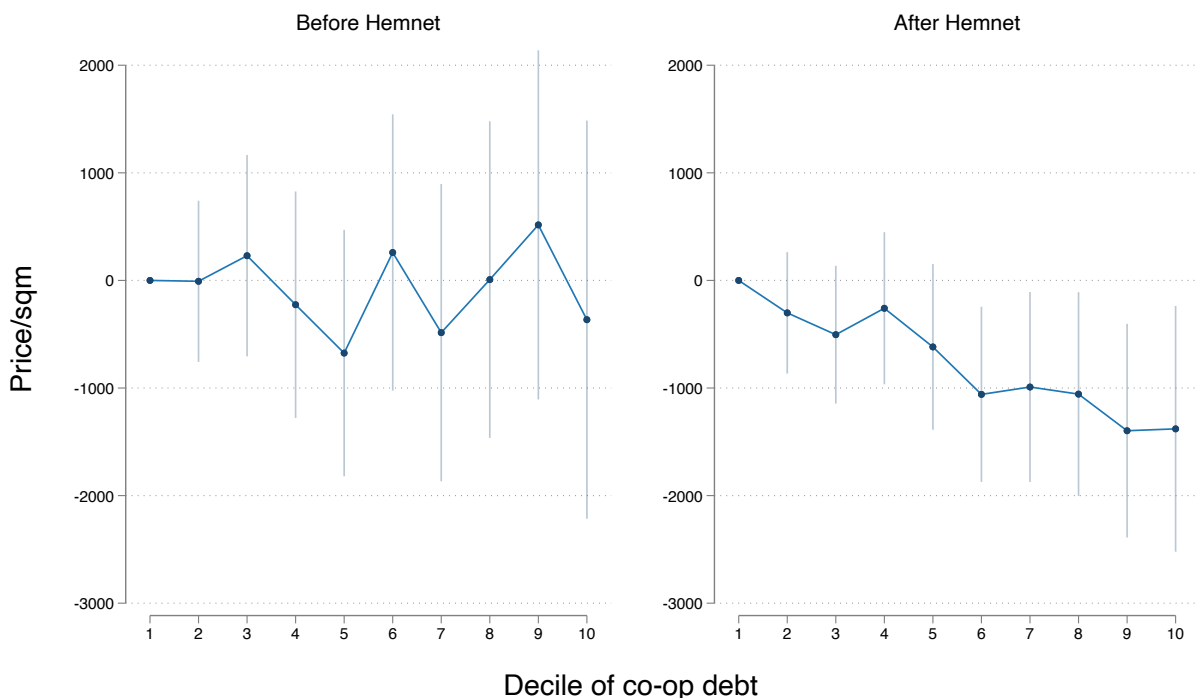


(b) Listing prices



Notes: This figure shows average monthly log sales prices, separately for apartments in co-ops rated A+, A and B. The top panel compares sales prices, while the second panel compares listing prices. The left panels compare A- to B-rated apartments, while the right panels compare A+ to A-rated apartments. Prices are residualized on the vector of controls used in the main analysis. The shaded area highlights September and October of 2018, which covers the period during which sales in my sample could plausibly have started being exposed to the *Hemnet* salience shock.

Figure 9: Relationship between co-op debt and sales prices before and after 6 October 2018 (*Hemnet* collaboration)



Notes: The figure shows mean square meter sales prices for apartments by deciles of co-op debt per square meter, generated by a two-way fixed effects regression conditioning on month-of-sale and co-op indicators, as well as the capital depreciation per square meter. The regressions are run separately for sales prior to and after 6 October 2018, when *Allabrf* ratings were introduced in *Hemnet* apartment listings. 95% confidence intervals around point estimates. The first decile is the omitted baseline category, normalized to zero.

9 Tables

Table 1: Descriptive statistics by *Allabrf* ratings

	Rating					<i>All</i>
	<i>C</i>	<i>B</i>	<i>A</i>	<i>A+</i>	<i>A++</i>	
Apartment sales[†]						
Sales price/sqm	50,588	50,400	52,363	51,894	55,437	51,949
Square meters	56.7	62.3	63.8	63.8	64.5	63.5
Year of sale	2018.9	2018.5	2018.4	2018.2	2018.2	2018.4
No. days on the market	23.8	24.3	22.9	21.0	19.9	22.7
No. of sales	424	19,105	71,875	24,052	513	115,969
Co-op characteristics^{††}						
No. sales in co-op per year	4.0	4.7	5.9	6.5	5.1	5.8
Building construction year	1957	1968	1966	1950	1941	1963
Dist. from central station (km)	6.79	8.05	7.22	6.73	4.65	7.28
Index score	1.29	2.15	2.91	3.79	4.60	2.92
Debt	10732.61	8938.25	6559.09	2751.76	991.12	6319.20
Fees	821.55	740.78	639.83	533.40	406.66	639.98
Other revenue	23.71	35.95	46.54	48.58	67.55	44.79
OPEX	1044.70	678.21	543.56	493.46	449.96	563.39
EBITDA	-351.94	2.50	78.65	86.96	106.57	62.77
Interest payments	196.00	170.80	118.22	48.54	18.66	115.66
Co-op leases land	0.24	0.24	0.25	0.17	0.08	0.23
No. of unique co-op/rating cells	100	3,668	11,069	3,425	91	18,353

Notes: Based on data on sales and co-op ratings from 2016 to 2020.

[†] Prices are measured in SEK. Distance from central station is the geographical (lat/long) distance, in kilometers, between the apartment and the central station of Stockholm, Göteborg or Malmö depending on city.

^{††} The index score refers to the weighted average of co-op sub-ratings that determines the overall rating. Number of co-op/rating clusters refers to a cell consisting of one co-op and its rating, which is matched with apartment sales that occurred in that co-op during the time over which that rating was active.

Table 2: Balance of baseline and fixed covariates

Outcomes	A vs. B			A+ vs. A		
	<i>Estimate</i>	<i>Mean</i>	<i>N</i>	<i>Estimate</i>	<i>Mean</i>	<i>N</i>
ln(Avg. baseline co-op prices)	0.004 (0.009)	10.64	84,872	0.008 (0.009)	10.65	90,324
Debt (2014)	-62.783 (128.141)	6,132.20	37,587	-126.187 (94.931)	4,761.81	41,829
Fees (2014)	0.537 (4.745)	658.01	37,587	1.897 (3.393)	619.81	41,829
Other revenues (2014)	-2.937 (7.333)	59.76	37,587	-5.677 (6.008)	59.03	41,829
Operating expenses (2014)	5.031 (12.582)	548.37	37,587	4.513 (10.481)	537.89	41,829
Interest payments (2014)	-4.011 (4.736)	190.23	37,587	-2.621 (3.441)	146.45	41,829
Cash flows (2014)	3.938 (11.493)	119.90	37,587	-12.583 (9.980)	105.43	41,829
Floor	0.074 (0.051)	2.54	77,547	-0.044 (0.059)	2.58	82,505
Dist. from central station (km)	0.018 (0.081)	7.43	84,890	0.107 (0.090)	7.49	90,336
Year of sale FE	Yes			Yes		
Locality FE	Yes			Yes		
Construction year decile FE	Yes			Yes		
Controls	Yes			Yes		

Notes: $p < 0.01 = ***$, $p < 0.05 = **$, $p < 0.1 = *$. Robust standard errors, clustered at the co-op level, in parentheses. The regressions are generated using a panel of co-op ratings and a number of fixed or baseline co-op characteristics. The main specification (equation 1) with full bandwidth is used in all regressions. *ln(Avg. baseline co-op prices)* are the co-op level average log sales prices during 2015 prior to the launch of *Allabrf*. For the few co-ops (less than 10%) that had no sales during this period, I use average prices in the latest year prior to 2015 where sales occurred, or the neighborhood average for buildings of similar age, in that order. *Co-op debt*, *fees*, *other revenues*, *operating expenses*, *interest payments* and *cash flows in 2014* measure the outcomes in SEK per square meter based on the annual report of 2014, e.g. before the rating system launched. *Floor* measure the number of floors of the apartment building. *Dist. from centre* measures the distance in kilometers of the sold apartment from the central station of the city it is located in.

Table 3: Effects of ratings on apartment prices

	Log prices/sqm		Sales price		Listing price	
	<i>Sales price</i>	<i>Listing price</i>	<i>Before Hemnet</i>	<i>After Hemnet</i>	<i>Before Hemnet</i>	<i>After Hemnet</i>
A vs. B	0.018** (0.007)	0.016** (0.007)	0.009 (0.011)	0.026** (0.010)	0.013 (0.011)	0.024** (0.010)
A+ vs. A	-0.006 (0.007)	-0.004 (0.007)	0.003 (0.012)	-0.010 (0.010)	0.006 (0.011)	-0.008 (0.009)
Observations (B to A)	84890	84890	16530	21532	16530	21532
Mean (B to A)	10.79	10.71	10.78	10.76	10.71	10.69
Observations (A to A+)	90336	90336	18888	22081	18888	22081
Mean (A to A+)	10.79	10.71	10.78	10.77	10.71	10.69
Year of sale FE	Yes	Yes	Yes	Yes	Yes	Yes
Locality FE	Yes	Yes	Yes	Yes	Yes	Yes
Construction year decile FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: $p < 0.01 = ***$, $p < 0.05 = **$, $p < 0.1 = *$. Robust standard errors, clustered at the co-op level, in parentheses. The dependent variable is the log prices for sales realized during the time at which a given co-op rating was active, e.g. from its creation until it was replaced by a new rating. In the third and fourth columns, the main specification is estimated based on sales one year before and after the *Hemnet* change, respectively. The reported coefficients capture the effects of passing the cutoff from the rating below, e.g. from *B* to *A* and *A* to *A+*, estimated in separate regressions. The specifications further include a linear control for the running variable (the *Allabrf* index score) as well as an interaction between the running variable and a dummy for passing the threshold, allowing for different slopes on different sides of the cutoff. Fixed effects for year of sale, building construction year deciles and locality (e.g. neighborhood) are included, as well as a dummy for the co-op land ownership status and linear controls for co-op debt, membership fees, and living area of the apartment. All specifications use the “full” bandwidth, i.e. including all co-ops that have obtained either of the two grades adjacent to a given cutoff.

Table 4: Pooled effects of ratings on number of unique bidders, LF sample

	Log square meter prices		No. of unique bidders		
	<i>Sales price</i>	<i>Listing price</i>	<i>Full sample</i>	<i>After Hemnet</i>	<i>Bidders > 1</i>
A vs. B	0.057*** (0.016)	0.055*** (0.015)	-0.150 (0.109)	-0.178 (0.116)	0.075 (0.126)
A+ vs. A	0.002 (0.015)	0.005 (0.015)	-0.156 (0.099)	-0.166 (0.116)	-0.245** (0.115)
Observations (B to A)	4456	4456	4456	3565	2781
Mean (B to A)	10.74	10.65	2.451	2.415	3.312
Observations (A to A+)	4625	4625	4625	3594	2943
Mean (A to A+)	10.73	10.65	2.480	2.442	3.316
Year of sale FE	Yes	Yes	Yes	Yes	Yes
Locality FE	Yes	Yes	Yes	Yes	Yes
Construction year decile FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: $p < 0.01 = ***$, $p < 0.05 = **$, $p < 0.1 = *$. Robust standard errors, clustered at the co-op level, in parentheses. The regressions are generated using data on number of unique bidders per sale from real estate agency *Länsförsäkringar Fastighetsförmedling* (LF), merged with the sales data from *Booli*. The dependent variables are recorded for sales realized during the time at which a given co-op rating was active, e.g. from its creation until it was replaced by a new rating. The reported coefficients capture the effects of passing the cutoff from the rating below, e.g. from *B* to *A* and *A* to *A+*, estimated in separate regressions. The specifications further includes a linear control for the running variable (the *Allabrf* index score) as well as an interaction between the running variable and a dummy for passing the threshold, allowing for different slopes on different sides of the cutoff. Fixed effects for year of sale, building construction year deciles and locality (e.g. neighborhood) are included, as well as a dummy for the co-op land ownership status and linear controls for co-op debt, membership fees, and living area of the apartment. All specifications use the “full” bandwidth, i.e. including all co-ops that have obtained either of the two grades adjacent to a given cutoff. *Full sample* refers to the matched sample of sales from *Booli*, the bidding data from LF, and the *Allabrf* rating data. *After Hemnet* restricts the sample to sales occurring after 6 October 2018 when *Hemnet* started showing the ratings in their ads. *Bidders > 1* restricts the sample to only include sales where there were more than one bidder in the corresponding auction.

Table 5: Effects of ratings on apartment prices by agent quality

	Before Hemnet		After Hemnet	
	<i>Listing price</i>	<i>Sales price</i>	<i>Listing price</i>	<i>Sales price</i>
Panel A: Below-median agents				
A vs. B	0.004 (0.013)	0.002 (0.013)	0.018* (0.011)	0.017 (0.011)
A+ vs. A	0.013 (0.011)	0.008 (0.012)	-0.011 (0.010)	-0.013 (0.010)
Observations (B to A)	8248	8248	10683	10683
Mean (B to A)	10.69	10.75	10.67	10.73
Observations (A to A+)	9460	9460	11020	11020
Mean (A to A+)	10.69	10.75	10.67	10.74
Year of sale FE	Yes	Yes	Yes	Yes
Locality FE	Yes	Yes	Yes	Yes
Construction year decile FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Panel B: Above-median agents				
A vs. B	0.023* (0.012)	0.018 (0.012)	0.030** (0.013)	0.036*** (0.014)
A+ vs. A	-0.002 (0.014)	-0.003 (0.014)	-0.004 (0.012)	-0.007 (0.012)
Observations (B to A)	8279	8279	10848	10848
Mean (B to A)	10.74	10.81	10.71	10.79
Observations (A to A+)	9424	9424	11057	11057
Mean (A to A+)	10.74	10.80	10.72	10.80
Year of sale FE	Yes	Yes	Yes	Yes
Locality FE	Yes	Yes	Yes	Yes
Construction year decile FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: $p < 0.01 = ***$, $p < 0.05 = **$, $p < 0.1 = *$. Robust standard errors, clustered at the co-op level, in parentheses. The dependent variable is the log prices for sales realized during the time at which a given co-op rating was active, e.g. from its creation until it was replaced by a new rating. The main specification is estimated based on sales one year before and after the *Hemnet* change, respectively. The reported coefficients capture the effects of passing the cutoff from the rating below, e.g. from *B* to *A* and *A* to *A+*, estimated in separate regressions. The specifications further include a linear control for the running variable (the *Allabrf* index score) as well as an interaction between the running variable and a dummy for passing the threshold, allowing for different slopes on different sides of the cutoff. Fixed effects for year of sale, building construction year deciles and locality (e.g. neighborhood) are included, as well as a dummy for the co-op land ownership status and linear controls for co-op debt, membership fees, and living area of the apartment. All specifications use the “full” bandwidth, i.e. including all co-ops that have obtained either of the two grades adjacent to a given cutoff. In Panel A (B), I restrict the sample to sales administered by below-median (above-median) real estate agents in terms of number of previous sales as well as recommendations and ratings on *Hittamäklare.se* (“Find a realtor”).

Table 6: Effect of co-op debt on sales prices before and after *Hemnet* collaboration

	Before Hemnet	After Hemnet	
	(1)	(2)	(3)
Debt per m ²	-0.013 (0.111)	-0.183*** (0.054)	-0.128** (0.058)
Observations	51151	63606	63606
Dep. var. mean	52018	51819	51819
Mean debt	5686	6151	6151
Co-op FE	Yes	Yes	Yes
Month/year FE	Yes	Yes	Yes
Rating FE	No	No	Yes

Notes: $p < 0.01 = ***$, $p < 0.05 = **$, $p < 0.1 = *$. Robust standard errors, clustered at the co-op level, in parentheses. The dependent variable in these regressions is the sales price per square meter of an apartment sale. The independent variable of interest is the debt per square meter of the co-op, as stated in the annual report available at the time of the sale. Hence, the estimated coefficients measure the effect on square meter prices of a one SEK increase in co-op debt per square meter. All regressions control for fixed effects at the co-op and month-of-sale level, as well as the co-op capital depreciation per square meter (also from annual report data). Rating fixed effects refer to the inclusion of indicator functions for having obtained a particular *Allabrf* rating. The sample is split around 6 October 2018, at which point the rating system was introduced at the *Hemnet* platform.

Table 7: Differences in co-op debt between A- and B-rated co-ops

	Bandwidth		
	<i>Full</i>	0.75	0.5
Difference in debt (A vs. B)	-2379	-1656	-1248

Notes: This table shows average differences in co-op debt per square meter of co-ops rated A vs. B, based on data from 2016 to 2020. The first column (*Full*) compares average differences between all A- vs. B-rated co-ops. The second and third columns restrict the sample only to co-ops within 0.75 and 0.5 index points around the rating cutoff—the same alternative bandwidths used in the robustness analysis (Table A.7).