Coordinated vs Efficient Prices: The Impact of Algorithmic Pricing on Multifamily Rental Markets

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Feb, 2023

Preliminary and Incomplete.
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Abstract

Algorithmic pricing can improve efficiency by helping firms set prices that are more responsive to changing market conditions. However, widespread adoption of the same algorithm can also lead to price coordination, resulting in elevated prices. In this paper, we examine the impact of algorithmic pricing on the U.S. multifamily rental housing market using hand-collected adoption decisions of property management companies merged with the data of market-rate multifamily apartments from 2005 to 2019. Our findings suggest that algorithm adoption helps building managers set more responsive prices; buildings with the software increase prices during booms but lower prices during busts, compared to non-adopters in the same submarket. However, we also find suggestive evidence of price coordination; markets with higher degrees of algorithm penetration charge significantly higher rents than markets with lower degrees of penetration, and experience price increases when their algorithm penetration increases. Overall, our back-of-envelope decomposition suggests quarter of the price impact may be attributed to price coordination at minimum, and the rest attributed to more responsive price setting.

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1 Introduction

The recent advances in computing technology have shifted the paradigm of price setting practices of firms through software that dynamically and automatically set prices. These types of software often leverage high-frequency data collected across firms operating in the same industry or in the same market to suggest optimal prices for managers. The algorithms also make decisions based on the past behaviors of other firms and forecast market demands, which makes them especially prone to be the hub that facilitate price coordination across firms using similar technologies. Moreover, these programs are often powered by artificial intelligence (AI), raising concerns that these pricing agents might just learn to jointly play a collusive strategy rather than engaging in a price war. For these reasons, the technology has recently attracted lots of attentions from researchers, policy makers, and antitrust agencies alike (Fortin, 2020; Mcsweeny and ODea, 2017; OECD, 2017).

The industry that has recently came under heavy scrutiny of antitrust authorities for using such technology is the multifamily housing industry of the U.S. Following an article by Propublica with a title "*Rent Going Up? One Company's Algorithm Could Be Why.*"[1] accusing the pricing software of RealPage, a multifamily management solution IT company, of pushing "prices above competitive levels," a series of class action lawsuits were filed against both the software company and landlords using the software (*Yusupov v. RealPage, Inc. et al*, 2023; *Navarro v. RealPage, Inc. et al*, 2022; *Bason v. RealPage, Inc.*, 2022). It is also reported that the Department of Justice has opened an investigation to look for evidences of price coordination among landlords using the software[2]. However, it is not known that whether the algorithm helped landlords to set efficient and competitive prices in light of the booming multi-family rental market, or it facilitated price coordination among the buildings driving up the prices.

Aside from the importance of the setting, there is a growing need for deeper understanding of pricing algorithms and more importantly, how they interact with varying market environments in practice. Many theoretical studies have been conducted under synthetic environments, yet there is no theoretical consensus on whether the algorithms end up facilitating collusion (Asker et al., 2022; Calvano et al., 2020; Mikls-Thal and Tucker, 2019; Brown and MacKay, 2021). To our knowledge, the only existing extensive empirical study is that of Assad et al. (2020), which examines

[1] https://www.propublica.org/article/yieldstar-rent-increase-realpage-rent

[2] https://www.propublica.org/article/yieldstar-realpage-rent-doj-investigation-antitrust

the effect of algorithmic pricing on German retail gasoline market. In contrast to the previous studies that focused on the potential for the algorithms to collude, we seek to provide a more comprehensive view of the issue. The algorithms can be a channel for coordinating on prices which has negative implications on welfare, but they can also be used to efficiently set rents in response to changing market conditions which may be welfare enhancing. We seek to disentangle the two effects in this paper.

The biggest obstacle in empirically analyzing the impact of pricing algorithm on a given industry is the availability of the adoption data. We hand-collected the adoption decisions of management companies from various sources and merged it with yearly panel of market-rate multifamily rental data from 2005 to 2019. We find that the 19 out of top 20 management companies have adopted pricing software, and by the end of 2019, about 25% of buildings or 30% of units in the data were using pricing algorithms. This data is close to ideal setting to study because of rich macro-economic shocks coming from the long panel structure, as well as rich cross-sectional variation across geographical markets with different degrees of penetration of the technology.

With this data, we move onto the empirical analysis to assess the impact of pricing software adoption on rent prices. We use within-market, across adopted building vs. non-adopted building variation to identify the potential efficiency in pricing that adopters may have over non-adopters. We find that the software helps managers to price more efficiently, supported by its heterogeneous effect across calendar year through business cycles. During the Great Financial Crisis, we find that the adopters lowered their prices compared to peers, and gained more in occupancy; during the boom market starting in 2013, we find that adopters increased rents while sacrificing some occupancy when compared to non-adopters in the same market. This shed light on potential efficiency channel that the algorithm has, helping managers to respond more quickly to the changing market conditions.

The building-level analysis is not suited for identifying the coordination effect. In the well-known literature of measuring the price impact of mergers, the threat to identification has been the competitive response of the non-merged parties, that are usually competing firms sharing the market (Dafny, 2009). This applies to this setting as well. If algorithm adopters raise their prices through coordination, it is in non-adopters' best interest to raise prices as well.[3] Hence analysis that looks at variations within-market, across building will not capture increase in prices resulting from the price coordination channel.

[3]Under the assumption that the buildings are competing on prices.

We show that across markets, higher penetration of the software leads to higher rents overall. First, we show an event study that the markets treated with sudden, sharp increase in buildings using the software experience considerably higher rent growth, and decline in market occupancy than those do not. Second, we show that that increase in rents increases almost weakly monotonically as the penetration of the algorithm strengthens. This suggests that during the boom market, the coordination effect complements the efficiency effect. We lastly conduct a simple, but an extremely conservative back-of-envelope exercise to bound the coordination effect against the efficiency effect. We find that about a quarter of the total effect can be attributed to the coordination effect.

Our findings are largely consistent with the theoretical studies of Asker et al. (2022) and Calvano et al. (2020) as well as the empirical findings of Assad et al. (2020). The algorithm exhibits heterogeneous effects on participants in markets with varying degrees of software penetration. In addition, we find that algorithms, when used right, may be welfare improving in helping landlords set efficient prices, which has not been empirically supported before.

The remainder of the paper proceeds as follows. Section 2 briefly provides background on the U.S. multifamily housing market and the pricing software used. Section 3 describes the data and shows stylized facts from the data. We show evidence that the algorithm helps landlords set efficient prices in Section 4, but we also find an evidence of price coordination and its implication on the market-level rents in Section 5. Finally, Section 6 concludes.

2 Multifamily Market and Pricing Software

2.1 Industry Background and Significance

The U.S. multifamily housing industry has experienced a fast-paced growth after the Great Recession, with 158% increase in value per square feet from 2010 to 2019[4]. While it has been an attractive investment opportunity for institutional investors with 80% increase in average nominal rents and 50% decrease in vacancy rates[5], multifamily units are primarily occupied by low-income demographics who do not have enough financial capability to own a property of their own and spend majority

[4]https://www.nmhc.org/research-insight/quick-facts-figures/quick-facts-investment-returns-on-apartments/vstock

[5]https://www.nmhc.org/research-insight/quick-facts-figures/quick-facts-market-conditions

of their income on rents.

Institutional investors often outsource the day-to-day operation of buildings in their portfolio to a management company. The management companies then "run" the buildings, setting monthly rents, managing lessees, running promotions, alongside with various maintenance activities. While there has been some noticeable consolidation of apartment *owners* that has caught the media's attention recently[6], more pronounced concentration has happened among the management companies. Greystar, the biggest management company in the U.S., has increased its number of units managing by 337% from 2010 to 2021[7], and other top 20 management companies as of 2022 have also shown a steady increase in number of units managing.

2.2 Algorithmic Pricing Software

The management companies rely on IT infrastructure to streamline their operation across thousands of units in dozens of buildings they manage across states. The management companies contract with enterprise solutions who develop proprietary property management software for implementation. These software companies provide a suite of services to construct a central database, manage bookkeeping, engage with tenants, automate lease renewals, monitor vacancies, assess market conditions, etc.

In addition to these services, three major companies started to offer rent optimization solutions starting early 2000s[8]. The "revenue management" solution is an automated pricing algorithm that suggests optimal rents in real time by unit type and lease lengths to property managers. It aims to take guess out of pricing rents in both new lease signing and renewal process. Investors often prioritized maintaining near full occupancy, which many property managers found as a suboptimal way of maximizing the return[9]. By 2011, around 15% of apartment units had adopted a version of pricing software[10], and in 2017, it is reported that 3 million units were using RealPage's Yieldstar after its acquisition of the largest competitor, Rainmaker LRO. In a report from Fitch, approximately 30% of total units in the U.S. were using

[6]https://www.propublica.org/article/when-private-equity-becomes-your-landlord

[7]https://www.nmhc.org/research-insight/the-nmhc-50/top-50-lists/2022-top-managers-list/

[8]Yardi RentMAXImizer, RealPage Yieldstar, and Rainmaker LRO

[9]"If you're at 97% or 98% occupancy, your rents are probably too low." https://www.investors.com/news/landlords-consider-how-to-raise-rent/

[10]https://web.archive.org/web/20110824021635/http://www.multifamilyrevenue.com/revenue-management-users-multifamily/

a RealPage software in 2021[11]. While it is unclear that all 19 million units use the company's pricing algorithm, it suggests that there has been great proliferation of algorithmic pricing across multifamily apartment management companies.

The details of how exactly these software compute optimal rents is not well-known. We were able to obtain a copy of presentation slides made in 2014 that showcases the inner workings of one of the software, RealPage's Yieldstar. The most notable point is that the software estimates demand elasticity and forecasts dynamic demand at bedroom-level based on lease length and renewal probability by fully utilizing selected competitors' prices and vacancies. See Appendix Figure A1 for the exact wordings from the slide deck, and Figure A2 and A3 shows the dashboard views for a property manager that displays price recommendations made by the software. All of this information is purely for providing data points to manager and the cognitive burden for a manager to act on this myriad of information is minimal; a manager can simply click either the "Accept Rates" or the "Review Rates" (if something seems so out of place) button located on both top and bottom of the table. Propublica reports that managers accept recommended rents up to 90% of times.

The pricing software both reacts to changes in market conditions and heavily utilizes the detailed, high-frequency data of competitors down to the granularity of daily price for individual units. The question is then, where do they get the data from? In one of their promotional videos, Yieldstar claims that they

> "leverage the statistical analysis collected from the industry's largest lease transaction database, spanning over 11 million units and millions of transactions a year. No one else has this tremendous scope of real time data that determines daily acceptions and opportunities for maximizing rents and reducing vacancy with utmost accuracy."[12]

While it is almost certain that Yieldstar utilizes its own clients' data to maximize other clients' profits, it is not clear whether this feature should be attributed to achieving competitive, efficient pricing or used to coordinate and maximize the joint profits of the using buildings.

[11] https://www.fitchratings.com/research/corporate-finance/fitch-assigns-first-time-b-idr-to-realpage-inc-outlook-stable-11-02-2021

[12] Yieldstar Revenue Management Overview Presentation Webinar, accessed by registration on Dec 1st, 2022.

3 Data and Stylized Facts

To shed more light on the two conflicting channels empirically, we use two main datasets. The first contains the data of market-rate multifamily buildings in the U.S. from REIS by Moody's Analytics. The second contains the adoption year of pricing software or "revenue management" software by management companies, hand collected from various sources. We discuss advantages and limitations of each data in following sections, then present stylized facts to motivate the main empirical analysis.

3.1 REIS

REIS by Moody's Analytics contains information on the market-rate buildings in the U.S., from 2005 to 2019. There are 37,216 unique buildings with 7.2 million units covered in the data across 30 states. According to Fannie Mae, there were approximately 375,000 market-rate properties with 17 million market-rate units in 2021[13]. Considering there were about 1.5 million new units constructed in between 2019 and 2021[14], we believe our data covers about half of the market-rate apartment units in the U.S. Table 1 shows brief summary statistics of the data.

Market-rate buildings are particularly attractive sample, since they are not subject to special subsidies or legal compensation. In the fourth quarter of each year, Moody's surveys owners and managers of these buildings and collect information on asking rents, occupancy, concessions, various amenities. The dataset contains building-year level observations spanning 14 years from 2005 to 2019 with the identity of management companies. REIS also provides its own definitions of markets. They assign each building to one of 625 "submarkets" in one of 50 "metros." Submarkets completely partition a metro without overlaps.

The limitations come from two sources. The first source is that the management companies were backfilled by Moody's from 2019, making the management company field for each building time-invariant. The decision to adopt pricing software is made on management company-level, and as mentioned in Section 2.1, and the property management industry had experienced a fair bit of consolidation over the past decade. These two facts can potentially lead to over-counting of adopters in earlier periods. Because we are misclassifying non-adopted buildings to be adopters (measurement error in the independent variable), this would put an attenuation bias towards zero

[13] https://multifamily.fanniemae.com/news-insights/multifamily-market-commentary/assessing-market-rate-affordable-multifamily-sector

[14] https://www.jchs.harvard.edu/sites/default/files/reports/files/Harvard_JCHS_The_State_of_the_Nations_Housing_2020_Re

for the estimates.

The second source of limitation is lack of high-frequency price data. The greatest advantages of high-frequency pricing data is that it can be used to detect structural breaks to infer adoption in absence of accurate adoption data as done in Assad et al. (2020). It can also highlight interesting price dynamics and responses to changes in competitors' prices as illustrated in Figure A2. This is not a major concern, however, since we were able to a collect fairly confident set of management companies who adopted the software along with *when* each of them had adopted.

3.2 Software Adoption Data

We collected the adoption data from three major sources. First source is yearly snapshots of a website that maintained and updated the list of management companies and owners who had adopted pricing software. The owner of the website solicited surveys to participants at a major multifamily housing conference from 2008 to 2011 and updated the list every year. See Figure 1 for an example of the website snapshots.

Second source is from various media outlets. Both Rainmaker LRO and Yieldstar had active media presence announcing their major customer acquisitions. Through their main news outlets, they not only announced customer acquisitions but also major updates (or "patches") to their price optimization software. See Figure 2 for an example of an article.

Lastly, we supplement the data using the list from AppsRunTheWorld.com. This company collects data on adoption of enterprise IT applications and sells insights to salesforces of IT companies for better leads targeting. We use the list of companies who uses Yieldstar software. While they survey the companies and record adoption dates, it can be a bit noisy since some of the adoption dates are inferred from web-scraped data. Fortunately, this data contains only a small fraction of adopters compared to the other two more credible sources.

The main limitation is, of course, the measurement error. We expect that we vastly underestimate the number of adopters towards the end of the time period of the data, since the collected lists only cover major management companies. We conducted a validation exercise against the current list of buildings that use a RealPage product[15]. Of 641 *buildings*, 274 buildings (42%) were using RealPage products as of 2022 but was not flagged as adopters in 2019 and 206 buildings (38%) and 146 buildings (22%) were rightly flagged as adopters and non-adopters in 2019, respectively. There are

[15]https://www.realpage.com/explore, Accessed Dec. 2022

minimal false-positives; only 15 (2.3%) buildings were flagged as adopters in 2019 but not using RealPage in 2022. The majority of these buildings were said to be using Rainmaker LRO, and it is possible that they decided not to switch over to RealPage following its acquisition in 2017. We expect that any significant effect net of selection bias is reassuring due to the presence of attenuation bias from the measurement error.

3.3 Descriptives

In this section, we present stylized facts by combining the REIS data with the hand-collected data on software adoption and discuss sample selection for the main analysis. Figure 3 shows penetration trend of pricing software across buildings appear in REIS. We were able to identify *which* software the management companies had adopted for the most part and the big jump in the market share of Yieldstar in 2017 is due to their acquisition of Rainmaker[16]. Since we are conditioning the sample on market-rate buildings, we expect these buildings to adopt pricing software more aggressively than other types of multifamily apartments. Compared to the guess of 15% penetration in 2012 made by the surveyor mentioned in Section 3.2, about 19% of units in the REIS data had adopted the software. At the end of data period in 2019, about 2.4 million, or 33% of units, and 9,124, or 25% of buildings in the data had adopted the software. Given RealPage was pricing three million units in 2017, this number seems to be an underestimation of proliferation of the software in 2019.

Despite the concern that the hand-collected adoption data may be prone to false negatives, the adoption data merged with REIS covers 19 out 20 top management companies, as shown in Table 2. These management companies not only has large shares of buildings in our data, but also according to the National Multifamily Housing Council (NMHC). More importantly, this subset includes management companies involved in the recent lawsuits, allowing us to examine the raw rent and occupancy trends of those compared to non-adopters.

Figure 4 does exactly that. Both Essex and Greystar have appeared in multiple lawsuits accusing them of price fixing through their software, especially in the Seattle metro area. This gives a peek at both channels of interest. Essex in 2009, for example, aggressively drops prices and retains much of their occupancy compared to the rest of the market right after their adoption. Greystar, who adopted the software in 2010, after the crisis, raises their rent more aggressively than the rest of the market and loses

[16]https://www.businesswire.com/news/home/20171204006136/en/RealPage-Closes-Acquisition-of-Lease-Rent-Options-LRO

occupancy. While it is not clear which channel is dominant from this figure, it hints that there may be some room for the efficiency channel, evidenced by lowering rents to gain occupancy during the downturn and increasing rents during the upturn. If any coordination channel exists, it will be suppressing rent drop during the downturn, but strengthening rent increase during the upturn.

Prior to moving onto more rigorous analysis, we compare key variables along with building characteristics between adopters and non-adopters. Table 3 compares key variables as well as some available characteristics of buildings between adopters and non-adopters. Adopters tend to have higher rents and lower occupancy rates than non-adopters but they seem to comprised of buildings with higher quality. They are more recently built, tend to be taller in number of floors, and tend to have more amenities that can be found in "luxury" apartments. It suggests that carefully controlling for building-specific covariates and covariate-specific time trend is necessary to measure the impact of adopting the pricing software on buildings.

4 Building-level Impact of Algorithmic Pricing

Supported by the qualitative evidence as well as the pricing pattern changes shown in Figure 4, we first show that buildings that have adopted the software respond to changes in demand conditions more flexibly compared to non-adopters, suggesting that buildings using the software have more information on the demand conditions than those who do not. In doing so, we follow the reduced-form analysis of Leisten (2022). Specifically, for building j in market m and time t, we run following regressions:

$$\begin{aligned}\log(rent_{jt}) &= \theta_j^r + \beta^{r,common} X_{mt} + \beta^{r,adopt} X_{mt} \cdot a_t(j) + \mu_{jt}^r \\ Occ_{jt} &= \theta_j^o + \beta^{o,common} X_{mt} + \beta^{o,adopt} X_{mt} \cdot a_t(j) + \mu_{jt}^o,\end{aligned}$$

where θ_j is the building fixed effects, X_{mt} contains the proxies for demand shifters such as level and changes of unemployment, income, migration, and housing price index, and the indicator $a_t(j)$ is 1 if building j has adopted the software at time t and 0 otherwise. Intuitively, the co-variation of prices and occupancies from the non-interacted part, $\left(\hat{\beta}^{r,common} X_{mt}, \hat{\beta}^{o,common} X_{mt}\right)$ captures the pricing response of buildings facing the demand shifts from the "common knowledge." The interacted part in addition to the common part, $\left(\hat{\beta}^{r,adopt} X_{mt}, \hat{\beta}^{o,adopt} X_{mt}\right)$, captures the pricing

schedule of adopters. If the adopters have indeed more information on demand than non-adopters, it should show more flexible price response to changes in occupancy rates.

Figure 5 visually shows the difference in slopes of price response curves between the two groups. The left-hand side imposes no sample restriction, and the right-hand side restricts to markets where there is only one adopter to condition out possible competitive response of non-adopters to adopters' pricing strategy. In both figures, the price response of adopters are more flexible than that of non-adopters; adopters lower prices more aggressively when occupancy is low, and raise prices more aggressively when occupancy approaches 100%. Restricting to markets with only one adopter shows starker information advantage that adopters have over non-adopters. Table 5 shows the difference in slopes between the two groups and statistical significance of the difference. The estimates suggest that while adopters have significant informational advantage over non-adopters, the gap closes once there are enough adopters in a given market due to the equilibrium effect that non-adopters are best responding to adopters' pricing decisions.

From the above exercise, it is straightforward to see why measuring the *average* price effect of adoption on buildings compared to non-adopters does not make much sense. First, the treatment effect of the software on buildings depends on the market's demand conditions. In a low-demand market, more responsive buildings will charge cheaper rents and fill up occupancy compared to non-adopters, and when the demand is high, these buildings will charge higher rents, staying below the 100% occupancy. Hence the relevant empirical question to measure the degree of efficient pricing is to estimate heterogenous treatment effects of the software during market downturns and upturns.

We first show two event study plots for two different, but specific cohorts of adopters to show the existence of treatment effect heterogeneity: a cohort of buildings adopted the software before the financial crisis and another cohort who adopted after the crisis. The outcome of interest is $\log(rent_{jt})$ and occ_{jt}, which are log of asking rents and occupancy rate of building j in year t, respectively. We regress both outcomes on calendar-year dummies leading up to the adoption, and after the

adoption. Specifically, for cohort Y that adopted the software in year Y,

$$\log(rent_{jt}^{Y}) = \sum_{\tau=Y-5}^{Y-2} \beta_t^{Y,r} 1\{t=\tau\} a(j) + \sum_{\tau=Y}^{Y+5} \beta_t^{Y,r} 1\{t=\tau\} a(j) + \beta^r X_{jt} + \theta_{mt}^r + \theta_j^r + \mu_{jt}^r$$
$$occ_{jt}^{Y} = \sum_{\tau=Y-5}^{Y-2} \beta_t^{Y,o} 1\{t=\tau\} a(j) + \sum_{\tau=Y}^{Y+5} \beta_t^{Y,o} 1\{t=\tau\} a(j) + \beta^o X_{jt} + \theta_{mt}^o + \theta_j^o + \mu_{jt}^o,$$

where X_{jt} are time-varying building level covariates, θ_{mt} is market-year fixed effects, μ_{jt} are residuals, and β_t are our coefficient of interest, which is plotted in Figure 6 for the 2007 and 2013 cohorts, i.e. $Y = 2007$ and $Y = 2013$. Note that since we are estimating the dynamic treatment effects for a specific cohort, and comparing the outcome of interest with the never-treated buildings, we are not subject to the concerns of estimating the dynamic treatment effects in the usual staggered diff-in-diff research design.

Since adoption decisions are made at the management company-level, it is unlikely that building-specific unobservable is correlated with company-level decision, similar to the case of gas stations in Assad et al. (2020). All of top 20 management companies in 2022 operates across dozens of states, and it is plausible that these adoption decisions are not driven by any one specific time-varying condition of a building.[17] We address the further concern of luxury vs. non-luxury apartments being on a different rental growth path by conditioning on metro-level, pre-adoption rent quartile, time trend through θ_{mt}. Both cohorts as well as the aggregate event study across cohorts do not exhibit pre-trend, further supporting the parallel trend assumption.

The figure shows the clear trade-off that the algorithm makes between occupancy and asking rents. During the market downturn of 2009, the 2007 cohort aggressively lowers their price and gains more in occupancy compared to the non-adopters. The cohort who adopted the software in 2013, however, exhibits significant price growth compared to non-adopters but with almost 1.5% point less occupancy.

To further highlight that the algorithm may help buildings set efficient prices in response to demand conditions, we plot the estimates of the calendar-year treatment effects across cohorts in Figure 7. That is, we are measuring the impact of adoption in year t on the buildings that were using the software in that year. We measure this by simply regressing outcomes of interest on calendar year dummies, interacted with whether the building had adopted by then:

[17] https://www.nmhc.org/research-insight/the-nmhc-50/top-50-lists/2022-top-managers-list/

$$\log(rent_{jt}) = \sum_{\tau=2006}^{2018} \beta_t^r 1\{t=\tau\} a_\tau(i) + \beta^r X_{jt} + \theta_{mt}^r + \theta_j^r + \mu_{jt}^r$$
$$occ_{jt} = \sum_{\tau=2006}^{2018} \beta_t^r 1\{t=\tau\} a_\tau(i) + \beta^o X_{jt} + \theta_{mt}^o + \theta_j^o + \mu_{jt}^o.$$

Since this regression estimates treatment effects across all cohorts, we also show the coefficients estimated using the procedure of Callaway and SantAnna (2020) along with the coefficients estimated from the regression above. This highlights the aforementioned point that the algorithms help buildings price more efficiently. In between 2008 and 2010, the algorithm advised buildings to lower their rents and gain more occupancy. During the boom period starting in 2013, the adopters were charging higher rents, and allows for some level of vacancy compared to the non-adopters.

There are three important points to be made from the empirical exercise that measures the impact of adoption *on a treated building*. First, the fact that the adoption leads to higher prices than non-adopters is not a direct evidence that the algorithm grants market power to the treated. In fact, this may suggest that buildings using the software are optimally pricing during the time of high-demand, which may be socially optimal. Second, and relatedly, without making more assumptions, we cannot distinguish whether the price advantage over non-adopters is due to additional market power or better information. We take the stance that this effect is purely driven by efficiency in pricing that adopters have over non-adopters for the remainder of the paper to be conservative. Lastly, the moderate 3% increase in rents is when compared to a similar, non-treated building *in the same market*. This is not to be mistaken with the equilibrium effect of the adoption. If buildings in the same market are competing on prices, it is optimal for the non-adopters to raise rents too if the adopters raise their rents. Hence, the building-level estimates are conditioning on the equilibrium response of competing buildings, and it is appropriate to examine the market-level impact of the algorithm adoption, similar to the literature studying the price impact of mergers (Dafny, 2009).

5 Market-level Impact of Algorithmic Pricing

We first show an evidence that the penetration of algorithm into a market raises rents and lowers occupancy regardless of the market condition. We define our "market"

as the interaction between the submarket predefined by REIS and the quartile of rents. This mimics how the building managers and the algorithm picks competitors to benchmark their rents as shown in Section 2.2. We leverage variations coming from sudden increase in share of adopters in a given market. We define the event as more than 30% point increase in the share over one year period. That is, over a third of the buildings in a market become adopters in one year.

The parallel trend assumption needs to be justified. Again, we lean on the fact that the adoption decisions are made on the company-level, and any specific market trend would not be correlated with the decision of the adoption. To sufficiently control for local, time-varying demand conditions that might have induced some companies to base their adoption decision off of, we control for levels and changes in unemployment rate, personal income, housing price index, and net migration. Then we run following regressions for market m in year t:

$$\log(rent_{mt}) = \sum_{\tau=-5}^{-2} \beta_\tau^r 1\{t(m) - t = \tau\} + \sum_{\tau=0}^{5} \beta_\tau^r 1\{t(m) + t = \tau\} + \beta^r X_{mt} + \theta_t^r + \theta_m^r + \mu_{mt}^r$$
$$occ_{mt} = \sum_{\tau=-5}^{-2} \beta_\tau^o 1\{t(m) - t = \tau\} + \sum_{\tau=0}^{5} \beta_\tau^o 1\{t(m) + t = \tau\} + \beta^o X_{mt} + \theta_t^o + \theta_m^o + \mu_{mt}^o,$$

where $t(m)$ denotes the year of treatment for market m, X_{mt} contains vector of market-level economic conditions, θ_m are market fixed-effects, θ_t are year fixed-effects, and μ_{mt} are residuals. The coefficients of interest are β_τ, which is plotted in Figure 8, along with those estimated from the procedure of Callaway and SantAnna (2020).

In both specifications, we do not see a strong evidence of pre-trend, and if anything, the pre-trend gets even weaker with the robust method of Callaway and SantAnna (2020). This suggests that there is an instantaneous increase in rents which keeps on increasing after 5 years from the event. The effect on occupancy rates show up slowly but it gets evident by the fourth year after the treatment. This is not driven by additional "treatment." We find that on average, post-treatment increase in adopter share is much less than that of non-treated markets. Hence, just one-time, but significant increase in share of adopters leads to persistent increase in rents and decrease in occupancy compared to the markets with lower share of adopters.

Supported by the evidence, we examine differential treatment effects of the software on markets by the degree of its penetration. The market we consider is submarket-rent quartile pairs. We categorize the markets into four bins by time periods and ten

bins by the degree of penetration. Each time period bin has three years: 2008-2010, 2011-2013, 2014-2016, and 2017-2019. We drop 2005 to 2007 due to low adoption shares, yielding noisy estimates. Cross-sectional markets are binned by their absolute share of algorithm adopters in 10% point increments. Table 6 shows the variation in penetration by the binned years. We find considerable mass to be at 0% by our market definition, and these markets will be considered as the "control" group. We then regress:

$$\log(rent_{mt}) = \sum_{T=1}^{T=5}\sum_{B=1}^{10} \beta_{T,B} 1\{(T(t) = T\} 1\{B_t(m) = B\} + \sum_{B=1}^{10} \beta_B 1\{B_t(m) = B\} + \beta X_{mt} + \theta_m + \theta_t + \mu_{mt},$$

where $T(t)$ denotes the year bin that year t belongs to, and $B_t(m)$ denotes the binned share of adopters that market m belongs to in year t. X_{mt} includes market-level economic conditions as well as average characteristics buildings in the market. We then plot $\hat{\beta}_{T,B} + \hat{\beta}_B$ for each T, B as shown in Figure 9. The coefficients that belongs to the periods before and during the financial crisis are in light blue, and the coefficients for the post-crisis period is plotted in light red. In general, regardless of the periods, the coefficients tend to increase with the penetration of the software up to 5%, meaning that the greater the penetration is, the larger the increase in average rents of the market. We believe that not accounting for the proliferation in the later periods are generating attenuation bias for the coefficients of the 2017 to 2019 bin. The pattern of the coefficients are robust to the market definition. We show coefficients from the same regression specifications when the market(m) is defined by simple zip code in Figure A4.

It is worth emphasizing that this effect captures the equilibrium response of non-adopters who belong in the same market as the adopters in addition to the direct effect from the adopters. Hence, even if the algorithm made buildings to lower prices in 2008 through 2010 it is still possible to have higher prices in markets with higher penetration than in markets with lower penetration. The intuition is that the building-level price effects are happening *within* a market, but the coefficients plotted in Figure 9 shows equilibrium effect on rents across markets with varying degree of penetration. Figure A5 shows the competitive effect of penetration of software on non-adopters only.

With these estimates, we proceed to do a back-of-envelope exercise to obtain a

rough magnitude of the impact of the adoption to the market overall. Suppose we only have two markets with identical buildings, one with zero percent adoption and the other with 100% adoption. If there is only efficiency gain during the boom period, the price difference between the two markets would be the same as building-level estimates from Section 4. If there is price coordination among adopters that pushes the market-level rents above that of efficient rents, that the market-level effect would exceed the building-level efficiency effect.

We emphasize that we are taking the most conservative steps we can in measuring the price effect coming from coordination among adopters. First, it is entirely possible that the higher rents that adopters charge conditional on the best response of the competitors is additional market power. We rule out this possibility and assume all building-level effect is in spirit of efficiency. Second, we further assume that algorithms may not reach the fully efficient prices until there are enough data points. To be conservative, we take the *maximum* of building-level effects across markets with varying level of penetration as shown in Figure A6, and consider it as the potential efficiency gain from the adoption. Figure 10 shows decomposition of the effects using conservative estimates on the left-hand side, and using the estimates from Figure A6 at face value on the right-hand side for the 2014 to 2016 period estimates. They show unweighted impact of adoption. We weigh the impact by the distribution of buildings in markets with corresponding penetration in Table 6. We find that, with the conservative estimates, the minimum of 25% of the increase in rents can be attributed to the coordination effect.

6 Conclusion

In this paper, we examined the impact of algorithmic pricing software adoption on the U.S. multifamily housing industry using hand-collected, unique datasets. We first document detailed inner workings of a pricing software and find that the software collects high-frequency data from clients of its own, then fully utilizes the collected data to respond to changes in a local market. We investigate two different channels that the algorithm impacts prices and occupancy of the market. First, we find robust evidence that the algorithm helps building managers to price more efficiently. The adopters tend to exhibit more responsive pricing function to the changes in local demand conditions. The treatment effect of the algorithm on the building-level is widely heterogeneous across calendar years; in the bust market, the algorithm lowers

rents and increases occupancy, and vice-versa during the boom market.

To measure the market-level, equilibrium impact of algorithm adoption and more importantly, impact that varies with degrees of penetration, we measure the market-level treatment effect of penetration. Through the sub-sample of markets that experience sudden "jump" in shares of adopters, we find significant price increase up to 5% and occupancy decrease by 0.8%. Furthermore, we find that across markets, high level of penetration leads to higher rents. This pattern is robust across time periods, market definitions, and regression specifications. Since the effect we find on the market-level already internalizes the building-level efficiency effect, we further conduct a rough, back-of-envelope decomposition and find that about 25% of the total price effect is driven by coordination effect at its minimum.

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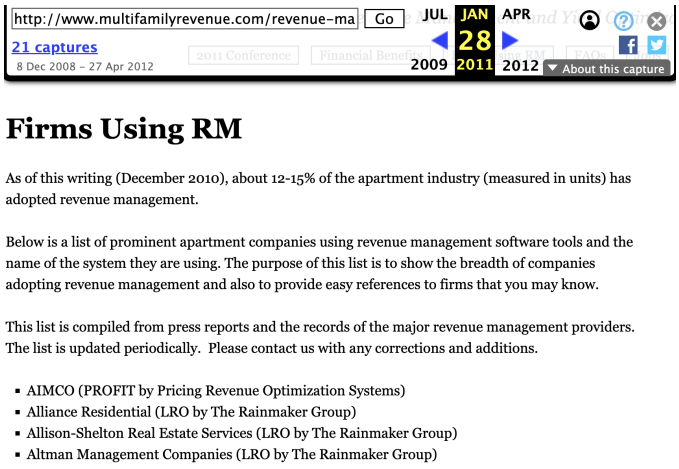
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7 Figures

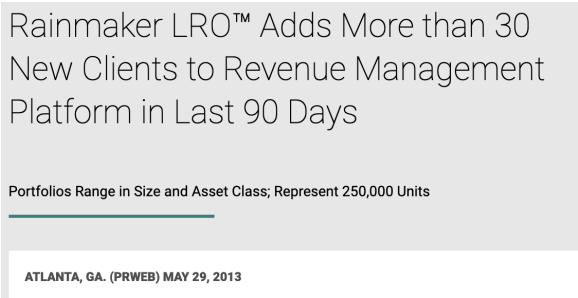
Figure 1. Snapshot of Surveyed List of Adopters



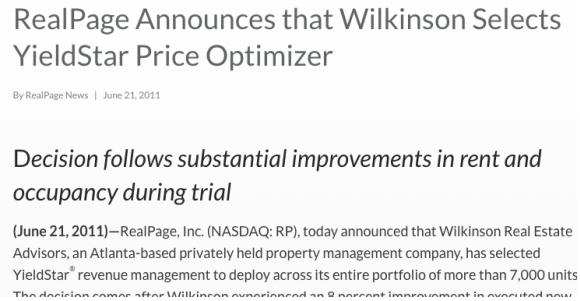
https://web.archive.org/web/20110128035809/http://www.multifamilyrevenue.com/revenue-management-users-multifamily/

Figure 2. Example Articles of Client Acquisition Made by Software Companies

(a) Rainmaker



(b) Yieldstar



(Rainmaker) https://www.prweb.com/releases/rainmakerlro/adds30newcompanies/prweb10779081.htm
(Yieldstar) https://www.realpage.com/news/realpage-announces-that-wilkinson-selects-yieldstar-price-optimizer/

Figure 3. Share of Adoption by Software

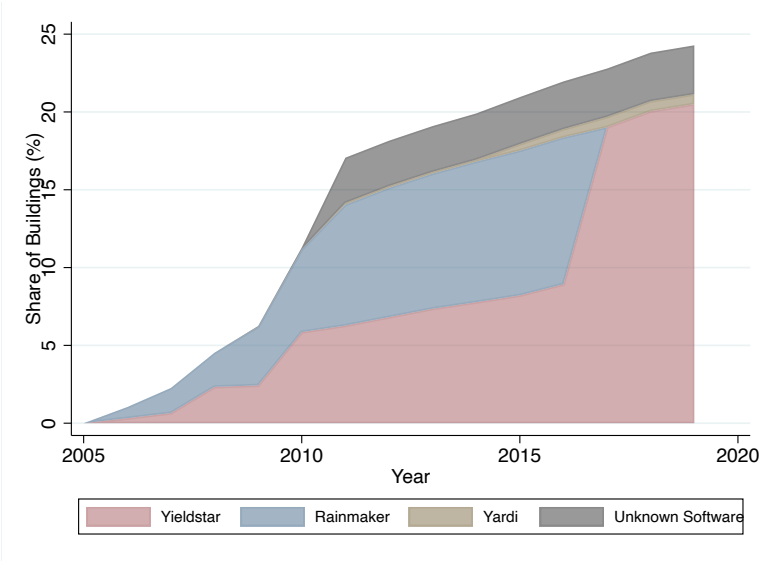
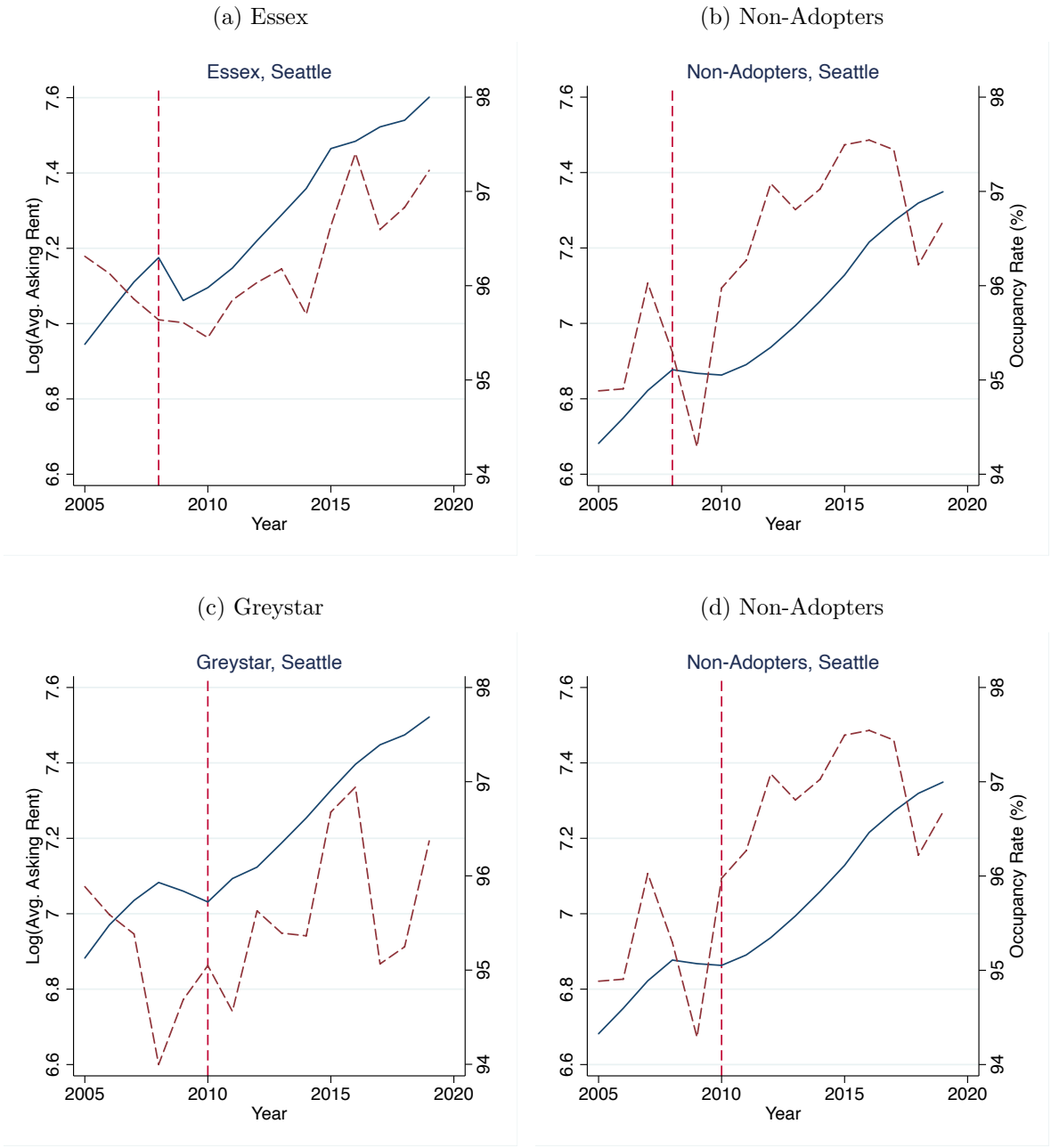


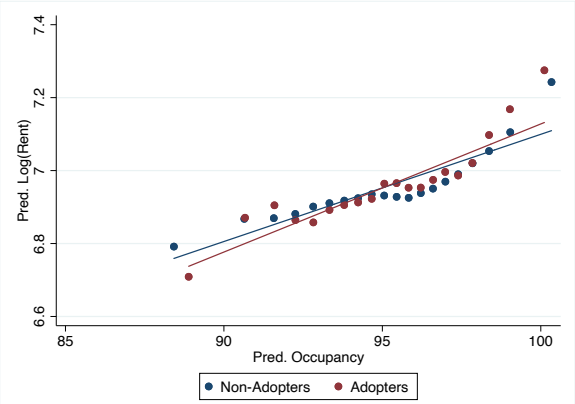
Figure 4. Case Study: Pricing and Occupancy Trend of Companies Adopted the Software



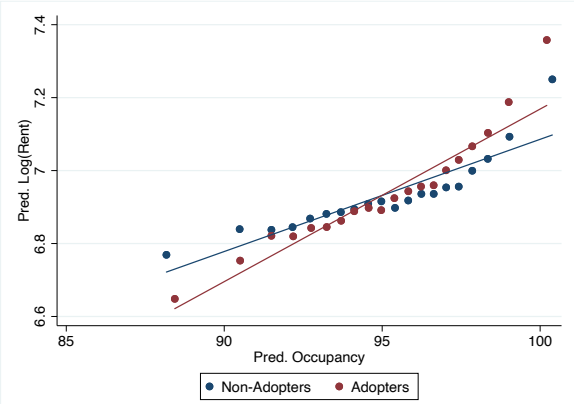
Restricting samples to Seattle metro-area apartments. Solid, navy line follows Log(Rent) and dashed, red line follows occupancy rate. The vertical dashed line indicates the year of adoption of each management company.

Figure 5. Pricing Schedule of Adopters vs. Non-Adopters

(a) All Adopters vs. Non-Adoters



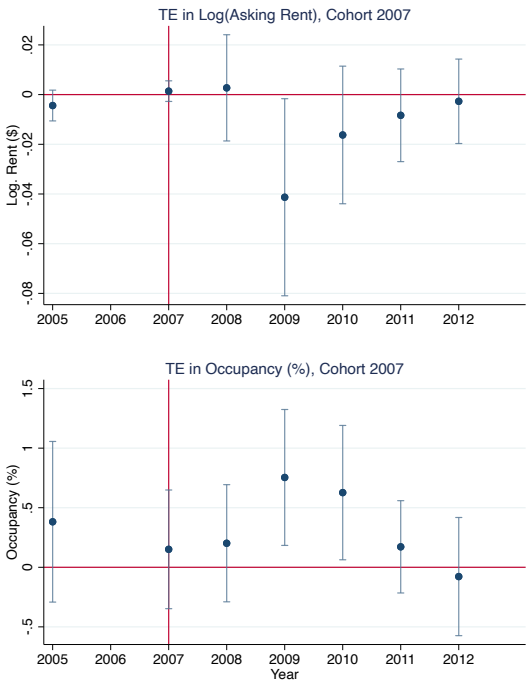
(b) Only Adopter in the market vs. Non-Adoters



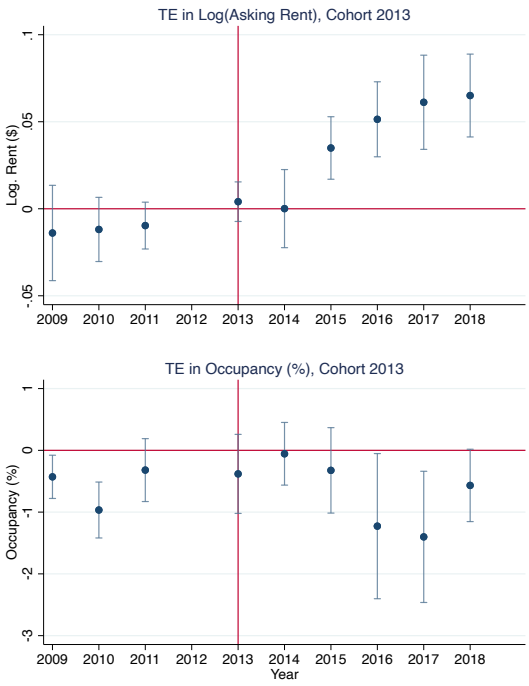
Binned scatterplots of predicted Log(Asking Rent) and occupancy as a function of market-level variables including levels and changes of housing price index, unemployment rate, net migration, average individual income, asking rents, and vacancies net of the building's. These variables are also interacted with whether the building had adopted the software or not. The "market" is the pre-defined submarket segmented by quartile of asking rents.

Figure 6. Dynamic TE of Adoption on Log(Asking Rent) and Occupancy Rate

(a) 2007 Adopters

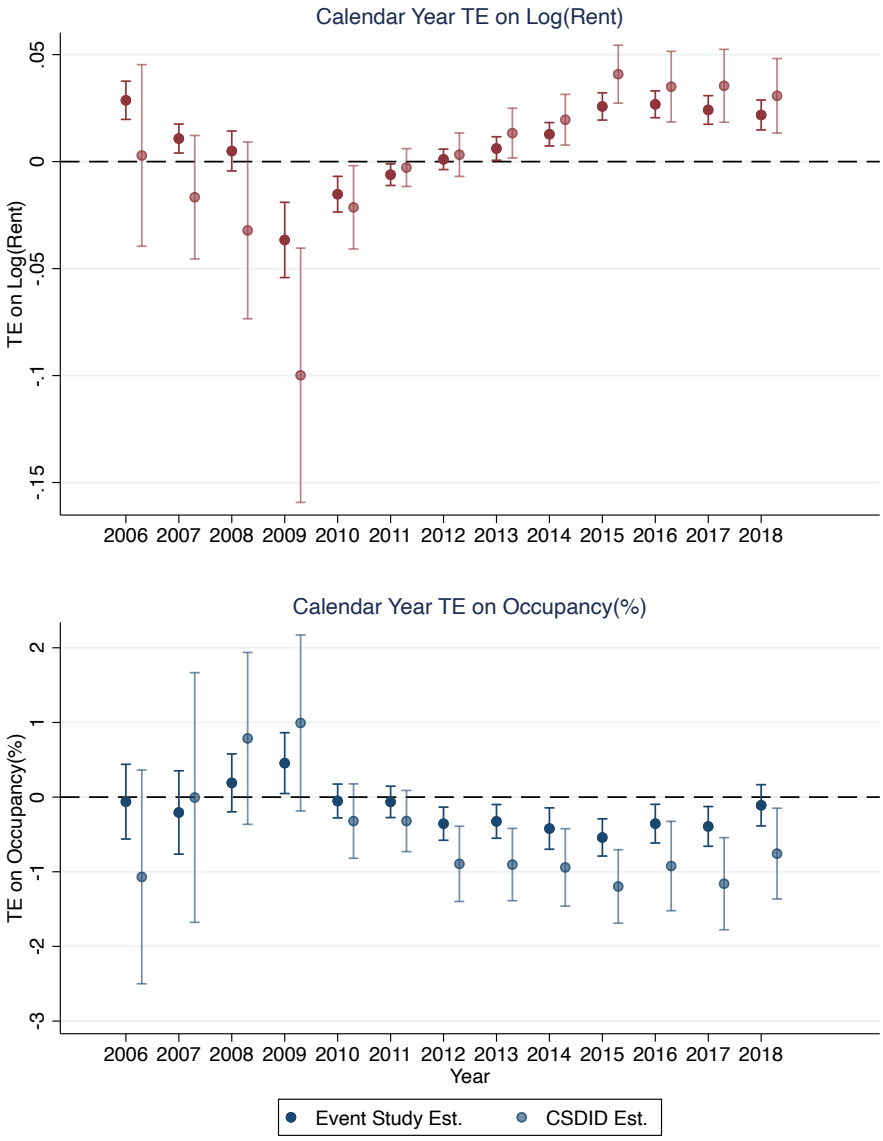


(b) 2013 Adopters



Sample restricted to buildings built before 2005. Building-level and time trend (year) fixed effects for the building's metro and pre-treatment period rent quartile are included. Controls include months of free rent offered, average concession offered in the submarket. Standard errors are clustered at the management company level.

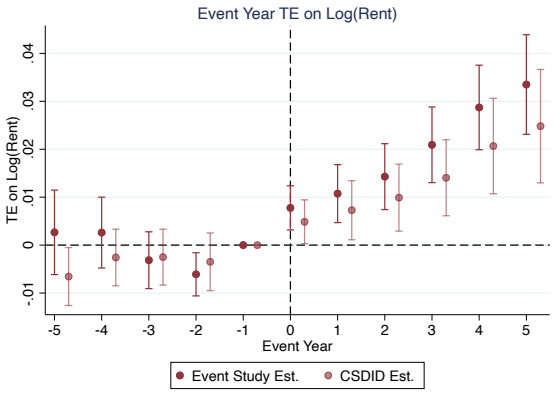
Figure 7. Calendar Year TE on Adopted Buildings



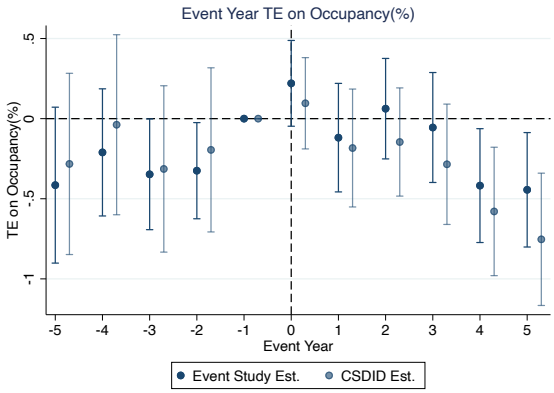
Sample restricted to buildings built before 2005. Building-level and time trend (year) fixed effects for the building's metro and pre-treatment period rent quartile are included. Controls include months of free rent offered, average concession offered in the submarket. For the Callaway and SantAnna (2020) specification (CSDID), building-level characteristic-specific time trends are also controlled through the doubly robust estimator in addition to the fixed effects. Standard errors are clustered at the management company level for both specifications.

Figure 8. Market-level TE from Sudden Increase in Share of Adopters

(a) On Log(Asking Rent)

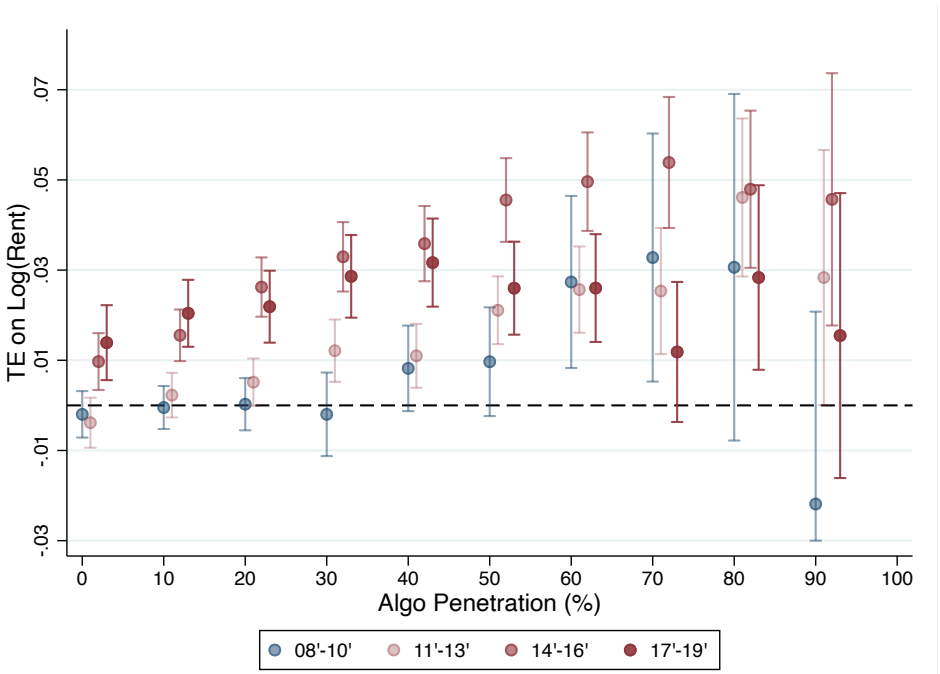


(b) On Occupancy Rate



Sample restricted to buildings built before 2005. Market is the pre-defined submarket segmented by quartile of asking rents. The event is defined as more than 30% point increase over one year in share of adopters relative to all buildings in a given market. Controls include levels and changes of housing price index, unemployment rate, net migration, average individual income, average characteristics of buildings in the market, as well as market and year two-way fixed effects. For the Callaway and SantAnna (2020) specification (CSDID), market level characteristic time trends are also controlled through the doubly robust estimator in addition to the fixed effects. Standard errors are clustered at the market level for both specifications.

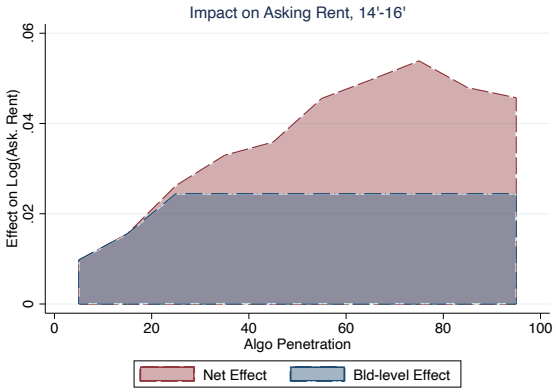
Figure 9. Market-Level Treatment Effects by Degree of Penetration, Submarket-Rent Quartile



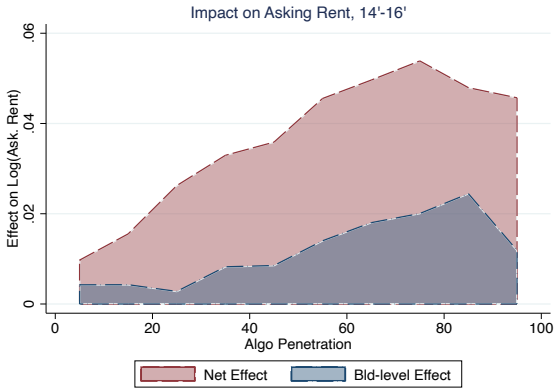
Market is the pre-defined submarket segmented by quartile of asking rents. For each year, markets are grouped into 10 absolute bins based on the percentage of adopted buildings relative to the total buildings in the market-year. Controls include levels and changes of housing price index, unemployment rate, net migration, average individual income, as well as average characteristics of buildings in the market, in addition to the market and year two-way fixed effects. Standard errors are clustered at the market level.

Figure 10. Decomposing Efficiency vs. Coordination Effect on Log(Asking Rent), 2014-2016

(a) Conservative



(b) Non-Conservative



Sample restricted to buildings built before 2005. Market is the pre-defined submarket segmented by quartile of asking rents. For each period bin, markets are grouped into 10 absolute bins based on the percentage of adopted buildings relative to the total buildings in the market-year.

8 Tables

Table 1. REIS Summary Statistics

Avg. Asking Rent($)	1373.9
	(825.8)
Occupancy Rate(%)	93.15
	(7.807)
Avg. Units	193.9
	(168.4)
$N_{building}$	37,216
$N_{company}$	11,523
N_{state}	30
N_{metro}	50
N_{submkt}	663

Table 2. Top Multifamily Building Management Companies

Company	Units Managed	Adoption	Adoption Date	NMHC Ranking (2019)
Greystar	320,598	1	2010	1
Lincoln Property Mgmt	123,920	1	2009	2
Pinnacle	91,977	1	2010	3
MAA	81,641	1	2007	7
Alliance Residential	74,281	1	2011	4
Equity Residential	70,979	1	2006	10
BH Management	63,650	1	2010	8
Avalon Bay	58,377	1	2008	11
Essex	54,361	1	2008	18
Camden	54,170	1	2006	21
Irvine Company	53,796	1	2010	17
Bozzuto	52,203	1	2010	12
United Dominion Realty	45,576	1	2007	30
Cortland	43,889	1	2013	26
Morgan Properties	42,527	1	2011	28
ZRS	36,594	1	2010	32
Bell Partners	35,979	1	2008	31
FPI Management	35,729	1	2011	5
Highmark Residential	32,490	0	-	19
Avenue5	32,353	1	2018	20

NMHC Ranking from https://www.nmhc.org/research-insight/the-nmhc-50/top-50-lists/2019-managers-list/

Table 3. Building characteristics comparison between adopters vs. non-adopters

	Non-Adopters	Adopters
Log(Avg. Asking Rent($))	7.03	7.27
	(0.47)	(0.47)
Occupancy Rate(%)	93.64	91.63
	(7.37)	(8.84)
Free Rent(Month)	0.03	0.04
	(0.02)	(0.02)
Num. Floors	3.88	4.97
	(4.38)	(6.11)
Year Built	1979.67	1995.05
	(23.93)	(19.47)
Frac. Pool	0.64	0.83
	(0.48)	(0.38)
Frac. Doorman	0.03	0.05
	(0.18)	(0.21)
Frac. Tennis Court	0.00	0.01
	(0.07)	(0.08)
Frac. Parking Garage	0.04	0.09
	(0.21)	(0.29)
Frac. Clubhouse	0.35	0.65
	(0.48)	(0.48)
$N_{building}$	28,092	9,124
$\text{Shr}_{building}$	75.5%	24.5%
N_{unit}	4,807,230	2,408,601
Shr_{unit}	66.6%	33.4%

Table 4. Building-level Calendar Year TE of Pricing Software Adoption

	TWFE		CSDID	
Year	Log(Ask Rent)	Occ(%)	Log(Ask Rent)	Occ(%)
2006	0.029***	-0.061	0.003	-1.069
	(0.005)	(0.255)	(0.022)	(0.730)
2007	0.011***	-0.206	-0.017	-0.006
	(0.003)	(0.285)	(0.015)	(0.853)
2008	0.005	0.191	-0.032	0.787
	(0.005)	(0.198)	(0.021)	(0.587)
2009	-0.037***	0.455**	-0.100***	0.993*
	(0.009)	(0.208)	(0.030)	(0.601)
2010	-0.015***	-0.052	-0.021**	-0.321
	(0.004)	(0.116)	(0.010)	(0.254)
2011	-0.006**	-0.064	-0.003	-0.321
	(0.003)	(0.107)	(0.005)	(0.209)
2012	0.001	-0.356***	0.003	-0.894***
	(0.002)	(0.113)	(0.005)	(0.257)
2013	0.006**	-0.325***	0.013**	-0.904***
	(0.003)	(0.115)	(0.006)	(0.247)
2014	0.013***	-0.421***	0.020***	-0.942***
	(0.003)	(0.141)	(0.006)	(0.265)
2015	0.026***	-0.541***	0.041***	-1.197***
	(0.003)	(0.127)	(0.007)	(0.251)
2016	0.027***	-0.356***	0.035***	-0.923***
	(0.003)	(0.132)	(0.008)	(0.305)
2017	0.024***	-0.392***	0.035***	-1.160***
	(0.003)	(0.136)	(0.009)	(0.315)
2018	0.022***	-0.110	0.031***	-0.757**
	(0.004)	(0.141)	(0.009)	(0.310)
N_{obs}	413,850			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Sample restricted to buildings built before 2005. Building-level and time trend (year) fixed effects for the building's metro and pre-treatment period rent quartile are included. Controls include months of free rent offered, average concession offered in the submarket. For the Callaway and SantAnna (2020) specification (CSDID), building-level characteristic-specific time trends are also controlled through the doubly robust estimator in addition to the fixed effects. Standard errors are clustered at the management company level for both specifications.

Table 5. Slope of Price Response Curves, Adopters vs. Non-Adopters

Sample	Estimate
All	0.0057***
	(0.0010)
Num. Adopt = 1	0.0166***
	(0.0019)
1 < Num. Adopt ≤ 5	0.0157***
	(0.0012)
Num. Adopt > 5	0.0047***
	(0.0015)

Table 6. Distributions of Markets by Penetration of Adopters

Year	0%	0-10%	-20%	-30%	-40%	-50%	-60%	-70%	-80%	-90%	-100%	Total
2005	2,506	0	0	0	0	0	0	0	0	0	0	2,506
2006	2,289	104	69	34	5	2	3	1	0	0	0	2,507
2007	2,108	142	135	83	20	9	8	2	0	0	0	2,507
2008	1,864	196	188	144	48	27	27	7	3	3	1	2,508
2009	1,627	256	266	197	76	33	37	8	3	3	2	2,508
2010	1,225	276	368	267	121	103	84	44	8	6	5	2,507
2011	896	277	388	326	198	128	140	85	25	27	18	2,508
2012	846	259	415	340	197	127	154	86	34	25	24	2,507
2013	799	258	413	345	198	155	164	94	28	32	22	2,508
2014	798	250	370	350	208	180	168	88	41	33	22	2,508
2015	771	256	377	322	229	146	172	123	56	34	22	2,508
2016	730	231	394	311	239	168	190	134	50	38	22	2,507
2017	684	244	385	324	247	195	196	115	53	40	25	2,508
2018	634	228	397	346	270	184	188	143	58	34	26	2,508
2019	596	252	371	374	271	177	216	147	53	33	18	2,508

The market definition used is submarket, rent quartile pair.

A Appendix Figures

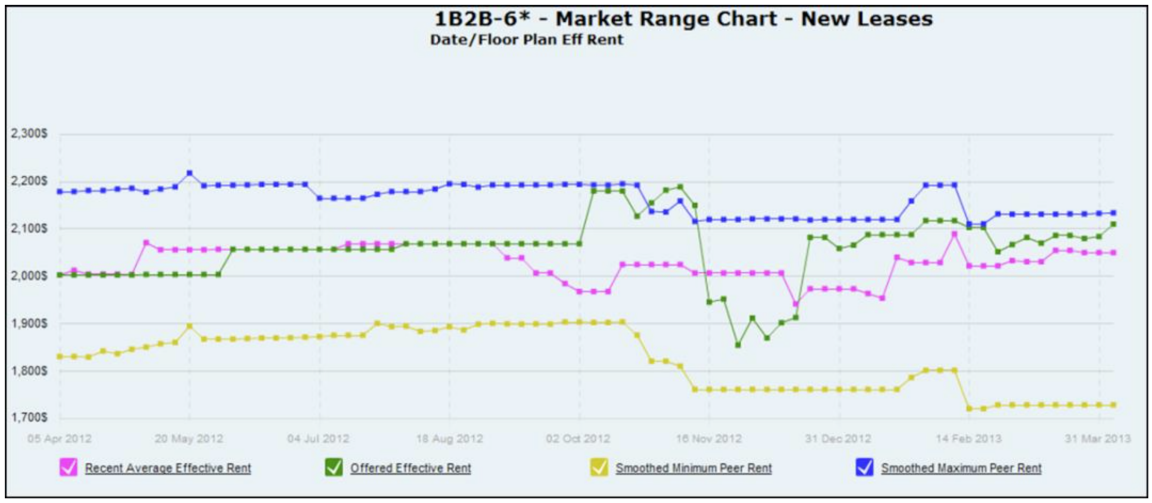
Appendix Figure A1. How Yieldstar optimizes rents

Bedroom Level Pricing

How the tool utilizes the competitive data:

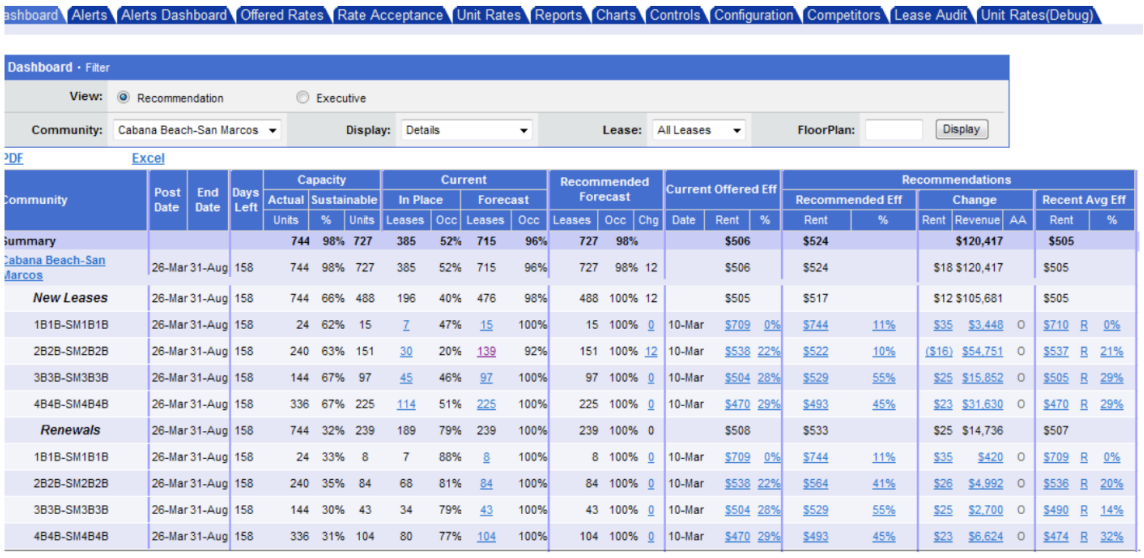
- Starts with your market survey, Operations approves the comps
- Dynamically calibrates elasticity for each bedroom type by:
  - Reading each lease and lease application for your asset
  - Determining the effective rent (net of all appropriate concessions)
  - Comparing the effective rent you achieve to the top and bottom of the competitive range for your selected competitors. Of note, the top and the bottom is a blending of multiple unit types to protect against "bad data"
  - The tool assigned a price position for each lease and aggregates to form a elasticity curve to truly define the price/demand relationship

Appendix Figure A2. Manager's view of dynamic pricing by Yieldstar



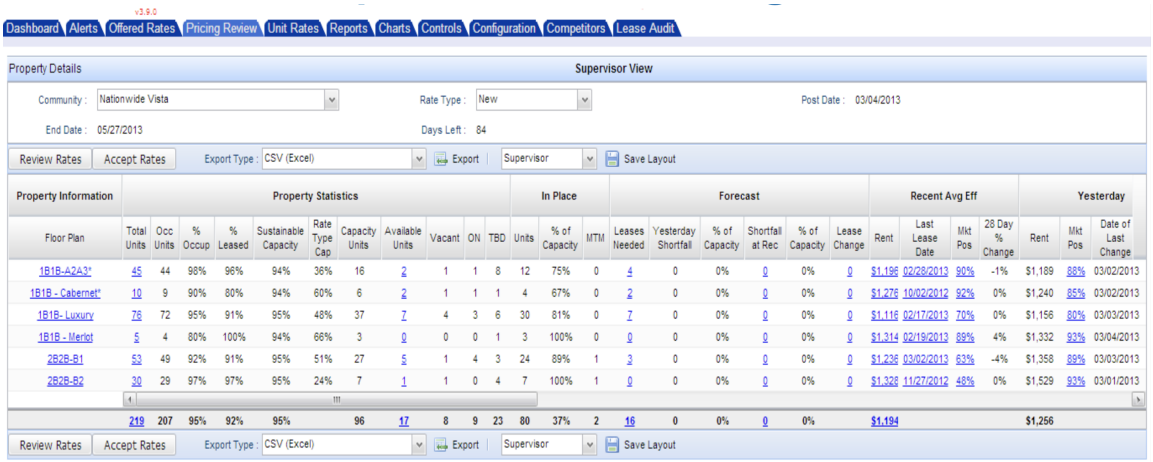
Appendix Figure A3. Manager's view of Yieldstar pricing dashboard

(a) Price recommendation made by Yieldstar



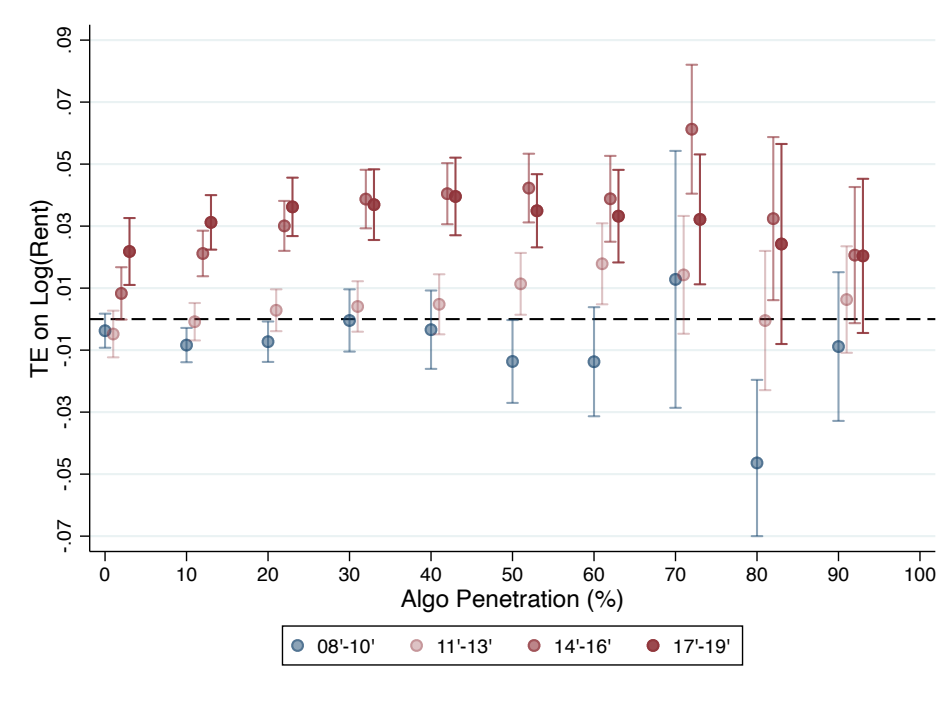
Community	Post Date	End Date	Days Left	Capacity Actual Units	Capacity Actual %	Capacity Sustainable Units	Current In Place Leases	Current In Place Occ	Current Forecast Leases	Current Forecast Occ	Recommended Forecast Leases	Recommended Forecast Occ	Recommended Forecast Chg	Current Offered Eff Date	Current Offered Eff Rent	Current Offered Eff %	Recommendations Recommended Eff Rent	Recommendations Recommended Eff %	Recommendations Change Rent	Recommendations Change Revenue	Recommendations Change AA	Recommendations Recent Avg Eff Rent	Recommendations Recent Avg Eff %
Summary				744	98%	727	385	52%	715	96%	727	98%			$506		$524		$120,417			$505	
Cabana Beach-San Marcos	26-Mar	31-Aug	158	744	98%	727	385	52%	715	96%	727	98%	12		$506		$524		$18	$120,417		$505	
New Leases	26-Mar	31-Aug	158	744	66%	488	196	40%	476	98%	488	100%	12		$505		$517		$12	$105,681		$505	
1B1B-SM1B1B	26-Mar	31-Aug	158	24	62%	15	7	47%	15	100%	15	100%	0	10-Mar	$709	0%	$744	11%	$35	$3,448	O	$710 R	0%
2B2B-SM2B2B	26-Mar	31-Aug	158	240	63%	151	30	20%	139	92%	151	100%	12	10-Mar	$538	22%	$522	10%	($16)	$54,751	O	$537 R	21%
3B3B-SM3B3B	26-Mar	31-Aug	158	144	67%	97	45	46%	97	100%	97	100%	0	10-Mar	$504	28%	$529	55%	$25	$15,852	O	$505 R	29%
4B4B-SM4B4B	26-Mar	31-Aug	158	336	67%	225	114	51%	225	100%	225	100%	0	10-Mar	$470	29%	$493	45%	$23	$31,630	O	$470 R	29%
Renewals	26-Mar	31-Aug	158	744	32%	239	189	79%	239	100%	239	100%	0		$508		$533		$25	$14,736		$507	
1B1B-SM1B1B	26-Mar	31-Aug	158	24	33%	8	7	88%	8	100%	8	100%	0	10-Mar	$709	0%	$744	11%	$35	$420	O	$709 R	0%
2B2B-SM2B2B	26-Mar	31-Aug	158	240	35%	84	68	81%	84	100%	84	100%	0	10-Mar	$538	22%	$564	41%	$26	$4,992	O	$536 R	20%
3B3B-SM3B3B	26-Mar	31-Aug	158	144	30%	43	34	79%	43	100%	43	100%	0	10-Mar	$504	28%	$529	55%	$25	$2,700	O	$490 R	14%
4B4B-SM4B4B	26-Mar	31-Aug	158	336	31%	104	80	77%	104	100%	104	100%	0	10-Mar	$470	29%	$493	45%	$23	$6,624	O	$474 R	32%

(b) Competitor data and recommendation acceptance

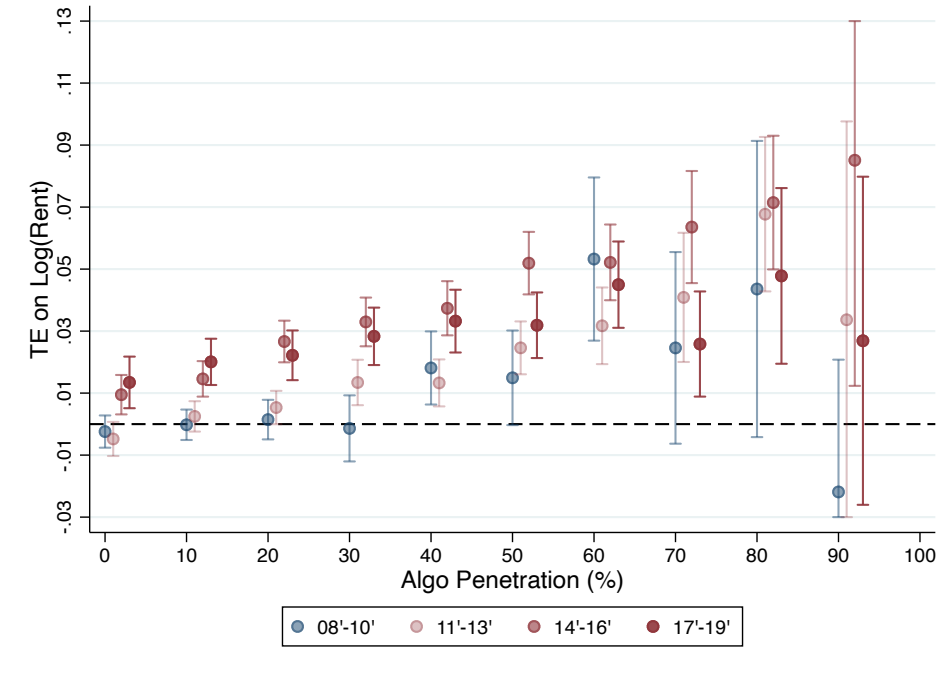


Property Information Floor Plan	Property Statistics Total Units	Occ Units	% Occup	% Leased	Sustainable Capacity	Rate Type Cap	Capacity Units	Available Units	Vacant	ON	TBD	In Place Units	% of Capacity	MTM	Forecast Leases Needed	Yesterday Shortfall	% of Capacity	Shortfall at Rec	% of Capacity	Lease Change	Recent Avg Eff Rent	Last Lease Date	Mkt Pos	28 Day % Change	Yesterday Rent	Yesterday Mkt Pos	Yesterday Date of Last Change
1B1B-A2A3*	45	44	98%	96%	94%	36%	16	2	1	1	8	12	75%	0	4	0	0%	0	0%	0	$1,196	02/28/2013	90%	-1%	$1,189	88%	03/02/2013
1B1B - Cabernet*	10	9	90%	80%	94%	60%	6	2	1	1	1	4	67%	0	2	0	0%	0	0%	0	$1,276	10/02/2012	92%	0%	$1,240	85%	03/02/2013
1B1B- Luxury	76	72	95%	91%	95%	48%	37	7	4	3	6	30	81%	0	7	0	0%	0	0%	0	$1,116	02/17/2013	70%	0%	$1,156	80%	03/03/2013
1B1B - Merlot	5	4	80%	100%	94%	66%	3	0	0	0	1	3	100%	0	0	0	0%	0	0%	0	$1,314	02/19/2013	89%	4%	$1,332	93%	03/04/2013
2B2B-B1	53	49	92%	91%	95%	51%	27	5	1	4	3	24	89%	1	3	0	0%	0	0%	0	$1,236	03/02/2013	63%	-4%	$1,358	89%	03/03/2013
2B2B-B2	30	29	97%	97%	95%	24%	7	1	1	0	4	7	100%	1	0	0	0%	0	0%	0	$1,328	11/27/2012	48%	0%	$1,529	93%	03/01/2013
	219	207	95%	92%	95%		96	17	8	9	23	80	37%	2	16	0	0%	0	0%		$1,194				$1,256		

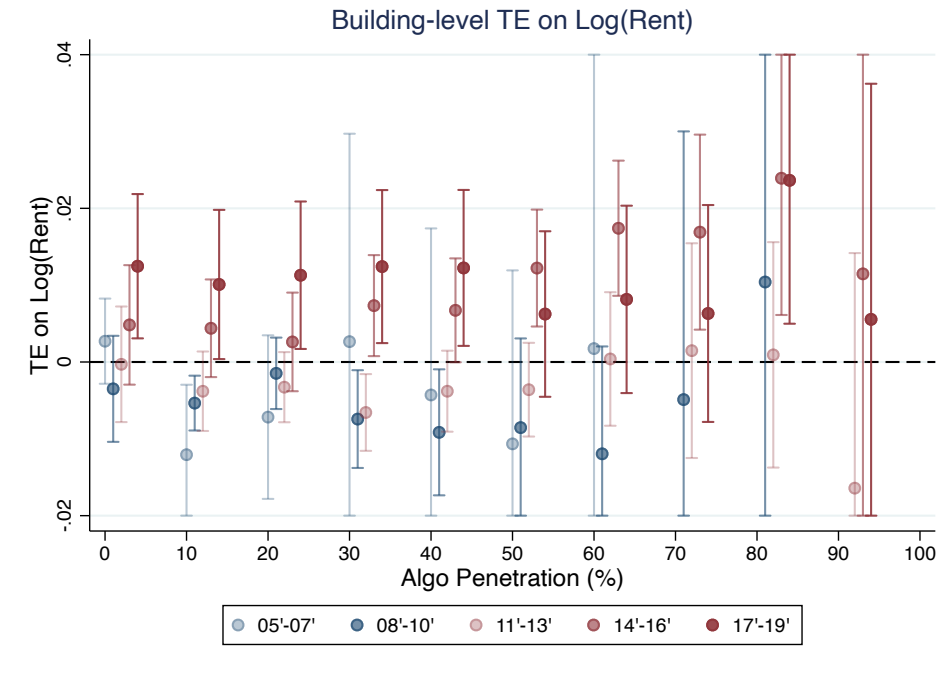
Appendix Figure A4. Market-Level Treatment Effects by Degree of Penetration, Zip



Appendix Figure A5. Market-Level Treatment Effects on Non-adopters by Degree of Penetration, Submarket-Rent Quartile



Appendix Figure A6. Building-Level Treatment Effects by Degree of Penetration of Software, Submarket-Rent Quartile



B Appendix Tables

Appendix Table A1. Top and Bottom 5 Metro Areas by Penetration, as of 2019

Metro	Adopted Blds	Total Blds	Penetration(%)
Top 5 Metros			
Raleigh-Durham	219	504	43
Seattle	573	1331	43
Suburban Virginia	236	580	41
Charlotte	221	546	40
Austin	283	734	39
Bottom 5 Metros			
Columbus	44	565	8
Cleveland	14	363	4
New Orleans	8	209	4
Cincinnati	16	486	3
Milwaukee	13	400	3

Appendix Table A2. Top and Bottom 10 Submarket Areas by Penetration, as of 2019

Metro	Submarket	Adopted Blds	Total Blds	Penetration(%)
Top 10 Submarkets				
Orange County	Irvine	72	78	92
Orange County	Newport Beach	14	17	82
Austin	Far Northwest	35	47	74
Fort Lauderdale	Plantation	20	27	74
Orange County	Mission Viejo	34	48	71
Denver	Arapahoe County	15	22	68
Austin	Near South Central	17	25	68
Dallas	Central Dallas	67	101	66
Seattle	Redmond	43	65	66
Charlotte	Carmel	33	50	66
Bottom 10 Submarkets				
Cincinnati	North	0	25	0
St. Louis	Airport/I-70	0	43	0
Memphis	Frayser	0	8	0
Milwaukee	Greenfield/Greendale	0	54	0
New Orleans	Southeast Orleans	0	10	0
Cincinnati	Highway 27/127	0	37	0
New Orleans	Kenner	0	13	0
New Orleans	Jefferson/River Ridge	0	23	0
Kansas City	North Kansas City	0	31	0
Fort Worth	Central Arlington	0	61	0