Gender and Workload Choices: Evidence from the Real Estate Brokerage Industry

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Abstract

The real estate brokerage industry is characterized by overlapping tasks and complex job dynamics. We investigate the differences in workload choices and performance outcomes across genders, and the trade-off between wage and cost. Using a large-scale dataset covering residential realtor activities in the Canadian province of Quebec between 2005 and 2017, we find that, women appear to be endowed with fewer work opportunities than men. However, for an additional unclosed task, women are able to obtain more new tasks and complete more unclosed tasks than men, after controlling agent fixed effects and agents' time-varying experience and ability, house and task attributes, and market conditions. Women also consistently attain a higher productivity gain (in terms of earned commissions) from increasing workloads but incur a higher cost (in terms of the average time spent to sell a listing). A simple back-of-the-envelope calculation implies a 15% gender gap in the trade-off between wage and time cost, suggesting that the workload choices by female agents is more likely due to their preference than their ability.

Keywords

Workload, Diversity, Equity, and Inclusion (DEI), Gender Pay Gap, Real Estate Brokerage

JEL: J16, J22, M11, M54, L85, R00

1. Introduction

Pioneered with the seminal work of Nobel Laureate Claudia Goldin in the 1980s, extensive research has shown that the occupational choices and preferences of women contribute to the gender wage gap. The real estate brokerage industry presents a unique platform to explore the wage gap between men and women for at least two reasons. First, as real estate agents are paid on a commission basis and have flexible hours, the brokerage industry is more accommodating to part-time workers than other routine-based, salaried jobs. This work flexibility makes the real estate sales profession attractive to women. Secondly, although entry into the real estate agent industry is relatively easy,[1] it remains a highly competitive field due to the nature of a realtor's job, which involves managing a range of overlapping tasks. In this context, workload, particularly measured as the number of unclosed listings (or tasks), becomes a crucial measure of an agent's choice and capacity to manage multiple responsibilities effectively. This also ties into the common stereotype of women being better multitaskers, a belief held by a significant portion of the public (e.g, Szameitat et al., 2015).[2]

We focus on how the workload level affects the productivity to study the interplay between gender, workload choices, and performance outcomes in the real estate brokerage industry. Prior studies in operation management (e.g., Coviello et al., 2015; KC, 2014; Tan and Netessine, 2014; Goes et al., 2018) suggest that a high workload level triggers two opposing mechanisms. On the one hand, each task contains inevitable idle times (e.g., a realtor waiting for potential buyers of a listed house), which is more likely filled if more overlapping tasks exist. That is, a high workload level can keep agents continuously busy so they waste less idle time. On the other hand, switching between tasks is not costless. As one resumes a previous task, after being interrupted for a while by a separate task, it takes time to recall the details of that previous task (e.g., recapping the selling points of a listed house). Overall, it is expected that the former

[1] Gaining a license is the only barrier to practice. The real estate broker exam is also relatively easy to pass. See Hsieh and Moretti (2003).
[2] This notion is also prevalent in the popular press, though scientific findings remain inconclusive, with varying results depending on the nature of tasks (Buser and Peter 2012, Hirnstein et al. 2019, Mäntylä 2013, Stoet et al. 2013).

will be more pronounced at lower levels of workload, while the latter at higher levels, giving rise to a curvilinear relationship between the workload level and productivity.

We deploy a comprehensive dataset covering all logged residential real estate sales activities in the province of Quebec, Canada from 2005 to 2017. Women make up a large percentage of the total labor force in this industry, mainly due to their stronger presence as part-time agents, similar to that in many other industries (e.g., healthcare and education).[3] To yield a meaningful workload analysis and address the broader question that whether women have different preferences and can perform equally well as men in full-time roles, we focus on agents at the top decile, who we can safely assume to be full-time workers.[4] Our descriptive statistics show that women are more inclined to work less, a trend that becomes especially pronounced during peak seasons. Our initial findings suggest that women have difference preferences: on average women work on fewer tasks and smaller tasks and are more likely to co-work with other agents. Yet, conditional on the same number of existing tasks (i.e., current workload level) and controlling agent fixed effects and agents' time-varying experience and ability, house and task attributes, and market conditions, women are better at obtaining new tasks and completing existing tasks than men for each additional workload added. Thus, it is likely preference rather than ability that explains women's selections of a lower workload.

The critical question arises: why do women, despite their evident capability in handling their workload, opt for fewer tasks? We adapt a conceptual model introduced by Le Barbanchon et al. (2021) to investigate how gender differences in the trade-off between wage (commission earnings) and costs (the average time spent on tasks) might influence agents' decisions to take on additional work. We construct a gender-specific acceptance frontier which allows us to separately estimate the willingness to pay (WTP) for a shorter time on tasks for both female and male agents, and how this influences their decisions to increase workload levels. This approach offers a nuanced understanding of how incremental workload

[3] Identified based on the U.S. Bureau of Labor Statistics Current Population Survey 2016's annual averages of employed people by detailed occupation.
[4] While selecting the top decile might appear arbitrary, our findings are consistently similar even when using different cutoffs (e.g., number of transactions they involved) to identify full-time agents.

affects earnings and the time spent on tasks, particularly in the context of gender differences in the real estate brokerage industry. Back-of-the-envelope calculations show that the 14.93% gender gap in the trade-off between wage and time cost. Importantly, this higher cost borne by women is evidenced across nearly the entire spectrum of workload levels observed in our data. Our finding offers a plausible rationale for why female agents may opt for fewer tasks and aligns with prior studies which established empirical connections between gender pay gaps and factors indicative of gender differences in preferences and constraints such as family obligations and a preference for job flexibility (e.g., Bertrand et al., 2010; Goldin, 2014; Cook et al., 2021).

This paper contributes to the literature on gender equality in the labor market. Recent studies on the gender pay gap suggest that men's seemingly higher wage disappears once we control work hours (e.g., Cook et al. 2021). Our results depart from this perspective and demonstrate that in real estate, controlling for observed characteristics, women are in fact more productive workers who are capable to attain more benefits from an additional workload. But female agents gain less than male agents from the trade-off between agent's revenue and cost, possibly due to their higher family responsibilities, consistent with the labor economics literature that women prefer occupations that offer better flexibility with family obligations (Bertrand 2011, Blau and Kahn 2017). These insights have broad policy implications in promoting women in real estate.

This paper contributes to the real estate brokerage literature (e.g., Han and Strange, 2015; Cunningham et al, 2022). Recent studies on agent gender and housing transactions provide mixed insights. Some studies suggest that female and male agents are not significantly different in their negotiation skills (e.g., Seagraves and Gallimore, 2013; Anderson et al., 2020; Cifci et al., 2023)[5] while Pham et al. (2022)

[5] For example, Seagraves and Gallimore (2013) suggest that female agents' superior performance in terms of the sale price and the time on task is caused by the selection of clients, not the agent's skills. Anderson et al (2020) suggest that gender differences in negotiation skills diminish after controlling for the value and other unobservable heterogeneities of the property. Cifci et al. (2023) focus on commercial real estate (CRE) agents and find no significant differences in performance as measured by transacted property price.

suggest that female and male agents are different in bargaining power.[6] In addition, Popov (2022) suggests that the existence of gender gap in earnings and such gap increases during the boom. Unlike prior literature which uses transaction-level data and studies the gender differences by using a gender indicator, we construct panel data consisting of agent-month to control agent's time-variant (e.g., experience and ability) and time-invariant (agent fixed effect) attributes. Our focus is the gender differences in the ability of adding and closing tasks for an additional level of workload as well as the trade-off between revenue and cost. Lastly, our study also offers new insights on workload and multitasking in operation management literature (e.g., KC, 2014; Tan and Netessine, 2014; Bray, 2016; Goes et al., 2018).

2. Institutional Background, Agent Workflow, and Sample Construction

Approximately two-thirds of North American residents own their homes, making real estate the most significant component in the average household's asset portfolio. According to the National Association of Realtors (NAR), more than 80% of houses are transacted with the assistance of licensed real estate agents, which makes the residential brokerage industry crucial to individual households and the economy.[7]

Realtors working with sellers (buyers) are often referred to as the listing (buying) agents. Listing agents provide services such as listing the house on the multiple listing service (MLS), marketing the house, advising on the listing prices and negotiation process, and assisting in closing a transaction. Buying agents

[6] For example, Pham et al. (2022) find that female buying agents have stronger bargaining power when deal with male listing agents.

[7] The 2023 National Association of Realtors (NAR)'s profile of home buyers and sellers shows that 89% of home sellers sold their houses and 89% of buyers purchased their houses with the assistance of real estate agents or brokers between July 2022 and June 2023. See, https://www.nar.realtor/research-and-statistics/research-reports/highlights-from-the-profile-of-home-buyers-and-sellers (last access: November 26, 2023). The real estate, rental, and leasing industry ranks the highest among all industry sectors in North America. The industry contributed 11.5 trillion in 2020 and 11.9 trillion in 2021 to United States' GDP, according to the Bureau of Economic Analysis (BEA) (https://www.bea.gov/data/gdp/gdp-industry, accessed on November 26, 2023). In Canada, the real estate industry is also the most important industry with a GDP contribution of 257 billion in 2020, 266 billion in 2021, and 267 billion in 2022 according to Statistic Canada. See https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610043403 (last access: November 26, 2023).

provide services such as assisting in searching for houses that match buyers' tastes, showing the houses, advising on the offer prices and negotiation process, and assisting in closing a transaction.[8]

The real estate brokerage job is organized by overlapping tasks. Figure 1 provides a stylized illustration of listing activities. There are three overlapping tasks – three listing tasks *i*, *j*, and *k* – during an agent's one busy episode. Each listing task starts with the agent signing a seller's representative agreement (SRA) with a customer who wishes to sell her house and ends with the closing of the sales transaction. At the start of each month, we count the agent's number of unclosed tasks on hand (*UnclosedTasks*). At the end of each month, we count the number of new tasks signed (*NewTasks*), the number of listing tasks sold (*SoldTasks*), and accumulate the total commission earned from her sold tasks (*EarnedComm*) during the month. Therefore, the start and end times of each task, together with the typical 3% commission rate (assuming an equal split with the buying agent), give rise to the values of *UnclosedTasks, NewTasks*, *SoldTasks*, and *EarnedComm* presented at the bottom of Figure 1 (area between the dashed lines shows the value of these three variables for Month *t*).

[Please insert Figure 1 about here]

According to NAR (2018), 63 percent of realtors are women. In addition, women make up the majority of real estate agents in all but 10 states (U.S. Census Bureau's American Community Survey 2020). Even during the "Great Resignation" in 2021, over 120,000 women joined the NAR.[9] Despite being the significant part of the labor force, women are much more likely to work part-time than men (43% versus

[8] A realtor can also conduct buying tasks for clients. Unlike the mandatory nature of an SRA in most provinces in Canada and states in U.S., a buyer's representative agreement between buyers and agents is often verbal, which leads to the unobservability of the exact buying task start time. Acknowledging the more important role of being a listing agent than a buying agent and the potential inaccuracy of the inference of the exact buying task start time, we conduct our baseline analysis using only listing tasks. Since the average service time (i.e., contract duration of an SRA) for listing tasks is around 6 months, we assume the average service time for buying tasks is also 6 months and subtract 6 months from the purchase time to infer buying task start time and extend the analysis to both listing and buying tasks in Appendix Table A.4 for robustness.

[9] https://www.nar.realtor/newsroom/op-eds-and-letters-to-the-editor/great-resignation-heres-why-women-who-work-in-real-estate-dont-quit (Last Access: November 26, 2023)

27% as reported by Census 2020) to prioritize childcare and family duties. This results in women making up over two-thirds of all part-time agents (NAR 2017).

To gain a deeper understanding of this dynamic, we turn to our extensive dataset, which includes residential realtor activities in Canada, a setting that mirrors other developed countries in examining gender differences (Blanchflower et al., 2023). Our raw dataset consists of the complete set of listings from 2005 to 2017 in the Canadian province of Quebec recorded by the Authority of Real Estate Brokerage in Quebec (OACIQ), which totals 963,926 listings by 23,969 unique agents.[10] Each listing contains detailed information on house characteristics, listing attributes, and identifiers of involved listing and buying agents.

To ensure a balanced comparison between women and men, considering the large existence of part-time agents and agents who do not treat real estate broker job as their primary job in this industry, our workload analysis concentrates on full-time agents who are sufficiently busy.[11] We achieve this by sorting agents based on their annual earned commissions and selecting the top 10 percentile of agents for each year. For each selected agent-year, we further remove months that start with zero unclosed task. This is because zero unclosed task could happen when an agent is completely inactive, making such a case irrelevant to our analysis. Zero unclosed task could also happen at the starting month of a busy period (e.g., Month t in Figure 1), which will guarantee the number of new tasks greater than one and hence bias the estimation results. Combining across 13 years, we retain 8,408 unique agents and 436,572 agent-month observations.

Our agent-month basis sample allows us to plot and analyze the proportion of flexible, inactive agents, segmented by gender and month. We define an agent being inactive in a specific month if his or her monthly number of active tasks, including both unclosed tasks (*UnclosedTasks*) and new tasks (*NewTasks*), is less than or equal to 1, which is roughly the bottom decile of agent-month active tasks. Figure 2 shows this proportion, averaged across years, is higher for women than men every single month. Interestingly, the

[10] The size of the real estate, rental and leasing industry in Quebec is comparable to that in state of Missouri or South Carolina in the US. Source: Statistic Canada and Statista (Last Access: November 26, 2023).

[11] The annual earned commissions for all agents between 2005 and 2017 are heavily right skewed with an average (median) of \$45.1k (\$72.4k). About 34% of agents earn less than \$30k. This follows the pareto principle (i.e., 80/20 rules) that are common in many self-employee industries. This indicates that most of workers in the real estate brokerage industry are part-timers and might not treat this job as their primary job.

gender gap, as shown in the dashed line, is more pronounced during the summer and winter months (e.g., July, August, December, and January), coinciding with the time of the year with more family duties (e.g., children's summer activities and holiday season house mundane). These periods are commonly viewed as the "hot season" for real estate sales (Ngai and Tenreyro 2014),[12] a factor that particularly disadvantages female agents in terms of earnings. Overall, for women seeking flexible work, the real estate brokerage industry seems to offer an attractive solution.

[Please insert Figure 2 about here]

3. Observed Gender Differences

3.1. Model-Free Evidence of Gender Differences

Table 1 provides summary statistics for our key variables, which are constructed at agent-month level. Our key variables include the agent's number of unclosed tasks on hand (*UnclosedTasks*), the number of new tasks signed (*NewTasks*), the number of listing tasks sold (*SoldTasks*), and the total commission earned from her sold tasks (*EarnedComm*). Average time on tasks (*AvgTOT)* measures the average duration, in months, that an agent spends on tasks that were sold within a specific month. We take the natural log of *EarnedComm* (i.e., *LnEarnedComm*) and the natural log of *AvgTOT* (i.e., *LnAvgTOT*) to enable an interpretation in terms of percentage increase in agent earning and time spent on tasks. If a listing is handled by multiple agents, we assume each agent equally contributes to the task and hence shares the commission equally.[13] *Team%Unclosed*, *Team%New*, and *Team%Sold* measure the average teamwork portion of unclosed tasks, new tasks, and sold tasks, respectively.[14] *AvgValUnclosed* (*ContractUnclosed*), *AvgValNew*

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[12] It's worth noting that July and August are significant months in Quebec, as they precede the school year, with July 1st known as "Moving Day" (*jour du déménagement*), a tradition stemming from a time when the province mandated fixed lease terms for rental properties.

[13] This even split between the listing or buying agents is a plausible assumption. The 1913 Code of Ethics adopted by the National Association of Real Estate Exchanges (the former NAR) states that its members shall "... always be ready and willing to divide the regular commission equally with any member of the Association who can produce a buyer for any client."

[14] For example, if agent *i* has two unclosed tasks: one is handled solely and one is handled with another agent, at the beginning of month t, the average teamwork portion of unclosed tasks is 25% ($UnclosedTasks_{it} = 1 - {}^{1.5}/_{2} = 0.25$), indicating that 25% of his unclosed tasks are co-worked with other agents.

(*ContratNew*), and *AvgValSold* (*ContractSold*) are the average house value (contract duration) of unclosed tasks at the beginning of a specific month and new and sold tasks in a specific month. Last, *FemaleAgent* is a binary variable denoting the gender of the agent.

As shown in Panel A, there are 47% of agent-months for female agents. An average agent has a total of 10.03 unclosed tasks at the start of a month, with a per-task potential commission (*AvgComUnclosed*) of \$5.43K. The average number of new tasks (*NewTasks*) and sold tasks (*SoldTasks*) per month is 2.06 and 1.16, respectively. The average monthly earning from commissions (*EarnedComm*) is \$8.2K and the average time spent on tasks (*AvgTOT*) for sold tasks is 2.78 months.

Panel B shows the gender gap statistics. First, our sample of full-time agents has a stronger male presence: 4,339 male agents versus 4,069 female agents (a 1.07:1 male-to-female ratio). Second, even within the top-tier agent population, there is still clear evidence of women taking more time off than men: 54.65 busy months per female agent versus 58.26 per male agent. Third, it seems female agents on average have fewer work opportunities in terms of both unclosed and new tasks, 9.25 versus 10.72 and 1.92 versus 2.18, respectively.

Despite having a marginally lower total potential commission from unclosed tasks (with an average of *UnclosedTasks*×*AvgComUnclosed* = \$52.08K for women compared to \$56.38K for men), female agents are better able to convert these tasks into successful sales (evidenced by a higher *SoldRatio5yrs*). Consequently, the discrepancy in earned commissions, at just \$0.24K, is significantly smaller than the \$4.3K gap in total potential commission. This suggests that in terms of abilities, female agents are not at a disadvantage relative to their male counterparts. Detailed definitions and statistics of our control variables are in Appendix Tables A.1 and A.2, respectively.

[Please insert Table 1 about here]

3.2. Model Evidence of Gender Differences

Our goal is to estimate the differences between female and male agents in their task selections and abilities. The main source of endogeneity (or omitted variable bias) arising from factors like house characteristics, task characteristics, market conditions, and agent heterogeneity. While completely eliminating endogeneity concerns is difficult, we adopt several strategies to mitigate them, as demonstrated in prior studies (Turnbull and Dombrow, 2007; KC, 2014; Cunningham et al., 2022).

First, we include a comprehensive list of variables to control for task and house characteristics. For task characteristics, we use *LnAvgComUnclosed* to measure the average possible commission of the agent's pending tasks at the beginning of the month (i.e., those captured by *UnclosedTasks*). We also include an array of house attributes, averaged across *UnclosedTasks*. Second, we include year-by-month fixed effects to account for seasonality and market conditions. Third, it is likely that more capable agents are likely to have more task options, a higher stock of potential commissions, and a greater likelihood of closing current deals while taking on new ones, we capture an agent's time-varying experience and ability by *ActiveYrs*, which measures the number of active years, and *SoldRatio5yrs*, which measures the average likelihood of house sold in the prior 5 years.[15] Lastly, we use agent fixed effects to control for innate and time-invariant agent heterogeneity.

3.2.1. Differences in Preferences (or Choices)

When workers are free to seek and choose their workload, are female and male agents different in selecting the composition of unclosed tasks, new tasks, and sold tasks? We compare gender differences in selecting the number of tasks, value of tasks, teamwork levels, and contract durations *without* agent fixed effects. In Panels A through C of Table 2, coefficients for *FemaleAgent* in Column (1) suggest that female agents have fewer unclosed tasks (Panel A) with a lower average value (Panel B), are more likely to co-work other agents (Panel C). Coefficients for *FemaleAgent* in Columns (2) and (3) show that in terms of new and sold tasks, female agents add and sell fewer tasks (Panel A), tasks with lower value (Panel B), and are more likely to co-work with other agents for sold tasks (Panel C). However, our analysis reveals minimal

[15] Using the average likelihood of house sold in the prior period yields similar results.

significant differences in contract duration (as shown in Panel D). The coefficient displays marginal statistical significance with negligible economic impact in Column (1), and it is insignificant in Columns (2) and (3).

Collectively, female agents have fewer unclosed tasks, lower average value of unclosed tasks, and are more likely to co-work with other agents. Compared with male agents, female agents have less competitive incentives (i.e., selecting tasks with lower value) and are more risk-averse (i.e., sharing tasks with other agents). These findings are consistent with the existing evidence suggested by psychologists and social scientists that female agents might be more risk averse (Byrnes et al., 1999) and shy away from competition (Gneezy et al., 2003; Iriberri and Rey-Biel, 2017; Niederle and Vesterlund, 2007). Murad et al. (2019) also suggest that competitive incentives affect women and men's selection to workload level.

Control variables have expected signs. For example, agents with more active years have more unclosed tasks, new tasks and sold tasks, and undertake larger deals. More unclosed tasks at the beginning of each month lead to more new tasks and sold tasks in that month due to momentum effects.

[Please insert Table 2 about here]

3.2.2.Differences in Abilities

Considering the observed differences in preferences, the subsequent inquiry pertains to potential disparities in capabilities. Specifically, given the existing unclosed tasks, are there differences in the abilities of female and male agents when it comes to acquiring new tasks or successfully converting existing unclosed tasks into sales? On the one hand, agents have limited time and effort to invest in existing and future tasks, which gives rise to a negative association between *UnclosedTasks* and *NewTasks*, as well as a *negative* relationship between *UnclosedTasks* and *SoldTasks* ("*capacity effect*"). On the other hand, the benefit of a high level of workload comes from better utilization of time segments that are otherwise idle (e.g., KC 2014, Goes et al. 2018). When an agent has more unclosed tasks, she might be more aware of such benefits and hence willing to accept more new tasks. It is also possible that an agent with more tasks on hand is viewed as more capable by customers and hence has more opportunities. These arguments give rise to a *positive* association between *UnclosedTasks* and *NewTasks*, as well as between *UnclosedTasks* and *SoldTasks* ("*momentum effect*").

To capture the curvilinear effect of workload on worker productivity, we follow prior literature discussed above to enter both the first and second-order terms of *UnclosedTasks* to the negative binomial model. In addition to the time-varying agent heterogeneity control variables detailed in Table 2, we also account for agent fixed effects to further control for inherent and constant agent differences and estimate the variations in their abilities.

In Table 3, the coefficients for *UnclosedTasks* are positive and significant, consistent with the benefit of idle time utilization dominating when the workload level is low. The negative and significant *UnclosedTasksSq* suggests that, as unclosed tasks increase, the marginal impact of *UnclosedTasks* decreases, consistent with the increasing cost of switching between tasks. In Columns (2) and (4) of Table 3, we interact *UnclosedTasks* (first and second order terms) with *FemaleAgent*. On average, a one-standard-deviation increase in *UnclosedTasks* is associated with an increase in the number of agent's new tasks (sold tasks) by 0.44 (0.90) for women and 0.40 (0.72) for men. We find that female agents have a higher marginal effect throughout at least 75% of *UnclosedTasks* in the data. For example, women consistently attain a higher benefit from increasing workload. When *UnclosedTasks* = 3 (first quartile), a one-unit increase in unclosed tasks increases new tasks (sold tasks) by 0.040 (0.080) units for women and 0.036 (0.066) units for men. When *UnclosedTasks* = 13 (third quartile), a one-unit increase in unclosed tasks increases new tasks (sold tasks) by 0.034 (0.064) units for women and 0.032 (0.056) units for men.

Collectively, the results suggest that female agents have better ability to gain from an additional unclosed task, in terms of adding new tasks and completing existing tasks. These findings are consistent with evidence that women might be better at working on a higher workload level because they are better at monitoring (Adams and Ferreira 2009; Wahid 2019) and are more accurate decision-makers in complex decision tasks (Chung and Monroe, 2001), have better leadership skills and unique abilities (Kim and Starks, 2016).

[Please insert Table 3 about here]

Combining the model-free observations discussed in Section 3.1 and the gender differences in preferences and abilities discussed in Section 3.2, the tendency of female agents to undertake less work is more likely due to their preferences rather than their ability. When controlling for agent fixed effects and focusing on the incremental impact of an additional unclosed task, female agents actually outperform male agents: holding the existing unclosed tasks constant, for each additional unclosed tasks, women demonstrate a greater willingness to take on more new tasks and are better able to convert opportunities into actual profits. In the following section, we will explore in greater detail the underlying reasons for the observed gender differences, specifically examining the trade-off between earnings (in terms of commissions) and costs (as measured by the time spent on tasks).

4. Explaining the Observed Gender Differences

4.1.1. An Illustrative Theoretical Framework

Our results thus far indicate that the reduced work opportunities for women are not attributable to a lack of ability. But why women choose to work less? Since real estate agents have the autonomy to set their own workloads, agents aiming to maximize utility should cease taking on more tasks when the incremental cost surpasses the additional benefits. We adopt a similar model introduced by Le Barbanchon et al. (2021), who study the relationship between gender differences in job search criteria, particularly in willingness to commute, and the gender wage gap. In their framework, they identify indifference curves in the log-wage-commute plane, demonstrating steeper curves for women due to their higher valuation of commute time. The model yields a reservation wage curve, which reflects the lowest wage a job seeker is willing to accept for a given commute time. The slope of this curve represents the willingness to pay (WTP) for a shorter commute. They find that this WTP is significantly higher for women, with the value of commuting time amounting to 80% of the gross hourly wage for men and 98% for women, suggesting women generally have a lower reservation wage and a shorter maximum acceptable commute compared to men.

We adapt this model to investigate how differences in gender might influence agents' decisions to take on additional work in the real estate brokerage context. Each agent aims to maximize their utility, $u(W,T)$, which is a function of wage (W) and the time spent on tasks (T). The agent's utility is modeled as $u(W,T) = ln(W) - \gamma ln(T)$. γ is the time elasticity of wage for changes in workload levels, holding the utility level constant. $\gamma > 0$, indicating that agent's utility increases with W and decreases with T. The utility, $u(W_0, T_0) = U$, at the original state, $S_0(W_0, T_0)$, serves as the baseline for the agent's decision-making.

Starting from S_0, an agent can take two possible actions, denoted as a: to increase workload capacity ($a = 1$) or to maintain it ($a = 0$). An increase in workload capacity is symbolized by a shift from an original state, $S_0(W_0, T_0)$, to a new state, $S_1(W_1, T_1)$, with $W_1 > W_0$ and $T_1 > T_0$. For a given utility, the reservation wage, $\omega(T)$, is a function of time spent on tasks (T). Since the indifference curves between wage and costs are identified as the joint distributions of reservation wage and acceptable time spent on tasks, to keep the agent on the baseline utility, $u(W_0, T_0)$, the reservation wage for a longer time on tasks (i.e., T_1) becomes $\omega(T_1) = \exp\left(ln(\omega(T_0)) + \gamma(ln(T_1) - ln(T_0))\right)$. This relationship yields the following reservation trade-off curve as

$$ln(\omega(T)) - ln(\omega(T_0)) = \gamma(ln(T) - ln(T_0)) \quad (1)$$

Figure 3 plots the trade-off between incremental percentage in wage (y-axis) and incremental percentage in time spent on tasks (x-axis) with the same utility level of U. The slope of the reservation trade-off curve, γ, represents the least incremental percentage in W needed to maintain the utility level U for each 1% increase in T. An agent will consider increasing her workload if the utility from potential new state exceeds the baseline utility. In other words, if the actual trade-off, depicted as the star point in the figure, lies above the reservation trade-off curve with a slope of γ^{actual} – meaning that the transition from the initial state S_0 to the new state S_1 results in an increase in commissions greater than what the slope of

γ would suggest (i.e., $ln(W_1) - ln(W_0) > ln(\omega(T_1)) - ln(\omega(T_0)))$ – then the agent is incentivized to increase their workload capacity in pursuit of a higher utility level.

[Please insert Figure 3 about here]

4.1.2. Inferred Gender Differences in the Trade-off between Wage and Time Spent on Tasks

Although we do not observe an agent's reservation wage and the maximum acceptable time spent on tasks, we observe the actual time elasticity of wage, γ^{actual}, as:

$$\gamma^{actual} = \frac{\Delta W\%}{\Delta T\%} \tag{2}$$

This elasticity measures the percentage increase in commissions for every 1% increase in time spent on tasks due to an increase in workload, specifically the number of unclosed tasks at the beginning of each month. An agent is incentivized to increase their workload capacity (i.e., transitions from S_0 to S_1 (i.e., $a = 1$)) if and only if $\gamma^{actual} > \gamma$. Now, we look at the gender differences in the choice of increasing their workload capacity by comparing the actual and reservation time elasticity of wage between women and men.

Considering family obligations and preferences, women typically favor flexibility and shorter working hours (e.g., Bertrand et al., 2010; Goldin, 2014; Cook et al., 2021; Le Barbanchon et al., 2021; Meekes and Hassink, 2022). Therefore, starting from the same state as male agents, (e.g., S_0), female agents may seek a greater increase in commissions for an equivalent rise in working time, given their heightened reservation elasticity. Also, a longer time on tasks might increase the risk of sale failures, further widening the gender gap in the reservation time elasticity of commission since women are more risk averse than men (Byrnes et al., 1999). Therefore, for a given workload, the reservation time elasticity of wage is higher for women than for men, $\gamma_{women} > \gamma_{men}$.

Using our data, we estimate the implied actual time elasticity of commission for female and male agents, respectively, and quantify the gender differences in this trade-off. In Columns (1) and (2) of Table 4, *LnEarnedComm* is the dependent variable. We use the same model specifications as in Table 3, which include a quadratic term, *UnclosedTasksSq* to capture the diminishing return of each extra unclosed task in generating earned commission. In Columns (3) and (4), we include average time on task (*LnAvgTOT*), i.e., the average duration, in months, that an agent spends on tasks that were sold within a specific month. The positive coefficients for *UncloseTasks* indicate that both the agent's wage (i.e., *LnEarnedComm*) and cost (i.e., *LnAvgTOT*) increase with the increases of the workload level, validating the trade-off between wage and time costs discussed in section 4.1.1. In Columns (2) and (4), we interact *UnclosedTasks* with *FemaleAgent*. The positive coefficients for the interaction term (i.e., *UnclosedTasks* ×*FemaleAgent*) suggest that, although female agents gain more than male agents in terms of earned commission, women incur a higher time cost than men for each additional *UnclosedTasks*.

To quantify the gender gap in the trade-off between earned commissions and time costs for each additional workload (i.e., implied γ^{actual}), we conduct a back-of-the-envelope calculation. We assume top agents are profit-maximizers and select the optimal trade-off point which balances the earned commission and the time on task. We hypothesize that the initial condition of the agent aligns with the sample average, which is considered to be the mean of the optimal workload levels. Using Models (2) and (4) in Table 4 as their revenue and cost functions, respectively, and setting the agent's optimal workload levels as the sample mean of 10.03 reported in Table 1, we can back out the implied γ^{actual} (i.e., % increases in earned commission per 1% increases in time spent on tasks) for an additional workload as 2.31 for men and 2.01 for women, representing a gender gap of 14.93%.[16]

[Please insert Table 4 about here]

Figure 4 plots the actual time elasticity of commission at different level of unclosed tasks in our sample for female and male agents, respectively. We observe a higher elasticity for male agents than that for female agents , i.e., $\gamma_{men}^{actual} > \gamma_{women}^{actual}$, in almost the entire range of workload levels in our data (i.e., the dash line is always above the solid line).

[16] See the calculation details in Appendix B.

[Please insert Figure 4 about here]

Since costs such as travel for client visits are assumed to be gender-neutral, the 14.93% gender gap is likely due to family obligations and preferences (e.g., Bertrand et al., 2010; Goldin, 2014; Cook et al., 2021; Le Barbanchon et al., 2021; Meekes and Hassink, 2022) and offers a plausible rationale for why female agents may opt for fewer tasks. Together, these results suggest that women are less incentivized to increase workload than men due to their higher reservation time elasticity of commission and lower actual time elasticity of commission.

5. Conclusion

The labor economics literature has long documented that women prefer occupations that offer better compatibility with family obligations (Bertrand 2011, Blau and Kahn 2017). Such gender difference helps explain the labor participation patterns we observe in the real estate brokerage industry. To gain a deeper understanding of the gender gap, we study the gender differences in preferences (or choices) and abilities between genders within the real estate brokerage industry. We initial analysis suggests that female agents have access to fewer work opportunities than men, in terms of both pending tasks at the beginning of a month and new tasks obtained during the month. However, after controlling agent fixed effects and agents' time-varying experience, house and task attributes, and market conditions, we find that for an additional unclosed task, female agents are able to obtain more new tasks from customers and convert more existing tasks to profits than men. Therefore, it appears that the reduced work opportunities for women are not due to a lack of ability but are more likely a reflection of their preferences such as attention to family duties (Polachek 1981, Gronau 1988, Adda et al. 2017).

Next, we analyze the impact of the workload on an agent's monthly earned commissions and average time on tasks (i.e., cost). We find that, for both men and women, a higher level of workload increases earned commissions and time spent on tasks but does so at a decreasing rate. Importantly, we show that, while women consistently attain a higher productivity gain from an additional workload, this benefit is offset by the need for additional time to complete these tasks. In other words, female agents face a bigger trade-off between revenue and cost than male agents, impacting their selections in tasks. Back-of-the-envelope calculations show that by adding a task, the implied actual time elasticity of earned commissions for female agents is 14.93% lower than that for male agents, implying a higher reward for male agents to increase their unclosed tasks. Therefore, the infamous job-flexibility penalty (Goldin 2014) comes in two flavors for women in real estate: a) more women choose to work part-time and receive a lower income; b) full-time female realtors face higher implicit costs (i.e., additional time on task), leading them to take on fewer tasks despite being more productive.

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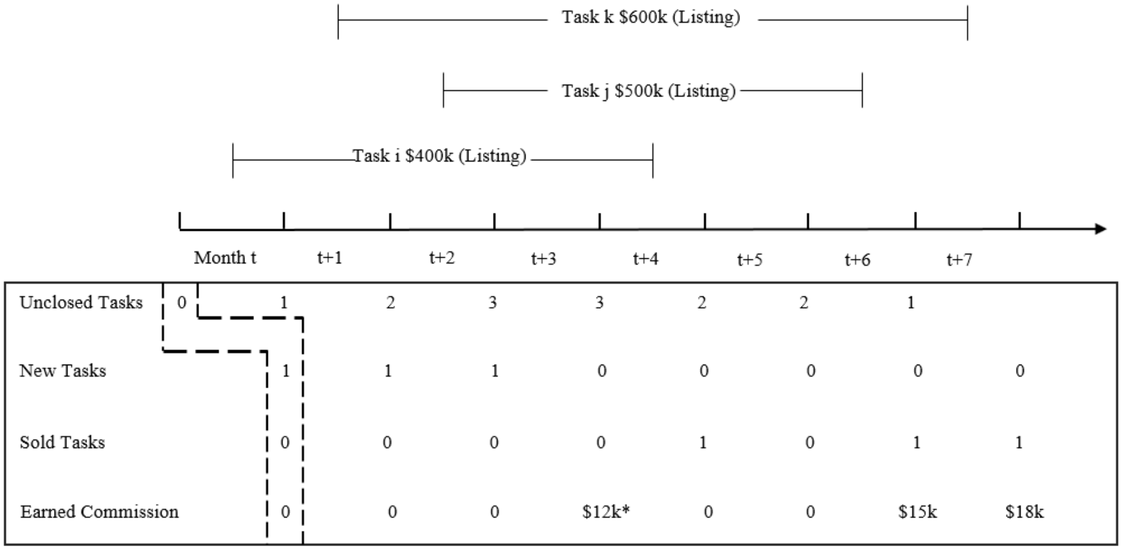
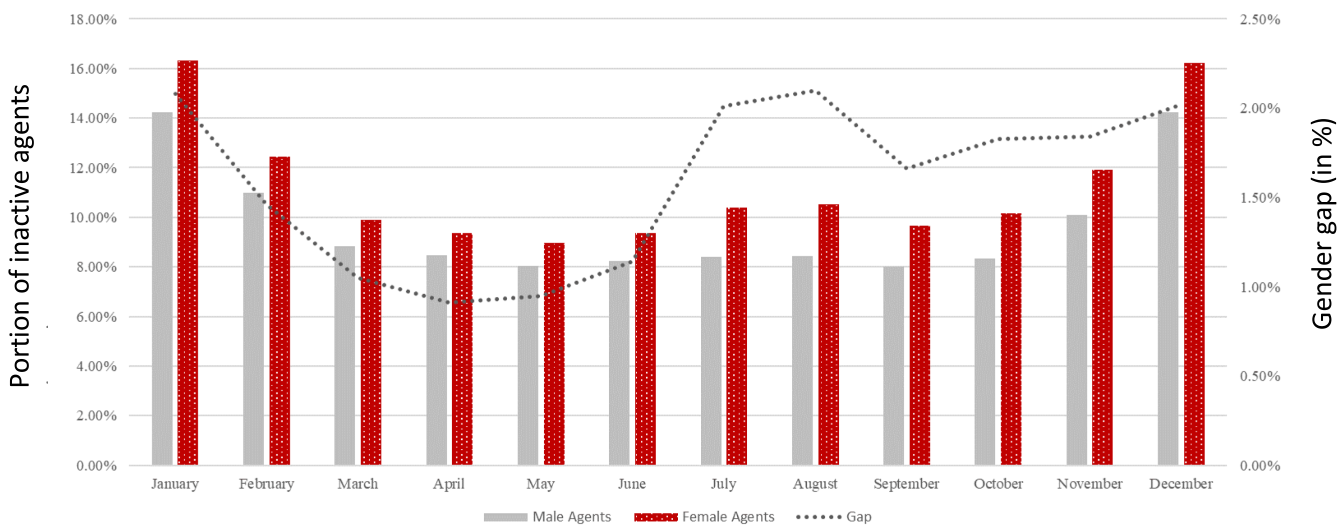
Figure 1: Real Estate Agent Workflow



* Earned Commission = 3% * $400k = $12k

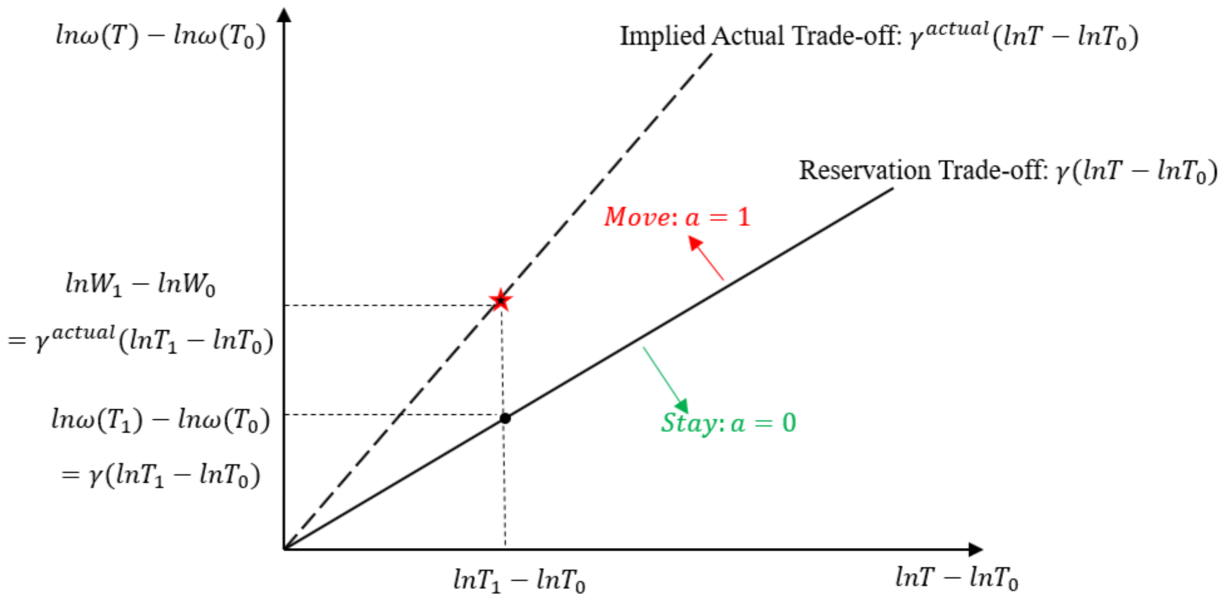
Note: This figure shows the workflow of a listing agent.

Figure 2: Proportion of Flexible, Inactive Agents by Gender and Month



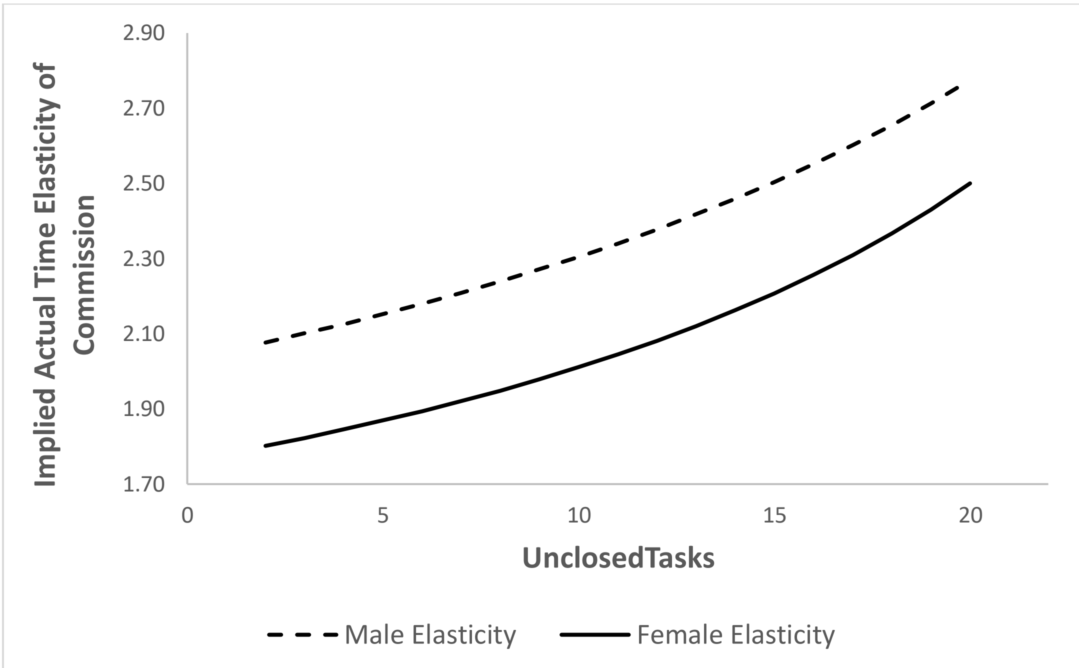
Note: We first identify an agent as an inactive agent in a specific month if his or her monthly number of tasks, including both unclosed tasks and new tasks, is less than or equal to 1, which is roughly the bottom decile of agent-month active tasks. Next, we plot the portion of inactive agents (by gender) each month on the left-hand-side axis. The dashed line represents the gender gap (i.e., % female inactive agents - % male inactive agents) on the right-hand-side axis.

Figure 3: Agent's Reservation Trade-off between Earned Commissions and Selling Times



Note: Figure 3 illustrates an agent's reservation trade-off between the earned commission and selling times with a utility level of U.

Figure 4: Gender Gap in Trade-off between Earned Commission and Month on Markets



Note: This figure shows the implied actual time elasticity of commission for agents (by gender) at different workload levels.

Table 1 Sample Descriptive Statistics

Panel A: Summary statistics for key variables

	N	Mean	Median	25th pctl	75th pctl	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
FemaleAgent	436,572	0.47	0.00	0.00	1.00	0.50
UnclosedTasks	383,773	10.03	7.00	3.00	13.00	10.46
NewTasks	363,320	2.06	1.00	0.00	3.00	2.38
SoldTasks	363,320	1.16	1.00	0.00	2.00	1.49
AvgValUnclosed ($, k)	289,820	309.44	274.88	217.84	352.04	164.52
LnAvgValUnclosed	289,820	12.55	12.52	12.29	12.77	0.40
AvgValNew ($, k)	229,434	291.08	254.68	197.78	334.65	165.61
LnAvgValNew	229,434	12.48	12.45	12.19	12.73	0.43
AvgValSold ($, k)	173,571	279.75	244.09	189.23	319.99	166.77
LnAvgValSold	173,571	12.43	12.41	12.15	12.68	0.44
Team%Unclosed	363,354	0.23	0.125	0.00	0.50	0.23
Team%New	269,325	0.23	0.125	0.00	0.50	0.25
Team%Sold	214,364	0.24	0.00	0.00	0.50	0.25
ContractUnclosed	363,354	9.52	9.06	6.95	11.55	3.55
LnContractUnclosed	363,354	2.19	2.20	1.94	2.45	0.37
ContractNew	269,325	7.70	6.90	5.57	9.48	3.43
LnContractNew	269,325	1.95	1.93	1.72	2.25	0.44
ContractSold	214,364	7.93	6.90	5.80	9.88	3.64
LnContractSold	214,364	1.98	1.93	1.76	2.29	0.43
EarnedComm ($, k)	213,934	8.20	5.54	3.24	9.74	9.83
LnEarnedComm	213,934	8.64	8.62	8.08	9.18	0.84
AvgTOT (months)	213,934	2.78	1.87	0.88	3.64	2.98
LnAvgTOT	213,934	0.53	0.63	-0.12	1.29	1.08
AvgComUnclosed ($, k)	213,934	5.43	4.57	3.21	6.38	4.11
LnAvgComUnclosed	213,934	8.43	8.43	8.07	8.76	0.55
AvgSalePrice ($, k)	213,934	236.90	205.00	150.50	273.75	168.84
LnAvgSalePrice	213,934	12.22	12.23	11.92	12.52	0.53
ActiveYrs	429,852	6.88	6.33	3.33	9.72	4.41
SoldRatio5yrs	408,108	0.57	0.58	0.46	0.70	0.19

Panel B: Gender gap statistics

	All agents	Male	Female	Diff.
	(1)	(2)	(3)	(3) – (2)
# of busy months	56.51	58.26	54.65	-3.62***
UnclosedTasks	10.03	10.72	9.25	-1.47***
NewTasks	2.06	2.18	1.92	-0.26***
SoldTasks	1.16	1.22	1.09	-0.13***
EarnedComm ($, k)	8.20	8.31	8.07	-0.24***
AvgTOT (months)	2.78	2.76	2.80	0.04***
AvgComUnclosed ($, k)	5.43	5.26	5.63	0.37***
ActiveYrs	6.88	7.06	6.67	-0.40***
SoldRatio5yrs	0.57	0.56	0.57	0.005***
# of Agents	8,408	4339	4069	

Table 2: Selection Differences between Female and Male Agents

Panel A: Selection of Tasks

Dependent Variable:	UnclosedTasks	NewTasks	SoldTasks
	Negative Binomial	Negative Binomial	Negative Binomial
	(1)	(2)	(3)
FemaleAgent	-0.0932***	-0.0337***	-0.0079***
	(-37.59)	(-9.91)	(-2.58)
ActiveYrs	0.0281***	0.0052***	0.0038***
	(31.22)	(10.13)	(7.69)
SoldRatio5yrs	-0.6321***	0.2858***	1.6415***
	(-14.89)	(14.75)	(75.29)
UnclosedTasks		0.0416***	0.0431***
		(56.41)	(48.25)
LnAvgComUnclosed		0.0511***	0.0074
		(4.26)	(0.66)
Team %Unclosed		-0.3644***	-0.2905***
		(-19.12)	(-16.13)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	383,773	363,320	363,320
LnAlpha	-0.8907***	-1.3602***	-1.7846***

Panel B: Average Value of Tasks

Dependent Variable:	LnAvgValUnclosed	LnAvgValNew	LnAvgValSold
	OLS	OLS	OLS
	(1)	(2)	(3)
FemaleAgent	-0.0035***	-0.0053***	-0.0029**
	(-6.46)	(-4.76)	(-2.20)
ActiveYrs	0.0018***	0.0017***	0.0004**
	(23.65)	(12.18)	(2.55)
SoldRatio5yrs	0.0488***	0.0386***	0.0807***
	(13.21)	(8.48)	(13.24)
UnclosedTasks		-0.0008***	-0.0008***
		(-15.52)	(-10.73)
LnAvgComUnclosed		-0.0544***	0.1868***
		(-8.72)	(33.50)
Team %Unclosed		-0.0382***	0.3042***
		(-4.11)	(35.61)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	289,820	229,434	173,571
Adj. R-squared	0.8455	0.6269	0.6304

Table 2: Selection Differences between Female and Male Agents (con't)

Panel C: Teamwork

Dependent Variable:	Team%Unclosed	Team%New	Team%Sold
	OLS	OLS	OLS
	(1)	(2)	(3)
FemaleAgent	0.0030***	0.0007	0.0010**
	(4.85)	(1.36)	(2.11)
ActiveYrs	-0.0040***	-0.0003***	0.0002***
	(-41.89)	(-4.02)	(3.47)
SoldRatio5yrs	0.0112***	0.0037*	-0.0027
	(3.05)	(1.83)	(-1.43)
UnclosedTasks		0.0004***	0.0001***
		(14.38)	(2.66)
LnAvgComUnclosed		-0.0119***	-0.0073***
		(-8.77)	(-5.82)
Team %Unclosed		0.8960***	0.9777***
		(253.02)	(471.21)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	363,354	269,325	214,364
Adj. R-squared	0.0369	0.7259	0.8184

Panel D: Average Contract Duration

Dependent Variable:	LnContractUnclosed	LnContractNew	LnContractSold
	OLS	OLS	OLS
	(1)	(2)	(3)
FemaleAgent	-0.0007*	0.0005	-0.0000
	(-1.73)	(0.38)	(-0.01)
ActiveYrs	0.0002***	-0.0027***	-0.0049***
	(4.64)	(-12.06)	(-24.28)
SoldRatio5yrs	0.0280***	0.1372***	0.1105***
	(13.99)	(18.36)	(17.27)
UnclosedTasks		0.0008***	0.0014***
		(8.88)	(14.08)
LnAvgComUnclosed		0.0033	0.0384***
		(0.71)	(8.74)
Team%Unclosed		0.0056	0.0513***
		(0.77)	(7.84)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	363,354	269,325	214,364
Adj. R-squared	0.8784	0.3451	0.3585

Notes: This table summarizes gender differences in selections of workload level, the value of tasks, teamwork level, and contract duration for unclosed tasks, new tasks, and sold tasks. *T*-values in parentheses. Standard errors are clustered at year-by-month level. *, **, ***Significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Ability Differences between Female and Male Agents – Workload

Dependent Variable:	NewTasks		SoldTasks	
	(1)	(2)	(3)	(4)
UnclosedTasks	0.0390***	0.0381***	0.0734***	0.0693***
	(49.81)	(42.54)	(32.77)	(30.86)
UnclosedTasksSq	-0.0002***	-0.0002***	-0.0006***	-0.0005***
	(-16.71)	(-17.50)	(-15.00)	(-14.44)
UnclosedTasks*FemaleAgent		0.0039***		0.0167***
		(2.78)		(3.12)
UnclosedTasksSq*FemaleAgent		-0.0001**		-0.0003***
		(-2.48)		(-2.82)
LnAvgComUnclosed	0.3397***	0.3393***	0.0310*	0.0286
	(23.65)	(25.55)	(1.77)	(1.45)
ActiveYrs	-0.0083***	-0.0083***	0.0319***	0.0319***
	(-7.87)	(-7.15)	(25.44)	(26.99)
SoldRatio5yrs	0.1262***	0.1267***	1.1513***	1.1597***
	(4.44)	(4.96)	(32.38)	(30.88)
Team%Unclosed	0.7905***	0.7900***	0.2171***	0.2137***
	(33.98)	(29.76)	(6.91)	(5.45)
Agent Fixed Effect	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes
YearMonth Fixed Effect	Yes	Yes	Yes	Yes
Observations	362,742	362,742	363,070	363,070
# of Agents	7,765	7,765	7,849	7,849

Notes: This table uses negative binomial models with panel data. *t*-values in parentheses. Standard errors are bootstrapped and clustered at agent and year-by-month levels. *, **, ***Significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Trade-off between Earned Commission and Time on task

Dependent Variable:	LnEarnedComm		LnAvgTOT	
	(1)	(2)	(3)	(4)
UnclosedTasks	0.0396***	0.0388***	0.0202***	0.0191***
	(37.39)	(33.78)	(17.87)	(15.65)
UnclosedTasksSq	-0.0003***	-0.0002***	-0.0002***	-0.0002***
	(-16.52)	(-15.37)	(-11.28)	(-10.00)
UnclosedTasks*FemaleAgent		0.0042***		0.0053***
		(2.79)		(2.74)
UnclosedTasksSq*FemaleAgent		-0.0001***		-0.0001***
		(-3.04)		(-3.24)
LnAvgComUnclosed	0.4302***	0.4303***	-0.2854***	-0.2852***
	(32.60)	(32.62)	(-14.65)	(-14.63)
LnAvgSalePrice			0.1631***	0.1631***
			(17.07)	(17.06)
ActiveYrs	-0.0355***	-0.0353***	-1.5957***	-1.5954***
	(-6.31)	(-6.28)	(-29.45)	(-29.44)
SoldRatio5yrs	0.4352***	0.4351***	-0.0131	-0.0133
	(18.37)	(18.36)	(-0.39)	(-0.40)
Team %Unclosed	-0.7049***	-0.7051***	-0.5294***	-0.5296***
	(-32.59)	(-32.69)	(-14.87)	(-14.88)
Agent Fixed Effect	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes
YearMonth Fixed Effect	Yes	Yes	Yes	Yes
Observations	213,934	213,934	213,934	213,934
Adj. R-squared	0.4897	0.4898	0.3654	0.3655

Notes: This table uses OLS models. *t*-values in parentheses. Standard errors are clustered at agent and year-by-month levels. *, **, ***Significance at the 10%, 5%, and 1% levels, respectively.

Appendix A: Additional Tables

Table A.1: Variable Definitions

Variables	Definitions
Panel A: Key Variables	
FemaleAgent	Gender dummy, = 1 if the agent is a woman, =0 if the agent is a man
UnclosedTasks	Total number of unclosed tasks at the beginning of the month
UnclosedTasksSq	Square of *UnclosedTasks*
NewTasks	Total number of new added tasks during the month
SoldTasks	Total number of sold tasks during the month
AvgValUnclosed	Average house value of *UnclosedTasks*
LnAvgValUnclosed	Natural log of AvgValUnclosed
AvgValNew	Average house value of NewTasks
LnAvgValNew	Natural log of AvgValNew
AvgValSold	Average house value of SoldTasks
LnAvgValSold	Natural log of AvgValSold
Team%Unclosed	Average teamwork level of UnclosedTasks
Team%New	Average teamwork level of NewTasks
Team%Sold	Average teamwork level of SoldTasks
ContractUnclosed	Average contract duration of UnclosedTasks
LnContractUnclosed	Natural log of ContractUnclosed
ContractNew	Average contract duration of NewTasks
LnContractNew	Natural log of ContractNew
ContractSold	Average contract duration of SoldTasks
LnContractSold	Natural log of ContractSold
EarnedComm	Amount of commission an agent earned from listing tasks during the month
LnEarnedComm	Natural log of *EarnedComm*
AvgTOT	Average time spent on tasks (in months) of houses sold during the month
LnAvgTOT	Natural log of *AvgTOT*
AvgComUnclosed	Average amount of commission an agent could be earned from UnclosedTasks
LnAvgComUnclosed	Natural log of AvgComUnclosed
AvgSalePrice	Average sale price of houses sold during the month
LnAvgSalePrice	Natural log of AvgSalePrice
ActiveYrs	Number of active working experience (in years) an agent has since the board has a record
SoldRatio5yrs	The average ratio of sold listing tasks in the prior 5 years
Panel B: House Attributes	
#BathroomList	Average number of bathrooms of houses listed at the beginning of the month
#BedroomList	Average number of bedrooms of houses listed at the beginning of the month
#DrivewayList	Average number of driveways of houses listed at the beginning of the month
#GarageList	Average number of garages of houses listed at the beginning of the month
AgeList	Average construction ages of houses listed at the beginning of the month
BuildingSizeList	Average building size of houses listed at the beginning of the month
ContractDurationList	Average contract duration of houses listed at the beginning of the month
DOPList	Average degree of overpricing of houses listed at the beginning of the month
HeckmanValList	Average Heckman value of houses listed at the beginning of the month
LotSizeList	Average lot size of houses listed at the beginning of the month
UrbanList	The portion of urban houses listed at the beginning of the month

Table A.2: Additional Summary Statistics

	Mean	Median	25%	75%	S.D.
Listing House Characteristics (N=419,979)					
#BathroomList	1.45	1.45	1.25	1.67	0.51
#BedroomList	3.20	3.29	3.00	3.67	0.91
#DrivewayList	3.51	3.64	2.67	4.45	1.50
#GarageList	0.76	0.71	0.47	1.00	0.48
AgeList	27.23	25.96	17.00	36.00	15.97
BuildingSizeList (sqft, thousand)	1.12	1.10	0.97	1.28	0.42
ContractDurationList (months	8.69	8.47	6.41	10.95	3.85
DOPList	0.024	0.005	-0.090	0.115	0.220
HeckmanValList ($, thousand)	290.68	265.31	205.45	340.86	174.34
LotSizeList (sqft, thousand)	18.59	13.00	7.23	24.08	18.20
UrbanList	0.65	0.75	0.40	1.00	0.35

Table A.3: Selection Differences between Female and Male Agents (Listing and Buying Tasks)

Panel A: Selection of Tasks			
Dependent Variable:	UnclosedTasksBoth	AddTasks	SuccTasks
	Negative Binomial	Negative Binomial	Negative Binomial
	(1)	(2)	(3)
FemaleAgent	-0.0692***	-0.0113***	0.0062**
	(-27.48)	(-4.41)	(2.10)
ActiveYrs	0.0162***	-0.0010**	-0.0006
	(23.18)	(-2.41)	(-1.34)
SoldRatio5yrs	-0.2637***	0.2865***	1.0298***
	(-10.27)	(22.05)	(47.91)
#UnclosedTasks		0.0313***	0.0368***
		(60.05)	(50.67)
LnAvgComUnclosed		-0.1716***	-0.1595***
		(-28.98)	(-23.44)
Team %Unclosed		-0.0675***	-0.0790***
		(-6.18)	(-6.27)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	362,672	332,934	355,560
LnAlpha	-1.2204***	-2.1272***	-1.2681***
Panel B: Average Value of Tasks			
Dependent Variable:	LnAvgValBoth	LnAvgValAdd	LnAvgValSucc
	OLS	OLS	OLS
	(1)	(2)	(3)
FemaleAgent	0.0029***	-0.0038***	-0.0021
	(3.04)	(-3.03)	(-1.42)
ActiveYrs	0.0031***	0.0007***	0.0015***
	(20.66)	(4.43)	(8.04)
SoldRatio5yrs	0.0533***	0.0478***	0.0818***
	(10.59)	(7.60)	(11.53)
#UnclosedTasks		-0.0009***	-0.0013***
		(-19.21)	(-21.63)
LnAvgComUnclosed		0.0733***	0.0324***
		(30.55)	(14.60)
Team %Unclosed		0.1354***	0.0943***
		(28.09)	(20.00)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	151,970	165,081	179,755
Adj. R-squared	0.7748	0.6542	0.5129
Panel C: Teamwork %			
Dependent Variable:	Team%Both	Team%Add	Team%Succ
	OLS	OLS	OLS
	(1)	(2)	(3)
FemaleAgent	0.0046***	0.0010**	0.0005
	(9.47)	(2.11)	(1.02)
ActiveYrs	-0.0022***	0.0002***	0.0004***
	(-31.73)	(3.86)	(5.78)
SoldRatio5yrs	-0.0136***	0.0044**	0.0372***
	(-3.67)	(2.41)	(17.22)
#UnclosedTasks		0.0003***	0.0000
		(12.89)	(0.30)

LnAvgComUnclosed		-0.0122***	-0.0031***
		(-18.84)	(-4.80)
Team %Unclosed		0.8684***	0.9604***
		(263.36)	(587.20)
House Characteristics	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes
Observations	357,167	296,761	242,506
Adj. R-squared	0.0521	0.6810	0.7222

Notes: *t*-values in parentheses. Standard errors are clustered at year-by-month level. *, **, ***Significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Ability Differences and Trade-off Differences between Female and Male Agents – Listing and Buying Workload

Panel A: Ability Differences between Female and Male Agents – Listing and Buying Workload				
Dependent Variable:	AddTasks		SuccTasks	
	(1)	(2)	(3)	(4)
UnclosedTasksBoth	0.0388***	0.0374***	0.0661***	0.0627***
	(39.50)	(37.94)	(33.33)	(31.16)
UnclosedTasksBothSq	-0.0002***	-0.0002***	-0.0004***	-0.0004***
	(-13.26)	(-12.23)	(-14.20)	(-13.23)
UnclosedTasksBoth*FemaleAgent		0.0045**		0.0119***
		(2.11)		(3.84)
UnclosedTasksBothSq*FemaleAgent		-0.0001*		-0.0002***
		(-1.67)		(-3.32)
Main Controls	Yes	Yes	Yes	Yes
Agent Fixed Effect	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes
YearMonth Fixed Effect	Yes	Yes	Yes	Yes
Observations	332,811	332,811	332,660	332,660
# of Agents	7,912	7,912	7,883	7,883
Panel B: Trade-off between Earned Commission and Time on task (Listing and Buying Tasks)				
Dependent Variable:	LnEarnedCommBoth		LnAvgTOT	
	(1)	(2)	(3)	(4)
UnclosedTasksBoth	0.0456***	0.0440***	0.0143***	0.0137***
	(38.95)	(34.85)	(16.20)	(13.87)
UnclosedTasksBothSq	-0.0003***	-0.0002***	-0.0001***	-0.0001***
	(-16.06)	(-14.20)	(-11.20)	(-9.68)
UnclosedTasksBoth*FemaleAgent		0.0053***		0.0026*
		(3.34)		(1.81)
UnclosedTasksBothSq*FemaleAgent		-0.0001***		-0.0000**
		(-2.97)		(-2.53)
Main Controls	Yes	Yes	Yes	Yes
Agent Fixed Effect	Yes	Yes	Yes	Yes
House Characteristics	Yes	Yes	Yes	Yes
YearMonth Fixed Effect	Yes	Yes	Yes	Yes
Observations	206,207	206,207	206,207	206,207
Adj. R-squared	0.4297	0.4298	0.3691	0.3691

Notes: This table reports results of testing gender difference in agent's ability and trade-off between agent's revenue and cost using both listing and buying tasks. Panel A uses negative binomial models with panel data and Panel B uses OLS models. Main controls are similar to main controls in Tables 3 and 4. *t*-values in parentheses. Standard errors are bootstrapped and clustered at agent and year-by-month levels. *, **, ***Significance at the 10%, 5%, and 1% levels, respectively.

Appendix B: Cost-benefit Calculations

This appendix shows a simple back-of-the-envelope calculation based on results in Columns (2) and (4) of Table 4, our preferred model of trade-off between agent's revenue (proxied by earn commission) and agent's cost (proxied by the time on task). We assume the optimal number of unclosed tasks (*UnclosedTasks*) at the beginning of each month equals x.

The log of earned commissions for men and women is

$$LnEarnedComm_{men} = 0.0388x - 0.0002x^2 + 8.202 \quad (A3)$$

$$LnEarnedComm_{women} = (0.0388 + 0.0042)x - (0.0002 + 0.0001)x^2 + 8.202 \quad (A4)$$

where 0.0388, -0.0002, 0.0042, 0.0001, 8.202 are coefficient estimates of *UnclosedTasks, UnclosedTasksSq, UnclosedTasks*FemaleAgent, UnclosedTasksSq *FemaleAgent* and *Intercept* in Column (2), respectively.

The log of average time on tasks for men and women is

$$LnAvgTOT_{men} = 0.0191x - 0.0002x^2 + 0.318512 \quad (A5)$$

$$LnAvgTOT_{women} = (0.0191 + 0.0053)x - (0.0002 + 0.0001)x^2 + 0.318512 \quad (A6)$$

where 0.0191, -0.0002, 0.0053, 0.0001, 0.318512 are coefficient estimates of *UnclosedTasks, UnclosedTasksSq, UnclosedTasks*FemaleAgent, UnclosedTasksSq *FemaleAgent* and *Intercept* in Column (4), respectively.

Take the first derivatives of both log earned commission and log average time on tasks equations for female and male agents and make them equal to zero:

$$\frac{\partial LnEarnedComm_{men}}{\partial x} = 0.0388 - 0.0004x \quad (A7)$$

$$\frac{\partial LnEarnedComm_{women}}{\partial x} = 0.043 - 0.0006x \quad (A8)$$

$$\frac{\partial LnAvgTOT_{men}}{\partial x} = 0.0191 - 0.0004x \quad (A9)$$

$$\frac{\partial LnAvgTOT_{women}}{\partial x} = 0.0244 - 0.0006x \quad (A10)$$

The trade-off ratio of the marginal log earned commission to the marginal log time on tasks for women and men are:

$$\frac{\partial LnEarnedComm_{men}}{\partial x} \Big/ \frac{\partial LnAvgTOT_{men}}{\partial x} = \frac{0.0388 - 0.0004x}{0.0191 - 0.0004x} \quad (A11)$$

$$\frac{\partial LnEarnedComm_{women}}{\partial x} \Big/ \frac{\partial LnAvgTOT_{women}}{\partial x} = \frac{0.043 - 0.0006x}{0.0244 - 0.0006x} \quad (A11)$$

We assume that the optimal workload level for men and women is 10.03 as shown in Panel B of Table 1. The trade-off ratio (or elasticity) for men at the optimal workload level, $\gamma_{men}^{\boldsymbol{actual}}$, is:

$$\gamma_{men}^{\boldsymbol{actual}} = \frac{0.0388 - 0.0004 \times 10.03}{0.0191 - 0.0004 \times 10.03} = 2.31 \quad (A13)$$

The trade-off ratio (or elasticity) for women at the optimal workload level, $\gamma_{women}^{\boldsymbol{actual}}$, is:

$$\gamma_{women}^{\boldsymbol{actual}} = \frac{0.043 - 0.0006 \times 10.03}{0.0244 - 0.0006 \times 10.03} = 2.01 \quad (A14)$$