THE GENDER GAP IN HOUSING RETURNS*

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Abstract

Housing wealth represents the dominant form of retirement savings for most American households. Using detailed data on housing transactions across the United States since 1991, we find that single men earn one percentage point higher unlevered returns per year on housing investment relative to single women, with couples occupying the intermediate range. The gender gap grows significantly larger after adjusting for mortgage borrowing: men earn 6 percentage points higher levered returns per year relative to women. Data on repeat sales reveal that women buy the same property for approximately 2% more and sell for 2% less. The gender gap in housing returns arises because of gender differences in the (1) location and timing of transactions, (2) choice of initial listing price, (3) negotiated discount relative to the list price, and (4) length of holding period. Gender differences in upgrade rates, preferences for housing characteristics, and listing agents appear to be less important factors. The gender gap varies with demographic characteristics, but remains large in regions with high average education, income, and house price levels.

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I. Introduction

Housing wealth accounts for the vast majority of most American households' wealth. Housing also differs from other common forms of household savings, such as bank deposits, bonds, and stocks, in that it is an illiquid and heterogeneous asset with prices determined through bilateral negotiation. Motivated by the existing research showing gender differences in financial sophistication, negotiation, and preferences (e.g., Sunden and Surette, 1998; Ayres, 1990; Babcock and Laschever, 2009), we investigate how men and women differ in their financial returns on housing investment.

We use detailed data from CoreLogic covering over 50 million housing transactions and matched property listings across the US from 1991 to 2017. For approximately 9 million transactions for which we can identify homeowner gender, and the initial purchase and eventual sale prices, we estimate the homeowner's annualized return. We find that single men earn more than 1 percentage point higher unlevered annualized returns relative to single women. Couples underperform single women on a raw unadjusted basis, but outperform single women and underperform single men after adjusting for location and timing of sales.

Most US home buyers purchase housing using mortgage debt with loan-to-value ratios of 80 percent or higher, and have not paid down a large fraction of the principal at the time of sale. Therefore, the real return earned is typically a levered return. We find that men outperform women by 6 percentage points per year after adjusting for leverage. The growth in the gender gap arises because leverage amplifies raw return differences.

The gender gap in housing returns exists in all states with comprehensive data coverage and in all years within our sample. It remains substantial in regions with high average education, income, and house price levels. However, the magnitude of the gender gap does vary with demographics, location, and time. Zip codes with lower average education, greater average age, and higher fraction single female are associated with a larger gender gaps. Controlling for education and age, regions with higher median family income surprisingly have larger gender gaps. The gender gap is largest in the right tail of the return distribution, although it also present at the median, and does not reverse in the left tail.

Next, we show that approximately half of the raw gender gap in housing returns can explained by gender differences in market timing, i.e., the choice of holding period, when and where to buy, and when to sell. Women earn lower returns on housing partly because they tend to buy when aggregate house prices are high and sell when they are low. The magnitude of the gender gap also varies with the business cycle, consistent with recent findings in Sakong (2019) showing a relation between cyclical housing transactions and wealth inequality.

In addition to market timing, we find that the gender gap arises from several other contributing factors. We begin by examining data on repeat sales of the same property. Holding the property fixed, and adjusting for local time trends in prices, we find that women buy the same property for 1-2% more than men and sell for 2-3% less. This difference in transaction prices can be decomposed into gender differences in the choice of listing price and negotiated transaction discounts relative to the listing price. Again using repeat sales data that allows us to hold the property fixed, we find that women purchase properties when they are listed at higher relative prices, and also choose to list for lower relative prices. In addition, women buyers negotiate worse discounts relative to the listing price for home purchases.

Together, our findings relating to listing prices and transaction discounts imply that women experience worse execution prices on real estate transactions at the points of purchase and sale. Differences in execution prices should matter much more for the annualized returns of short-term investors than for the returns of long-term buy-and-hold investors. Consistent with this insight, we find that the magnitude of the gender gap in annualized returns decays sharply with holding length. The gender gap in housing returns is greater for homeowners with shorter tenure in their properties, because they "trade" assets more often, so variation in execution prices matter more for their returns.

Finally, we find that differences in preferences for certain types of homes do not substantially affect the gender gap in housing returns. Men and women differ in their choices of home type (e.g., new construction and number of bedrooms) and listing agent, but controlling for these features does not significantly affect the gender gap in housing returns.

We also explore several potential alternative explanations. First, men may invest more in housing maintenance and upgrades, such that their real investment return is lower than implied by analysis using only the sale price and purchase price (Harding et al., 2007). We find that men are more likely to list homes that have been upgraded or renovated, but the difference in upgrade rates across genders is small. The gender gap in housing returns remains large in a restricted sample for which the house listing does not mention upgrades or renovations. Aside from upgrades and renovations that are noted in property listings, men may also invest more in routine maintenance. A simple model in which men invest more in routine maintenance each year should translate into a gender gap in housing returns that does not vary with holding period. Instead, we observe a gender gap in housing returns that decays sharply with holding period. This pattern is more consistent with a gap in returns that arises from fixed gender differences in execution prices.

Second, women outlive men on average, and older individuals may earn worse returns on housing for reasons unrelated to gender. While we lack data on individual age, we continue to find a large gender gap for homes sold after short holding periods of less than four years, which are less likely to have been held by older individuals.

We also consider whether the higher returns earned by men may represent compensation for holding riskier properties. We do not find evidence of greater downside risk in housing returns for the men in our sample. However, we caution that we do not observe other outcomes such as bankruptcy that may differ by gender.

Our findings are related to existing research examining gender differences in stock market participation and portfolio allocation between stocks and bonds (e.g. Sunden and Surette, 1998; Bajtelsmit and VanDerhei, 1997; Hinz et al., 1997). While gender differences in financial investments are an important area of study, it is equally or more important to study gender differences in housing investment, given that housing represents a much larger proportion of the typical U.S. household's savings portfolio.

Our paper is also related to a large literature documenting gender differences in the ability and willingness to negotiate. This literature has shown that women have more negative outcomes when negotiating in laboratory settings, as well as in labor market and automobile and product market settings (e.g., Ayres, 1990; Ayres and Siegelman, 1995; Castillo et al., 2013; Exley et al., 2016; Leibbrandt and List, 2014; List, 2004; Morton et al., 2003). Our findings that women purchase homes with lower discounts relative to listing price and choose to list homes at lower prices suggests that gender differences in negotiation may also play a role in housing markets. However, we do not claim to rule out other explanations such as gender differences in preferences. For example, women may equal men in negotiation ability, but care more about purchasing a particular home or derive greater utility from a fast, low-risk, or non-confrontational negotiation process. It is not the goal of this paper to disentangle the role of negotiation ability from preferences. Our findings nevertheless show that variation in housing returns are large and may help explain the gender gap in wealth accumulation at retirement (Neelakantan and Chang, 2010).

Finally, our research question is related to contemporaneous work by Andersen et al. (2018), hereafter referred to as AMNV, which examines gender differences in negotiations for real estate transactions in Denmark. Our analysis differs from and complements AMNV in several ways. AMNV (along with related research by Harding et al. (2003)) is focused on demographic variation in negotiation and bargaining power, while we are interested in the total gender gap in housing returns from the perspective of wealth accumulation. We are interested in factors contributing to this gender gap beyond negotiation; for instance, we show that women earn lower returns partly due to market timing. We also find large gender differences in transaction prices using repeat sales data in the US, while AMNV find smaller and insignificant differences using repeat sales data in Denmark. These results complement each other, and suggest that the gender gap may vary by country and culture.

II. Data and Measurements

In this section, we present a summary of the data sources for our analysis, describe the construction of key measures, including identification of gender, and summarize the overall data set.

A. Corelogic deeds and listings data

Our main housing transaction data comes from data gathered by CoreLogic from county deeds records. This data includes arms-length transactions (sales between two unaffiliated parties), non-arms-length transactions, and mortgage refinancings (non-transaction deed events). Each observation reflects a housing transaction, containing information on the date of the transaction, the sale price (if the property changed hands), the exact address of the property, and the names of both sides of the transaction. This last set of data fields allows us to partially identify the gender of the participant, as well as the number of participants on each side of the transaction (discussed further below).

To supplement the transactions data with time-varying measures of the properties' characteristics, we link the deeds dataset by property location to a dataset of property listings also constructed by CoreLogic.[1] These data come from Multiple Listing Service (MLS) systems operated by regional real estate boards. Each listing includes a large number of fields describing the property and the status of the listing. These include when the property is listed, the list price, and the listed property features such as the number of bedrooms and bathrooms and age of the structure. If the listing sells, we observe the close date, sale price, and the associated buyer agent.

B. Identification of gender and relationships

We identify the gender and family structure of the buyers and seller on each transaction using reported names on the deed. For each deed record, CoreLogic reports the full name of the first and second

[1] Properties are uniquely identified via parcel number (assigned by county deeds offices) and county code.

owner on a deed, and in the case of sale, the full name of the first and second seller. We identify two pieces of information from these name fields: first, we parse the fields to identify exactly how many parties exist on each side of the transaction, since in some cases, couples are transcribed as "John and Mary Smith" in one field, rather than being split across fields as "John Smith" and "Mary Smith." Second, we use the first names to probabilistically assign a gender to each party in the transaction. We follow Chari and Goldsmith-Pinkham (2017) and use data from Tang et al. (2011) to measure the probability that a given name is male or female (based on self-reported data to Facebook). Then, for all names with probability greater than 95%, we assign either male or female. For those who do not match, or whose probabilities are less than 95%, we treat as unknown genders.

Identification of the number of parties, and their respective genders, allows us to group parties into four groups (on each side of the transaction): single male, single female, couples (2 individuals with both genders identified), and other, where other is the residual category and will include single individuals without gender identified, couples where only one gender is identified, and couples where neither gender is identified. For each transaction, this grouping is done both on the buyer and seller side.

These measures of gender and relationships may be subject to measurement error. There are three types of concerns. First, we fail to identify gender for some individuals, and they will be relegated into the "Other" category. This is quite likely with non-Anglo-Saxon names where the gender is less predictable based on name. Second, we may miscategorize some individuals incorrectly by gender. Given our cutoff for gender is above 95% certainty, we are less concerned about this, but it is possible. Finally, some single men and women identified in our data may actually correspond to couples who choose (or follow local convention) in recording only a single name in a real estate transaction.

C. Measuring unlevered returns and levered returns

In our full dataset of transactions, we are able to identify consecutive arms-length market transactions for each property. Using these subsequent transactions, we can identify the realized unlevered return for property i in period t: $r_{it} = \frac{P_{it} - P_{is}}{P_{is}}$, where P_{is} is the previous market transaction price on the property in period s. To ensure that we correctly measure r_{it} for single male, single female, and couples, we focus on the subsample of returns that has three restrictions: (1) we have identified the gender and family structure in both period t and s, (2) the gender and family structure of the seller in period t corresponds to the gender and family structure in period s and, (3) names of the buyers in period s is sufficiently close to the names of the sellers period t by string matching distance. This final sample is our main analysis sample for returns. This substantially restricts our analysis sample, since we need to observe multiple transactions and correctly identify gender and family structure, but ensures that we are not incorrectly measuring returns.

In reality, the majority of homeowners in the United States buy their homes using debt, with leverage of five-to-one or higher. Moroever, this leverage tends to persist over a long period of time, with long duration mortgages whose fixed amortization schedules pay mainly interest upfront. Therefore, the real return earned is typically a levered return. Ideally, given the mortgage type, term, interest rate and down payment, we could exactly identify the levered return. However, many of these fields are missing from the data. Instead, we provide several simple approximations to provide an estimate of levered returns.

First, we construct the initial downpayment (the "investment") in period s (Equity_s), and inital mortgage amount Mortgage_s used to buy the home. We then calculate the average interest rate in the year-quarter of initial purchase by taking the 30-year fixed rate mortgage rate from Freddie Mac. Using this interest rate i, we calculate the relative principal pay down at every monthly duration horizon, and use this to identify the share of remaining mortgage principal outstanding at period t (Mortgage_t). This allows us to calculate the total cash out payment for the home at the time of sale: $\text{Equity}_t = P_t - \text{Mortgage}_t$. To approximate the levered returns, we calculate the time s net present value of total principal paydown payments $\{W_{iu}\}_{u=s}^{t}$ using a discount rate equal to the mortgage interest rate i and calculate the "investment" as both the initial equity investment and the discounted sum of the principal paydown. As a result, our levered return is $r_{it}^{\text{lev}} = \frac{\text{Equity}_{it} - (\text{Equity}_{is} + \sum_{u=s}^{t} W_{iu}/(1+i)^{t-u})}{\text{Equity}_{is} + \sum_{u=s}^{t} W_{iu}/(1+i)^{t-u}}$. Note that in the case of a full cash purchase, $r_{it}^{\text{lev}} = r_{it}$.

The key ingredient for our approximation to leverage is knowing the initial mortgage amount. However, in many cases the mortgage amount is missing. In these cases, this is typically because the home was purchased with only cash and no mortgage was involved – in 2017, for example, 28.8% of all housing transactions were done with all cash, and in the 2000s this number was around 20%.[2] However, in the 1990s, the share of missing mortgage amounts is substantially higher, and suggests that there may also be missing data issues. As a result, we impute the mortgage amount in several ways. In our first case, we assume that mortgage amounts are zero in all transactions with missing mortgage amounts. In the second case, we assume that missing mortgage amounts are 80% of the

[2] See the discussion in the Wall Street Journal here, for example: https://www.wsj.com/articles/want-that-house-youd-better-pay-in-cash-1512469800

overall housing value (the most common mortgage loan-to-value ratio). Finally, we provide a simple benchmark for converting all of the unlevered housing returns into levered returns by assuming all purchases were done with an 80% LTV mortgage. This holds fixed any potential leverage differences across transactions, and instead converts the unlevered returns into a measure that correctly captures the high degree of leverage that most homeowners face.

Finally, with both the unlevered and levered returns, we annualize to adjust for the length of holding period.

III. Empirical Results

This section describes our regression methodology and summarizes our main results measuring the difference in returns between single men, single women, and couples. We then assess the various channels that can explain this difference in returns.

A. Estimation approach

Our main analysis takes two forms. Both approaches use a simple linear regression framework to account for potential differences across gender. The first is an analysis of the unlevered and levered returns:

$$r_{it} = \text{Single Female}_{it}\beta_1 + \text{Couple}_{it}\beta_2 + X_{it}\tau + \epsilon_{it}, \tag{1}$$

where Single Female_{it} is an indicator for a single female seller in period t and Couple_{it} is an indicator for a couple seller in period t in our main return sample. As a result, β_1 and β_2 capture the relative effect when compared to Single Male_{it}, the omitted category. X_{it} captures our potential controls, which most importantly include five-digit zip code interacted with sale-year-month fixed effects. This fixed effect will effectively compare two houses sold within the same year-month and zip code, and capture any unobservable differences based on location or the housing cycle. In many cases, we will report the *residualized* return, which will demean the returns using a regression of r_{it} on zip-by-sale-year-month fixed effects.

Our second set of analyses, focusing on the channels affecting housing return, is similar but uses alternative outcome measures, such as the $\log(\text{Sale Price})_{it}$:

$$Y_{it} = \text{Single Female}_{it}\beta_1 + \text{Couple}_{it}\beta_2 + X_{it}\tau + \epsilon_{it}. \tag{2}$$

Since these outcomes are not measured in percent differences, we additionally include a property fixed effect in X_{it} to capture unobserved quality in the property that may be correlated with gender or family structure. To better estimate this property fixed effect, we include transactions that are not included in our returns data sample.

B. Baseline Results

We begin by showing how realized housing returns differ by the gender and relationship status of the homeowner. We use observations at the sale transaction level. The sample is restricted to observations for which the gender of all sellers can be identified, and for which we can match the identity of the seller at the time of sale to the identity of the buyer at the time of initial purchase. In column 1 of Table 1, we find that single women earn 1.6 percentage points lower unlevered annualized returns than single men (the omitted category). Controlling for zip-year-month fixed effects (representing the location and time of sale) in column 2 and property holding length in column 3 shrinks the gender gap slightly. Women underperform men by 1.1 percentage points after adjusting for the location and timing of transactions.

We also find that couples (identified through transactions with two sellers, one male and one female, underperform single women on an unadjusted basis. Column 1 shows that couples earn 0.4 percentage points lower unlevered returns than single women. However, the relative returns for couples is very sensitive to the inclusion of controls for zip-year-month fixed effects. After controlling zip-year-month fixed effects in column 2 and property holding length in column 3, couples earn higher returns than single women but underperform single men. These results show that couples earn lower returns primarily due to poor market timing, but outperform single women holding the location and transaction period fixed. We examine how market timing impacts returns in more detail in the next subsection. Our findings are consistent with the possibility that couples face time constraints in real estate transactions due to child care and the school calendar system.

In Table 2, we assess variation in housing returns after accounting for mortgage debt. Column 1 uses a measure of levered returns in which we assume zero mortgage borrowing for observations with missing mortgage data while Column 2 assumes an 80% LTV for all observations with missing mortgage data. Column 3 creates a hypothetical levered return for each observation assuming exactly 80% LTV. We use this latter measure of levered returns as our baseline measure in future tests because it is less sensitive to large outlier levered returns driven by a subset of households with very high

LTV or 95% or greater. This measure also has the benefit of representing the expected gender gap for households with the modal LTV of 80% in the data. Using this measure, we find that women underperform men by 6 percentage points per year after adjusting for leverage. The gender gap using the other measures of levered returns in columns 1 and 2 yield larger gender gaps. Couples earn returns in the intermediate range; they outperform women by 2 percentage points and underperform men by 4 percentage points. In general, adjusting for leverage leads to a much larger gender gap in housing returns because leverage amplifies differences in raw returns.[3]

In addition to examining the gender gap in mean returns, we also compare the distribution of returns across gender groups, residualized by zip-year-month fixed effects and with the average level of returns added back in. Figures 1 and 2 show realized unlevered and levered returns at various percentiles of the return distribution for each gender group. This set of figures reveal that the gender gap exists in all parts of the return distribution except for the left tail where women and men fare equally poorly. However, the gender gap is larger at the 90th percentile of the returns distribution than at the median.

In Figure 3, we show the density of realized returns. The figures again show that men weakly outperform women at all parts of the return distribution, with the largest differences in the right tail. In Figure 4, we zoom in to the return near zero, where all gender groups have distributions with missing mass just to the left of zero. This dip in the distribution is consistent with the disposition effect (see e.g., Shefrin and Statman, 1985), in which people are reluctant sell at less than their initial purchase price. Finally, Figures 1 through 3 show that men do not have worse left tail outcomes than women in terms of realized returns. Therefore, compensation for greater downside risk in realized returns cannot explain the higher average returns for men in our sample. However, we again caution that we don't observe other adverse outcomes such as personal bankruptcy costs that may differ by gender.

C. Heterogeneity and Timing

In Table 3, we explore how the average gender gap in housing returns within a zip code varies with zip-level demographics from the 2010 American Community Survey. We measure the gender gap in each zip code as the average difference between male and female residual realized returns (the

[3]Appendix Figure A4 plots the average loan-to-value (LTV) at the time of initial purchase for each gender group over time. In Panel A, we report the LTV for the sample with mortgage amount data, while in Panel B we report the share of transactions with missing mortgage data information. Single men have higher LTV conditional on non-missing mortgage data, but also have higher rates of missing mortgage data. Because missing mortgage data can represent cash purchases or true missing data, we cannot draw strong conclusions about differences in leverage across gender.

residual return represents the return after adjusting for the zip-year-month mean). We regress the zip-level gender gap on zip-level demographics. We find that the gender gap in housing returns is significantly larger in zip codes with a greater fraction of residents with a high school or lower level of education, a greater fraction of elderly residents above the age of 60, and a greater fraction of single female households. Controlling for other demographics, the fraction of black residents within a zip code does not significantly predict the gender gap in returns. Finally, the gender gap increases with median family income controlling for these other zip-level demographic variables.

In Table 4, we present the average gender gap across quartiles of various zip-level demographic characteristics. This table reports simple averages within each quartile of each demographic variable, without conditioning for other demographic variables. Observations are at the zip-code level and equally weighted. As before, we find that the magnitude of the gender gap decreases with education, and increases with age, and fraction single female, although the relations are not always linear. The gender gap increases with fraction black. We also find that the gender gap remains large even in zip codes in the top quartile in terms of education, income, and house prices (measured relative to the state-year-month average).

Figure 6 shows the magnitude of the average difference in realized returns between single men and women across all states in our sample.[4] With the exception of Montana, for which we lack comprehensive data coverage, the gender gap is positive in all states within our sample. We believe that variation in the gender gap could be caused by differences in data quality and estimation error across states. As noted earlier in Section B, some single men and women identified in our data may actually correspond to couples who choose (or follow local convention) in recording only a single name in a real estate transaction. To the extent that we estimate gender and couple status with error, we are likely underestimating the single male-female gender gap. If the degree of estimation error also varies across states, that could contribute to variation in the estimated gender gap across states.

Figures 5 and A3 show how the average and median realized returns varied over time and across gender groups. Average and median returns on housing are positive in all years of our sample, but display significant business cycle variation, with the highest returns in the run-up to the housing market crash in 2006. The magnitude of the gender gap in returns appears to increase with average returns, although the gender gap remains large in magnitude in recent years and does not exhibit a strong secular decline over time.

[4] We exclude states where the number of observations is less than 500.

Figures A1 and A2 show how the composition of transactions by gender group varies over time. Changing composition combined with business cycle variation in average returns implies that gender differences in market timing can play a large role in the overall gender gap. In Table 5, we explore how much of the overall gender gap can be explained by differences in market timing, i.e. the choice of the exact month in which to buy and sell, as well as the holding length. As we move from column 1 to column 5, we introduce more detailed control variables for market timing, including zip-year-month fixed effects for the initial purchase transaction and zip-year-month fixed effects for the sale transaction. We also control for the interaction between year-month of purchase and year-month of sale fixed effects, which subsume the control variable for holding length. We find that market timing has a particularly large impact on the return gap between couples and single men. 80% of the original return gap can be explained by couples being relatively worse at market timing. Market timing also contributes to the male-female gender gap, albeit to a lesser extent. We find that approximately half of the gender gap in returns in Column 2 (our baseline specification, which already includes zip-year-month fixed effects for the sale transaction) can be explained by more detailed control variables for market timing. A potential explanation for these results is that frictions associated with childcare and school year cycles limit the ability of couples and single mothers to advantageously time real estate transactions.

D. Other Mechanisms

So far, we have shown that the gender gap in housing returns can be partly explained by gender differences in the market timing of when the home is purchased and sold, as well as the overall holding period. In this section, we explore gender variation in transaction prices, listing prices, transaction discounts, holding length, and other housing and listing characteristics.

The unlevered annualized return on housing depends mechanically on the ratio of the sale price to the initial purchase price, adjusted for holding length. To assess gender variation in each transaction price, we exploit repeat sales data and control for zip-year-month fixed effects to account for time trends within a zip code. Each observation in this analysis is a transaction. To better estimate property fixed effects, we do not restrict the sample to buyers or sellers with identified genders and matched names across sales and initial purchase. All observations corresponding to non-identified single women, single men, and couples are included and coded as the "other" category. Thus, our sample size expands to cover over 50 million observations.

The results in Table 6 show that women purchase homes at approximately 1-2% higher prices than men, holding the property fixed and adjusting for local time trends in prices. Women also sell the same property for 2-3% less than men. Couples do worse than single women in terms of paying higher purchase prices, but also outperform women in terms of selling at higher prices.

We can also examine how transaction prices vary with the match between categories of sellers and buyers. In Table 7, we compute the residual log transaction price as the residual from a regression of transaction prices on property fixed effects and zipcode by year-month fixed effects. The residual log transaction price has a mean of zero, with higher values indicating a higher transaction price than expected (conditional on the property and local time trends). The table reports the average residual log transaction price for each possible match between seller and buyer types. Among the four possible matches between male and female sellers and buyers, the highest transaction prices occur when there is a male seller and female buyer, and the lowest transaction prices occur when there is a female seller and male buyer. Matches with couples yield mixed results; in general, couple buyers pay higher than expected prices but couple sellers also sell for higher than expected prices.

The gender variation in transaction prices can be decomposed into gender variation in list prices at the time of purchase and sale and negotiated discounts relative to the listing price. For this analysis, we restrict the sample in Table 6 to observations that can be matched to MLS data on home listings, leading to approximately 10 million observations. Holding the property fixed and adjusting for local time trends in listed prices, we find in Table 8 that women choose to purchase the same property when it is listed for approximately 2.5% higher than when it is purchased by men, and then choose to list the same property for 2-3% less than when it is listed by men. Couples again fall somewhere between men and women. The gap between couples and single men in sale listing prices shrinks dramatically with the inclusion of zip-year-month fixed effects, again consistent with poor market timing being a major factor in the returns earned by couples.

Next, we examine how negotiated discounts vary by gender. We measure purchase and sale discounts as (listing price - transaction price)/listing price $\times$ 100, so a larger purchase discount contributes to a higher return on housing investment and a larger sale discount contributes to a lower return on housing investment. In Table 9, we find that women buyers purchase homes at approximately a 0.5 percentage point lower discount relative to men. Women sellers do not sell homes at greater discounts than men. However, women sellers remain at a disadvantage, because while they offer the same discount as men, they choose to list the same property at a 2-3% lower listing price. The discounts negotiated by couple buyers and sellers also display interesting patterns. Couple buyers lie between single men and women in terms of purchase discounts. However, couples negotiate significantly lower discounts than even single men when selling properties. In combination with the earlier results on listing prices, we find that couple sellers list the same property at slightly less than single men, but are much less likely to agree to a significant discount relative to the chosen list price.

We can also examine how transaction discounts vary with the match between categories of sellers and buyers. In Table 10, we compute the residual discount as the residual from a regression of discounts on zipcode by year-month fixed effects. The residual discount has a mean of zero, with higher values indicating a better outcome for buyers and a worse outcome for sellers, all else equal. The table reports the average residual discount for each possible match between seller and buyer types. Among the four possible matches between male and female sellers and buyers, the highest discount occurs when there is a female seller and male buyer, and the lowest discount occurs when there is a male seller and female buyer.

In Tables 6-9, we used the full data sample of transaction prices and listing prices, to better estimate property fixed effects from repeat sales data. The estimated coefficient for the single female indicator represents the gender gap in the dependent variable within a large data sample including home buyers and sellers that are not included in our housing returns sample (inclusion in the returns sample requires that the seller identity match the previous transaction's buyer identity). To isolate the gender gap in transaction prices, list prices, and discounts that correspond to observations in our returns sample, we present supplementary analysis in Appendix Tables A1-A3, in which the indicator variables for male, female, and couples are only generated for observations in our returns sample. In order to preserve our ability to estimate property fixed effects, we categorize all other observations into the "other" category. Hence the male, female and couple dummies should only capture the effects for the subset of transactions we identify in our main returns sample. A caveat to this analysis is that we do not observe list prices and discounts for all observations in our returns sample, so these tables are not meant to present an exact decomposition of the gender gap in housing returns.

Given the gender differences in listing prices and discounts, one may wonder whether women benefit from less aggressive list pricing and transaction discount negotiation with faster transaction times. For approximately 2 million observations, we also observe the number of days on market between listing and sale resolution. In Table 11, we find that women purchase and sell homes with 3% shorter transaction periods relative to men. Couples have 4% shorter transaction periods than men for home purchases, but have 0.8% longer transaction periods for home sales. This pattern for couples matches the evidence in Table 9 for transaction discounts. Couples appear to value fast resolution when purchasing and are more reluctant to offer negotiate discounts when selling. In column 3, we find that the gender gap in realized returns remains large after controlling for the days on market for purchases and sales.

The gender gap in listing prices and transaction discounts together imply that women experience worse execution prices on real estate transactions at the points of purchase and sale. Differences in execution prices should matter much more for the annualized returns of short term investors than for the returns of long term buy-and-hold investors. In a simple model in which women buy properties for δ fraction more and sell δ fraction less then men and hold for t years, we expect that women will earn $2\delta/t \times 100$ percentage points lower annualized unlevered returns than men.[5] Given that δ is approximately 0.02 in our sample, and the average holding period is approximately 4 years, the gender gap in execution prices predicts a gender gap in unlevered annualized returns of 1 percentage point, which matches our findings in Table 1.

In Figures 7 and 8 , we plot how the level of annualized housing returns and the gender gap in annualized returns varies with holding length in years. The level of annualized housing returns declines with holding length, consistent with earlier results in Table 1, possibly because different types of homeowners and properties are correlated with holding length. More interestingly, the gender gap (i.e., the difference in annualized returns for men vs. women) declines sharply with holding length, consistent with the intuition that differences in execution prices should matter more for the annualized returns of shorter term investors. The gender gap in housing returns is greater for homeowners with shorter tenure in their properties, because they "trade" assets more often, so any advantage or disadvantage in execution prices will matter more for their returns.

The gender gap in housing returns could also arise because of differences in preferences for housing characteristics that directly affect returns. In addition, home buyers and sellers often receive assistance from real estate agents. While we currently lack data on agents for home buyers, we do observe the identity and proxies for quality of the seller's listing agent. In Tables 12 and 13, we find that gender is predictive of the types of properties held, e.g., square footage, number of bedrooms, whether it was

[5] Let P_0 represent the market price of the property at the time of purchase. Suppose that the market value of the property grows by a fraction r each year. Suppose men buy and sell at the market price, so their annualized return equals r regardless of the holding period. Suppose that women buy properties for a fraction δ more and sell for δ less than the market price and hold for a period of t years. We can solve for the annualized return for women r_F such that $[(1 + r_F)^t = (1 - \delta) * P_0 * (1 + r)^t]/[(1 + \delta) * P_0]$. Solving for r_F after applying the approximation that $log(1 + x) \approx x$ for x close to zero implies that $r_F = r - 2\delta/t$

new construction at the time of purchase, popularity of the listing agent, etc. Further, these characteristics are predictive of the housing return. However, controlling for detailed home characteristics does not have a large impact on the estimated magnitude of the gender gap in returns (as evidenced by the small difference in coefficients on single female between columns 2 and 3 in Table 12. This analysis shows that women do not sort on average toward a set of housing characteristics that are associated with lower returns.

E. Alternative Explanations

The results in Tables 12 and 13 also help address a potential alternative explanation. Men may invest more in housing maintenance and upgrades. In particular, single men may be more likely than single women to purchase fixer uppers, which would explain why men buy at low prices and sell at high prices, holding the property fixed. Given that maintenance and upgrades are costly, men's real investment return may be lower than implied by analysis using only the sale price and purchase price. In Table 13, we find that men are more likely to list homes that have been upgraded or renovated, but the difference in upgrade rates across genders is small. In Table 12, we find that the gender gap remains large after controlling for whether the house has been upgraded or renovated, and in Table 14, we find that the gender gap in housing returns remains large in a restricted sample for which the house listing does not mention any synonyms for upgrades, renovations, new features, expansions, etc.

Aside from upgrades and renovations that are noted in property listings, men may also invest more in routine maintenance. A simple model in which men invest more in routine maintenance each year predicts a gender gap in housing returns that does not vary with holding period. Instead, we observe a gender gap in housing returns that decays sharply with holding period. This pattern is more consistent with a gap in returns that arises from fixed gender differences in execution prices at the points of purchase and sale (a simple model of differences in execution prices predicts that the gender gap equals $2\delta/t$ which approximately matches the shape of the decay in the data).

Another potential concern is that gender may be correlated with age within our sample. Women outlive men on average, and older individuals may earn worse returns on housing for reasons unrelated to gender.[6] While we lack data on individual age, we continue to find a large gender gap for homes sold after short holding periods of less than four years, which are less likely to have been held by older individuals moving into retirement homes. We also find in Table 14 that the gender gap in

[6] After the death of a spouse, widows or widowers may sell homes at a discount for a variety of reasons. Such cases are excluded from our returns analysis because we require that the homeowner be single at the time of home purchase as well as the time of home sale in order to be classified as single male or single female.

annualized returns is smaller for longer holding lengths. This pattern is expected and is a mechanical consequence of the annualization of investment returns given fixed differences in execution prices at the points of purchase and sale, as discussed earlier in relation to Figure 8.

IV. Conclusion

We uncover a large gender gap in the returns to housing investment in recent decades in the US. This gender gap is likely to be an important contributor to gender differences in wealth accumulation and welfare, given that housing wealth represents the dominant form of savings for most US households. Using detailed data on housing transactions across the US, we find that single men earn one percentage point higher unlevered returns per year on housing investment relative to single women, with couples occupying the intermediate range. The gender gap in raw returns grows significantly larger after adjusting for mortgage borrowing: men earn more the 5 percentage points higher levered returns per year relative to women. Using data on repeat sales, we show that women buy the same property for approximately 2% more and sell for 2% less. The gender gap in housing returns arises because of gender differences in the location and timing of transactions, choice of initial listing price, negotiated discount relative to the list price, and holding period. While the gender gap varies with demographic characteristics, it remains substantial in regions with high average education, income, and house price levels. It also has not displayed a secular decline over time.

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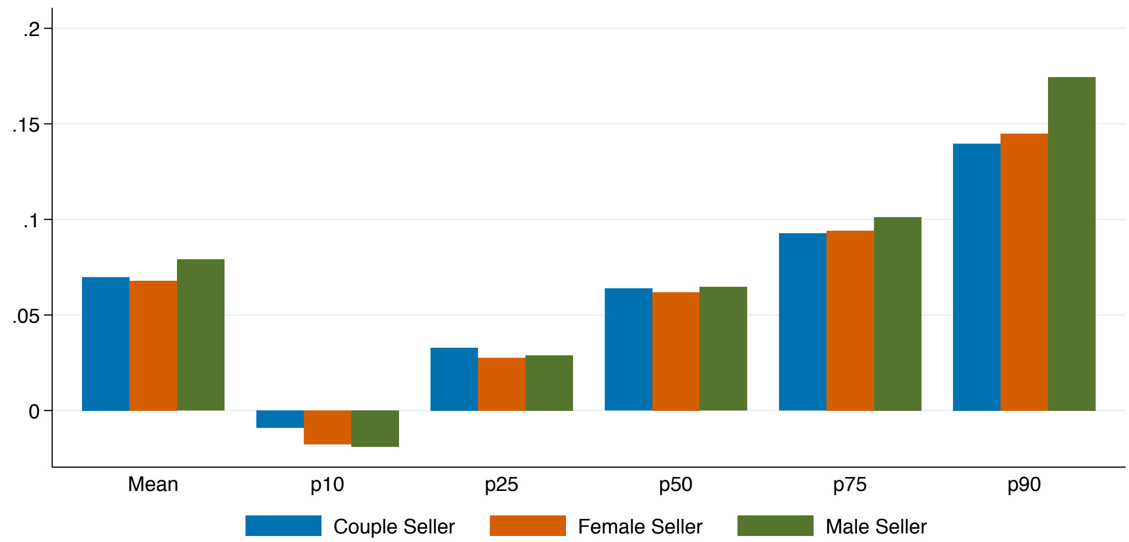
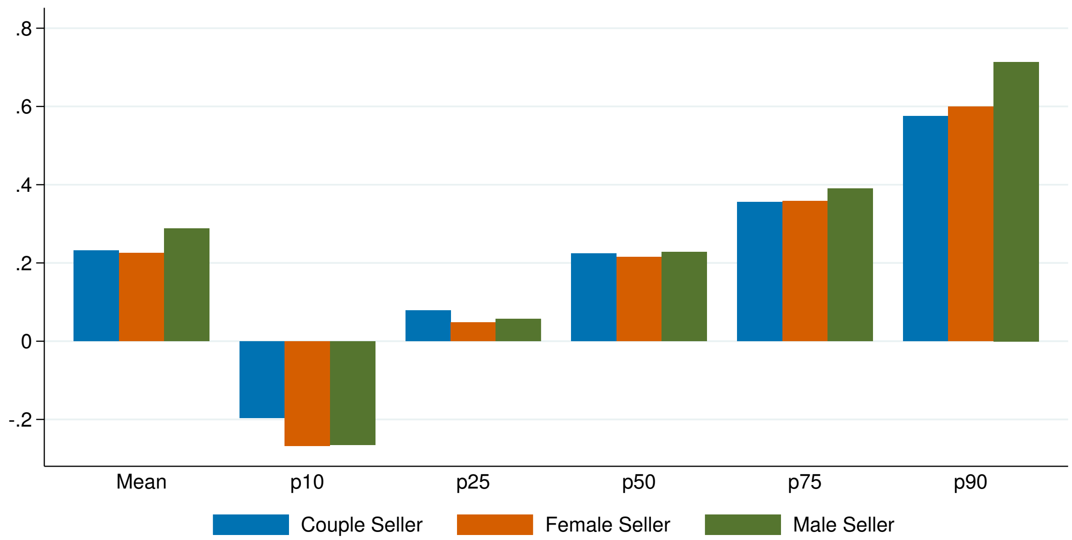
Figure 1: Distribution of realized returns by gender group



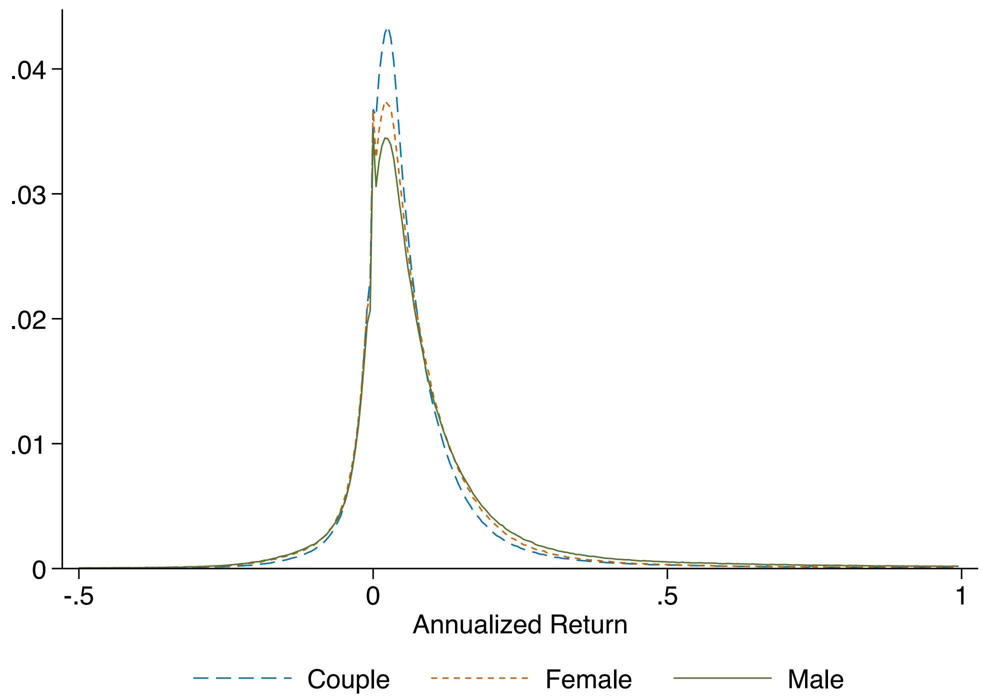
Note: This figure plots summary statistics for the residualized realized returns for housing transactions by three gender groups: couples, single women, and single men. The residualization is achieved by regressing the returns on zip-by-sale-year-month fixed effects, and taking the residuals. Then, the overall mean is added back to each residual. The first column in each set is for couples, the second is for single women, and the third is for single men. See Section II.B for more details on the definition of gender and family structure.

Figure 2: Distribution of realized levered returns by gender group



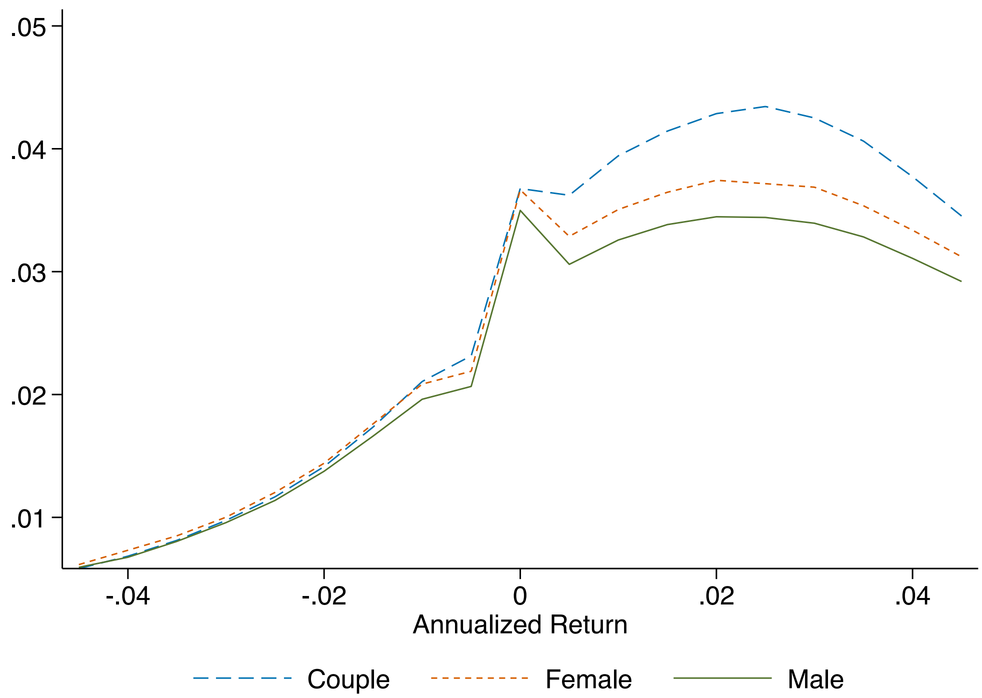
Note: This figure plots summary statistics for the residualized realized levered returns for housing transactions by three gender groups: couples, single women, and single men. The residualization is achieved by regressing the levered returns on zip-by-sale-year-month fixed effects, and taking the residuals. Then, the overall mean is added back to each residual. The levered returns are calculated following the formula is Section C. The first column in each set is for couples, the second is for single women, and the third is for single men. See Section II.B for more details on the definition of gender and family structure.

Figure 3: Density of realized returns by gender group



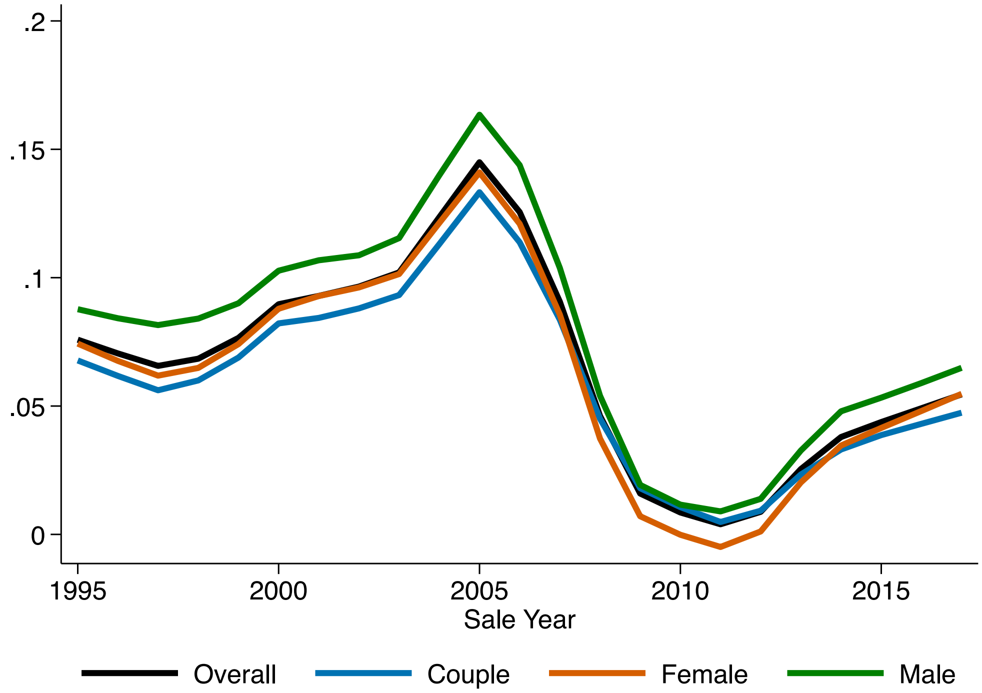
Note: This figure plots the density plot of the realized returns for housing transactions by three gender groups: couples, single women, and single men. Returns less are truncated at -50% and +100% for the purposes of this figure. See Section II.B for more details on the definition of gender and family structure.

Figure 4: Loss aversion and realized returns by gender group



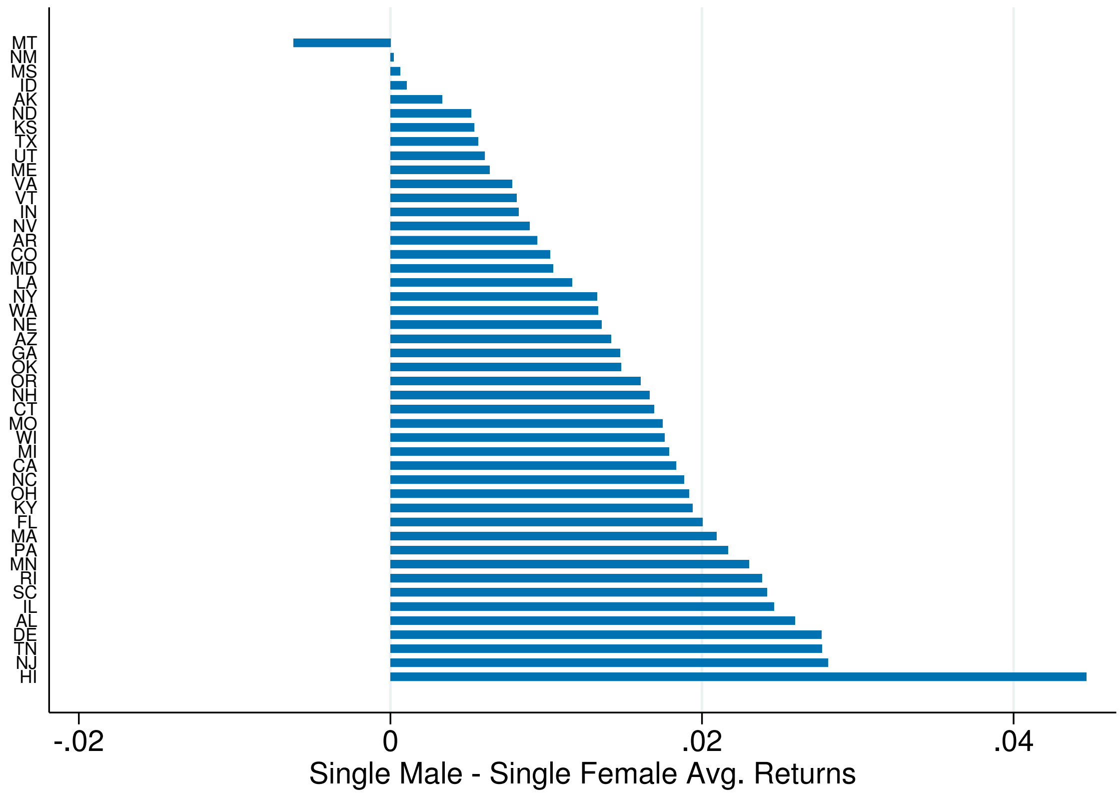
Note: This figure plots the density plot of the realized returns for housing transactions by three gender groups: couples, single women, and single men. Returns less are truncated at -4% and +5% for the purposes of this figure. See Section II.B for more details on the definition of gender and family structure.

Figure 5: Average realized returns over time by gender group



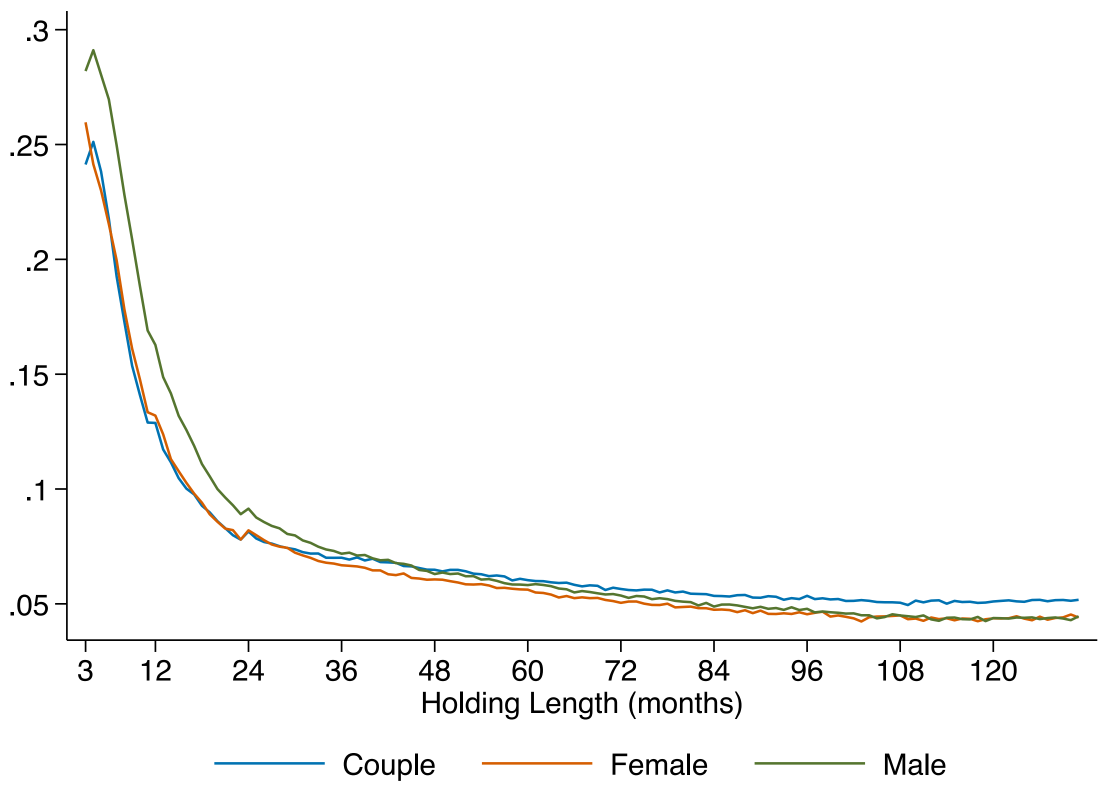
Note: This figure plots the average realized return for couples, single women, and single men over the sale year. As our sample begins in 1991, we begin this figure in 1995 to allow for sufficient data to avoid truncation. See Section II.B for more details on the definition of gender and family structure.

Figure 6: Difference in realized returns between single men and women across states



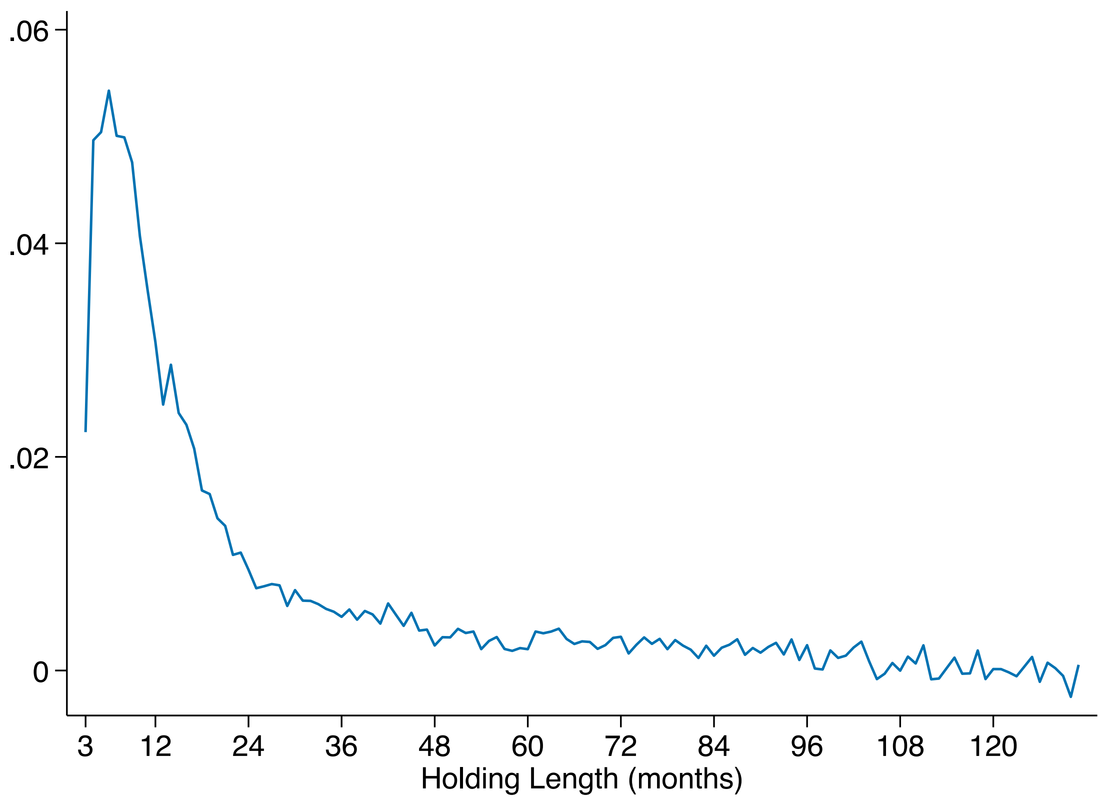
Note: This figure plots the average difference in realized returns between single men and women across states. We exclude states where we observe less than 500 transactions for both single men and women combined. See Section II.B for more details on the definition of gender and family structure.

Figure 7: Realized returns over holding periods



Note: This figure plots the average residualized realized returns for couples, single women and single men over holding periods. We exclude holding periods longer than 11 years. See Section II.B for more details on the definition of gender and family structure. See Appendix Figure A5 for the relative distribution of transactions across holding lengths.

Figure 8: Difference in realized returns between single men and women over holding periods



Note: This figure plots the average difference in residualized realized returns between single men and women over holding periods. We exclude holding periods longer than 11 years. See Section II.B for more details on the definition of gender and family structure. See Appendix Figure A5 for the relative distribution of transactions across holding lengths.

Table 1: Housing Returns: Unlevered

	Unleveraged Ann Return		
	(1)	(2)	(3)
Single Female	-0.016***	-0.013***	-0.011***
	(0.000)	(0.000)	(0.000)
Couple	-0.020***	-0.012***	-0.007***
	(0.000)	(0.000)	(0.000)
Holding Length			-0.006***
			(0.000)
Zip-Year-Month FE	No	Yes	Yes
R-squared	0.005	0.354	0.379
Observations	9,351,419	9,351,419	9,351,419

Note: This table shows how realized unlevered housing returns differ by the gender and relationship status of the homeowner. We use observations at the sale transaction level. The sample is restricted to observations for which the gender of all sellers can be identified, and for which we can match the identity of the seller at the time of sale to the identity of the buyer at the time of initial purchase. The omitted group is single males. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2: Housing Returns: Levered

	Lev Ann Ret (missing=0%)	Lev Ann Ret (missing=80%)	Lev Ann Ret (LTV=80%)
	(1)	(2)	(3)
Single Female	-0.077***	-0.292***	-0.060***
	(0.005)	(0.072)	(0.001)
Couple	-0.138***	-0.522***	-0.045***
	(0.005)	(0.064)	(0.001)
Holding Length	-0.110***	-0.282***	-0.041***
	(0.001)	(0.007)	(0.000)
Zip-Year-Month FE	Yes	Yes	Yes
R-squared	0.177	0.158	0.330
Observations	8,674,859	8,677,638	9,351,419

Note: This table shows how realized levered housing returns differ by the gender and relationship status of the homeowner. Levered returns are calculated as explained in Section C. In all future tables, we use levered returns assume an initial LTV of 80% as the our measure of the levered return unless otherwise noted. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: Heterogeneity by Zip-Level Demographics: Regressions

	Male - Female Unleveraged Ann Return	Male - Female Leveraged Ann Return
	(1)	(2)
Frac Black	0.004	0.019
	(0.006)	(0.028)
Frac HS education or less	0.024***	0.089**
	(0.009)	(0.043)
Frac 60+	0.025***	0.133***
	(0.009)	(0.047)
Frac Single Female	0.038***	0.188***
	(0.012)	(0.057)
Log Median Family Income	0.011***	0.052***
	(0.003)	(0.014)
R-squared	0.003	0.003
Observations	14,310	14,310

Note: This table shows how the average gender gap in housing returns within a zip code varies with zip-level demographics from the 2010 American Community Survey. We measure the gender gap in each zip code as the average difference between male and female residual realized returns (the residual return represents the return after adjusting for the zip-year-month mean). We regress the zip-level gender gap on zip-level demographics. Standard errors are adjusted for heterskedasticity. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Heterogeneity by Zip-Level Demographics: Quartile Averages

Male - Female Leveraged Ann Return	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	(1)	(2)	(3)	(4)
Frac Black	0.051	0.051	0.059	0.070
Frac HS Education or Less	0.048	0.053	0.061	0.058
Frac 60+	0.038	0.047	0.064	0.065
Frac Single Female	0.046	0.055	0.050	0.078
Median Family Income	0.057	0.059	0.052	0.055
House Price	0.075	0.063	0.050	0.041

Note: This table presents the average gender gap in levered housing returns across quartiles of various zip-level demographic characteristics. This table reports simple averages within each quartile of each demographic variable, without conditioning for other demographic variables. Observations are at the zip-code level and equally weighted.

Table 5: Returns: Market Timing

	Leveraged Ann Return				
	(1)	(2)	(3)	(4)	(5)
Single Female	-0.083***	-0.062***	-0.060***	-0.054***	-0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Couple	-0.105***	-0.072***	-0.045***	-0.041***	-0.016***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Holding Length		-0.047***	-0.041***	-0.030***	
		(0.000)	(0.000)	(0.006)	
Zip-SaleYM FE	No	No	Yes	Yes	Yes
Zip-BuyYM FE	No	No	No	Yes	Yes
SaleYM FE x BuyYM FE	No	No	No	No	Yes
R-squared	0.004	0.081	0.330	0.484	0.630
Observations	9,351,419	9,351,419	9,351,419	9,351,419	9,351,419

Note: This table shows how realized housing returns differ by the gender and relationship status of the homeowner, after introducing control variables for the timing of housing transactions. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Transaction Price

	Log(Purchase Price)		Log(Sale Price)	
	(1)	(2)	(3)	(4)
Single Female	0.013***	0.018***	-0.032***	-0.027***
	(0.001)	(0.001)	(0.001)	(0.001)
Couple	0.023***	0.029***	0.007***	0.014***
	(0.002)	(0.001)	(0.001)	(0.001)
Other	0.085***	0.015***	-0.064***	-0.054***
	(0.005)	(0.003)	(0.002)	(0.001)
Property FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Zip-Year-Month FE	No	Yes	No	Yes
R-squared	0.794	0.886	0.793	0.887
Observations	52,883,866	52,883,866	52,883,866	52,883,866

Note: This table examines gender variation in transaction prices. We use repeat sales data that allows us to control for property fixed effects. We also control for zip-year-month fixed effects to account for time trends within a zip code. Each observation is a transaction. To better estimate property fixed effects, we do not restrict the sample to buyers or sellers with identified genders and matched names across sales and initial purchase. All observations corresponding to non-identified single women, single men, and couples are included and coded as the "other" category. Single males are the omitted category. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Transaction Price: Matching between Buyers and Sellers

Residual Log(Transaction Price)	Male Seller	Female Seller	Couple Seller	Other Seller
	(1)	(2)	(3)	(4)
Male Buyer	0.0093	-0.0079	0.0158	-0.0235
Female Buyer	0.0155	0.0030	0.0181	-0.0111
Couple Buyer	0.0147	-0.0018	0.0223	-0.0031
Other Buyer	0.0137	-0.0007	0.0187	-0.0053

Note: This table examines how transaction prices vary with the match between categories of sellers and buyers. We compute the residual log transaction price as the residual from a regression of transaction property prices on property fixed effects and zipcode by year-month fixed effects. The residual log transaction price represents the actual transaction price minus the predicted price conditional on the property fixed and adjusting for local time trends. The residual log transaction price has a mean of zero. The table reports the average residual log transaction price for each possible match between seller and buyer types.

Table 8: List Price

	Log(Purchase List Price)		Log(Sale List Price)	
	(1)	(2)	(3)	(4)
Single Female	0.024***	0.025***	-0.031***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
Couple	0.021***	0.019***	-0.028***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Other	-0.053***	-0.044***	-0.140***	-0.086***
	(0.001)	(0.001)	(0.002)	(0.002)
Property FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Zip-Year-Month FE	No	Yes	No	Yes
R-squared	0.885	0.936	0.888	0.937
Observations	10,483,011	10,483,011	10,483,011	10,483,011

Note: This table examines gender variation in list prices chosen by home sellers. We use repeat sales data that allows us to control for property fixed effects. We also control for zip-year-month fixed effects to account for time trends within a zip code. Each observation is a listing matched to a sales transaction. To better estimate property fixed effects, we do not restrict the sample to buyers or sellers with identified genders and matched names across sales and initial purchase. All observations corresponding to non-identified single women, single men, and couples are included and coded as the "other" category. Single males are the omitted category. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Discounts Relative to the Listing Price

	Purchase Discount		Sale Discount	
	(1)	(2)	(3)	(4)
Single Female	-0.505***	-0.485***	-0.008	-0.010
	(0.010)	(0.006)	(0.016)	(0.009)
Couple	-0.363***	-0.291***	-0.504***	-0.314***
	(0.013)	(0.005)	(0.015)	(0.009)
Zip-Year-Month FE	No	Yes	No	Yes
R-squared	0.002	0.209	0.002	0.208
Observations	20,043,064	20,043,064	20,043,064	20,043,064

Note: This table examines how negotiated transaction discounts vary by gender. We measure purchase and sale discounts as (listing price - transaction price)/listing price $\times$ 100, so a larger purchase discount contributes to a higher return on housing investment and a larger sale discount contributes to a lower return on housing investment. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10: Discounts Relative to the Listing Price: Matching between Buyers and Sellers

Residual Discount	Male Seller	Female Seller	Couple Seller	Other Seller
	(1)	(2)	(3)	(4)
Male Buyer	-0.0186	0.106	-0.219	-0.033
Female Buyer	-0.204	-0.128	-0.359	-0.363
Couple Buyer	0.010	0.156	-0.160	-0.181
Other Buyer	0.033	0.109	-0.130	0.603

Note: This table examines how negotiated transaction discounts vary with the match between categories of sellers and buyers. We measure discounts as (listing price - transaction price)/listing price $\times$ 100, so a higher discount benefits buyers and hurts sellers, holding the list price constant. We compute the residual discount as the residual from a regression of discounts on zipcode by year-month fixed effects. The residual log transaction price represents the actual discount minus the predicted discount conditional on local time trends. The residual discount has a mean of zero. The table reports the average residual discount for each possible match between seller and buyer types.

Table 11: Days on Market

	Sale Log(Days on Mkt)	Purchase Log(Days on Mkt)	Leveraged Ann Return
	(1)	(2)	(3)
Single Female	-0.031***	-0.034***	-0.077***
	(0.003)	(0.003)	(0.002)
Couple	-0.041***	0.008***	-0.087***
	(0.003)	(0.003)	(0.002)
Sale Log(Days on Mkt)			-0.017***
			(0.001)
Purchase Log(Days on Mkt)			-0.020***
			(0.001)
Zip-Year-Month FE	Yes	Yes	Yes
R-squared	0.415	0.309	0.361
Observations	2,024,580	2,024,580	2,024,580

Note: This table examines how days on market, measured as the number of days between listing and sale, varies with gender, and contributes the gender gap in housing returns. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 12: Controlling for Timing and Property Characteristics

	Leveraged Ann Return		
	(1)	(2)	(3)
Single Female	-0.067***	-0.034***	-0.030***
	(0.002)	(0.001)	(0.001)
Couple	-0.079***	-0.015***	-0.017***
	(0.002)	(0.001)	(0.001)
Log(Age of Unit)			0.040***
			(0.001)
Foreclosure			-0.019**
			(0.009)
Garage			-0.022***
			(0.002)
Pool			-0.014***
			(0.001)
Cooling			-0.009***
			(0.002)
Fireplace			-0.013***
			(0.001)
Basement			0.007***
			(0.002)
Waterfront			0.004*
			(0.002)
Short Sale			-0.368***
			(0.004)
Bathrooms			0.000
			(0.002)
Log(Sq Ft)			-0.006***
			(0.002)
Bedrooms			0.007***
			(0.001)
Log(List Agent Popularity)			-0.002***
			(0.000)
Upgraded			0.035***
			(0.001)
New Construction			0.004*
			(0.002)
Property Type FE	No	No	Yes
Zip-SaleYM FE	No	Yes	Yes
Zip-BuyYM FE	No	Yes	Yes
SaleYM FE x BuyYM FE	No	Yes	Yes
R-squared	0.003	0.679	0.686
Observations	3,089,718	3,089,718	3,089,718

Note: This table examines how the gender gap in housing returns varies with additional control variables for market timing and property and listing agent characteristics. The sample is restricted to observations for which we have listings data on property characteristics. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13: Selection of Property Characteristics

	Upgraded	New Construction	Log(House Age)	Log(Sq Ft)	Log(Agent Popularity)
	(1)	(2)	(3)	(4)	(5)
Single Female	-0.009***	0.002***	-0.020***	-0.066***	-0.019***
	(0.001)	(0.000)	(0.003)	(0.001)	(0.002)
Couple	0.000	0.033***	-0.137***	0.143***	0.148***
	(0.001)	(0.001)	(0.004)	(0.002)	(0.003)
Zip-Year-Month FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.299	0.274	0.515	0.448	0.255
Observations	3,542,111	9,351,419	2,211,953	2,007,061	4,000,582

Note: This table examines gender differences in preferences for property and listing agent characteristics. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 14: Subsamples

	Holding Length < 4	Holding Length >= 4	No Upgrades	Upgrades
	(1)	(2)	(3)	(4)
Single Female	-0.123***	-0.002***	-0.059***	-0.095***
	(0.002)	(0.000)	(0.002)	(0.003)
Couple	-0.124***	0.027***	-0.058***	-0.104***
	(0.002)	(0.001)	(0.002)	(0.003)
Zip-Year-Month FE	Yes	Yes	Yes	Yes
R-squared	0.354	0.487	0.370	0.347
Observations	4,054,072	5,297,347	2,406,965	1,135,146

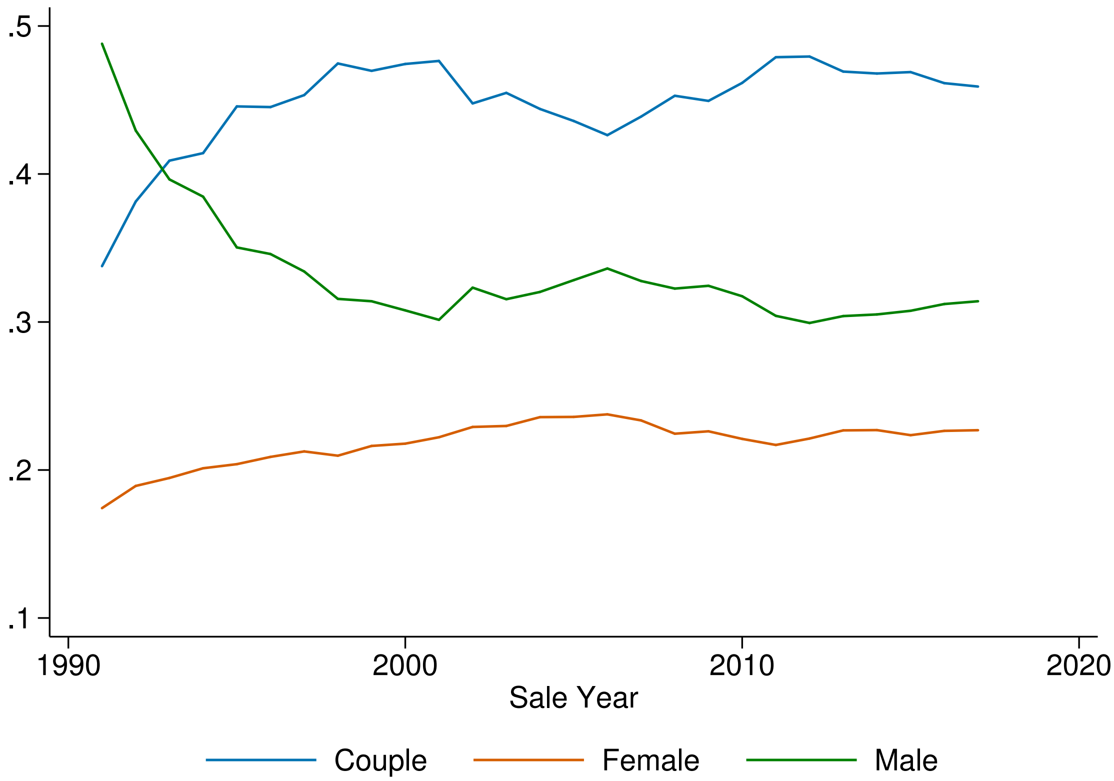
Note: This table estimates the gender gap in housing returns for subsamples of the data. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Online Appendix for

The Gender Gap in Housing Returns

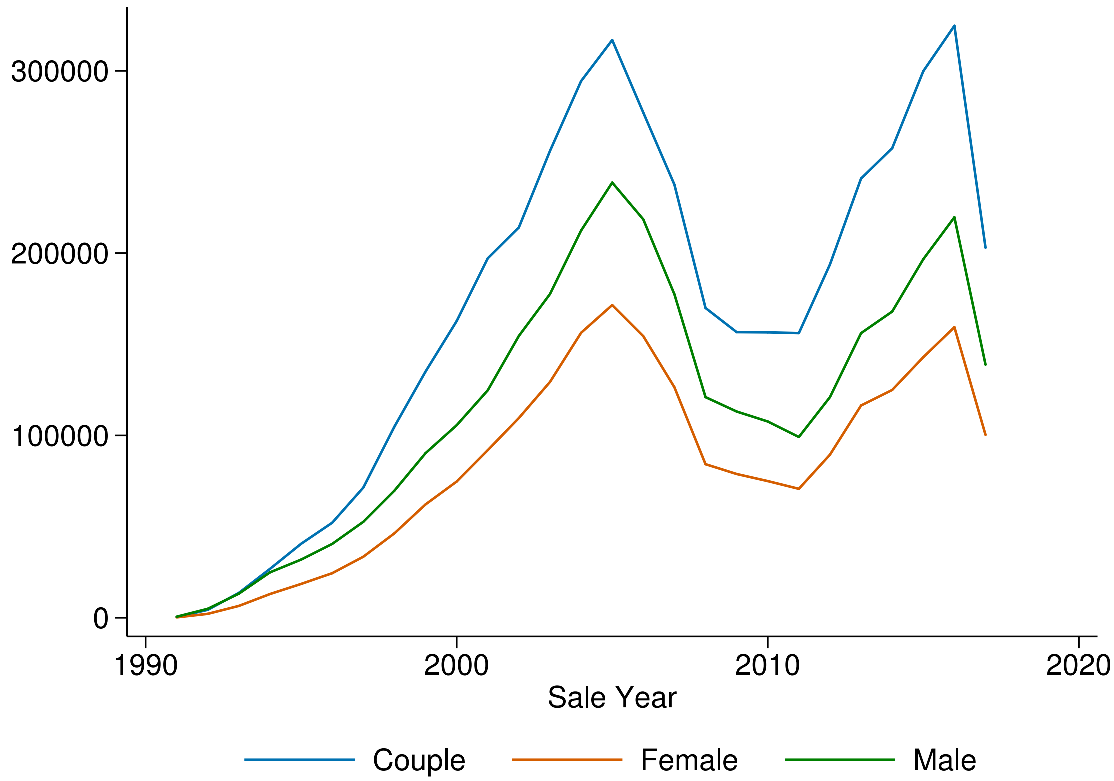
Paul Goldsmith-Pinkham Kelly Shue

Figure A1: Composition of transactions by gender group over time



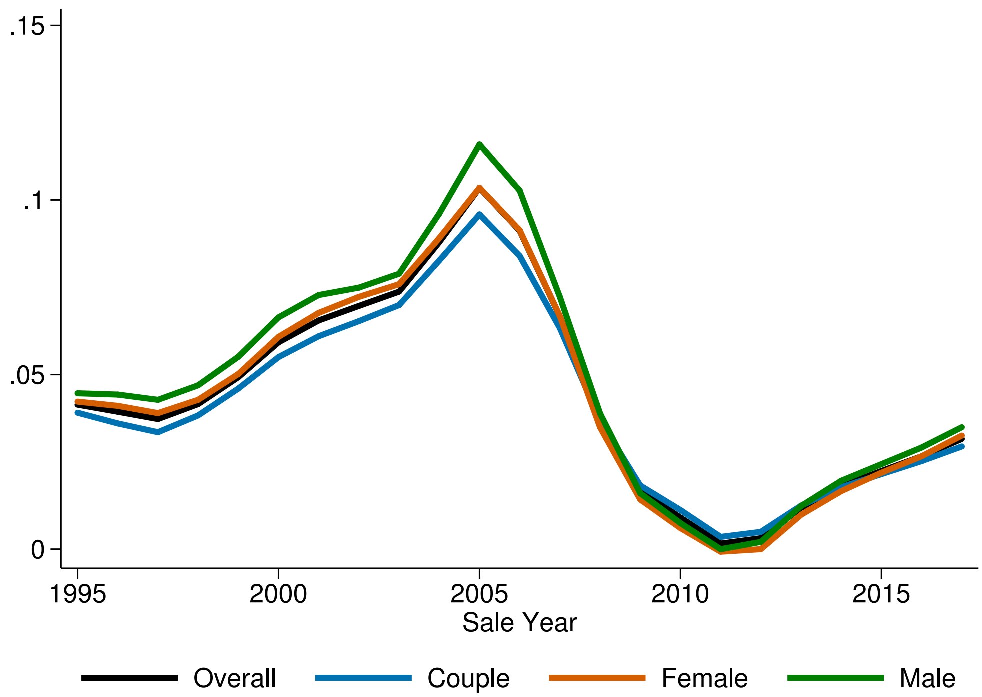
Note: This figure plots the relative composition of transactions across couples, single males and single females within the sample of transactions used for returns estimation. See Section II.B for more details on how we identify gender and family structure.

Figure A2: Transactions over time



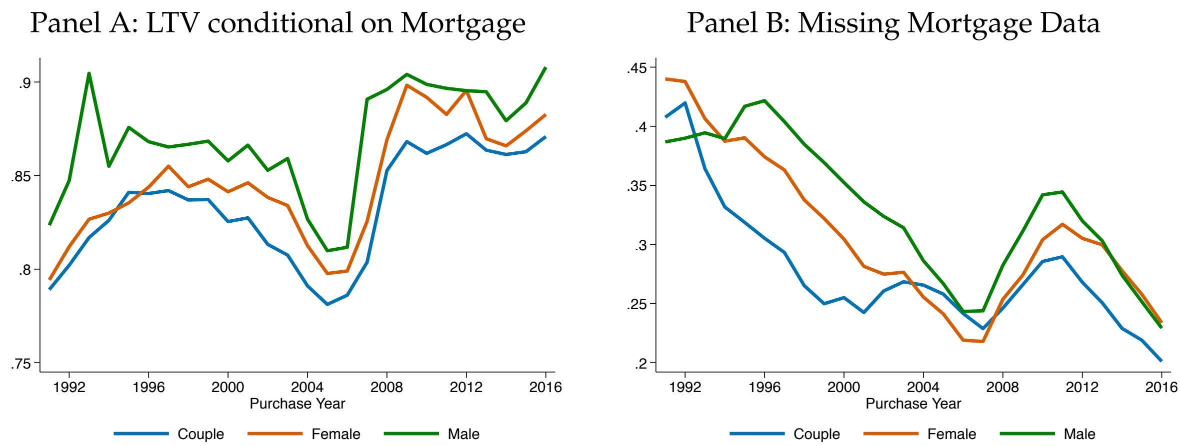
Note: This figure plots the total number of transactions across couples, single males and single females within the sample of transactions used for returns estimation. See Section II.B for more details on how we identify gender and family structure.

Figure A3: Median realized returns over time by gender group



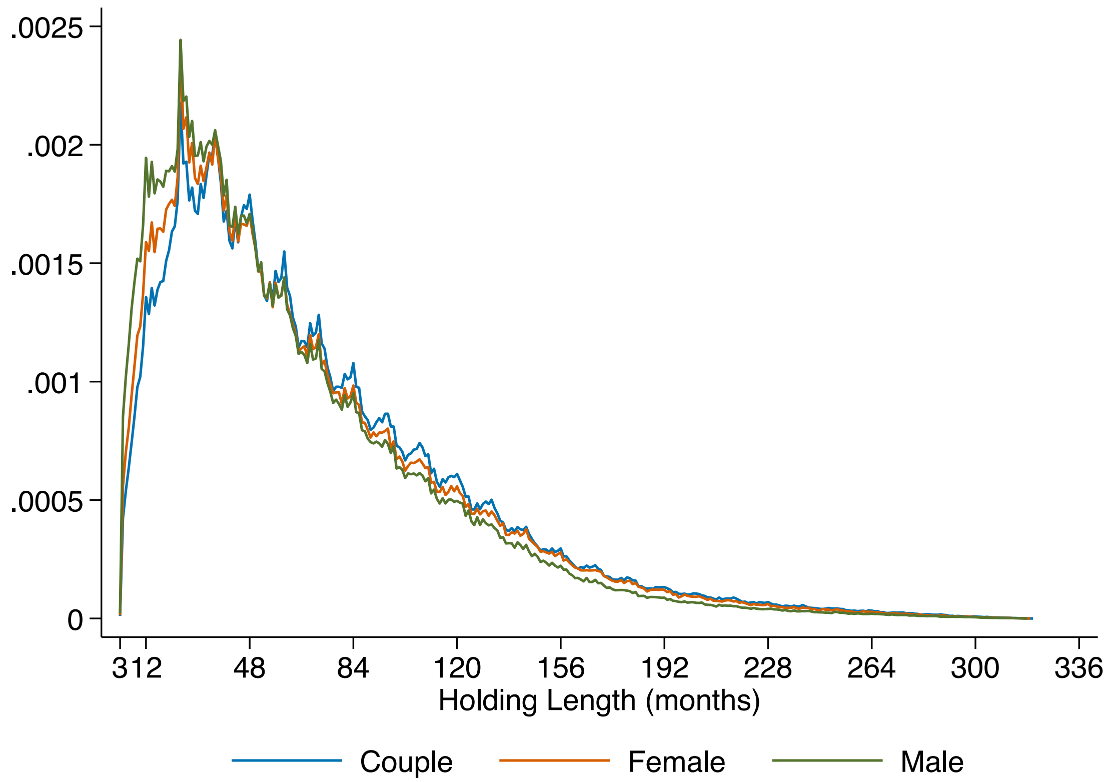
Note: This figure plots the median realized return for couples, single women, and single men over the sale year. As our sample begins in 1991, we begin this figure in 1995 to allow for sufficient data to avoid truncation. See Section II.B for more details on the definition of gender and family structure.

Figure A4: Original LTV over time by gender group



Note: This figure presents information on LTV at time of purchase across couples, single women and single men. In Panel A, we plot the average LTV at time of purchase, conditional on having information on a mortgage (i.e. conditional on a loan). In Panel B, we plot the share of transactions with missing mortgage data. This combines two forces: individuals with full cash transactions, and observations with pure missing data.

Figure A5: Transaction share by holding length



Note: This figure plots the distribution of transactions for couples, single women and single men across holding lengths for our analysis sample with returns. We restrict our sample to have a minimum of 3 months holding period.

Table A1: Transaction Price, Focus on Subsample with Returns Data

	Log(Purchase Price)		Log(Sale Price)	
	(1)	(2)	(3)	(4)
Single Female	0.017***	0.018***	-0.020***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Couple	0.013***	0.010***	-0.002	0.008***
	(0.002)	(0.001)	(0.002)	(0.001)
Other	0.075***	0.027***	-0.080***	-0.044***
	(0.002)	(0.001)	(0.002)	(0.001)
Property FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Zip-Year-Month FE	No	Yes	No	Yes
R-squared	0.793	0.886	0.793	0.886
Observations	52,883,866	52,883,866	52,883,866	52,883,866

Note: This table is similar to Table 6, except that all indicator variables for male, female, and couples represent observations in our housing returns sample. To preserve the ability to estimate property fixed effects, we categorize all other observations into the "other" category. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A2: List Price, Focus on Subsample with Returns Data

	Log(Purchase List Price)		Log(Sale List Price)	
	(1)	(2)	(3)	(4)
Single Female	0.017***	0.019***	-0.016***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Couple	0.016***	0.011***	-0.020***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Other	0.060***	0.023***	-0.094***	-0.050***
	(0.001)	(0.001)	(0.001)	(0.001)
Property FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Zip-Year-Month FE	No	Yes	No	Yes
R-squared	0.884	0.935	0.885	0.936
Observations	10,483,011	10,483,011	10,483,011	10,483,011

Note: This table is similar to Table 8, except that all indicator variables for male, female, and couples represent observations in our housing returns sample. To preserve the ability to estimate property fixed effects, we categorize all other observations into the "other" category. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A3: Discounts Relative to the Listing Price, Focus on Subsample with Returns Data

	Purchase Discount		Sale Discount	
	(1)	(2)	(3)	(4)
Single Female	-0.275***	-0.227***	-0.062***	-0.040***
	(0.011)	(0.008)	(0.009)	(0.006)
Couple	-0.250***	-0.168***	-0.017	-0.007
	(0.017)	(0.008)	(0.015)	(0.007)
Other	0.158***	0.032***	0.764***	0.420***
	(0.015)	(0.007)	(0.017)	(0.008)
Zip-Year-Month FE	No	Yes	No	Yes
R-squared	0.001	0.208	0.004	0.209
Observations	20,043,064	20,043,064	20,043,064	20,043,064

Note: This table is similar to Table 9, except that all indicator variables for male, female, and couples represent observations in our housing returns sample. We categorize all other observations into the "other" category. Standard errors are clustered by zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.