Local Housing Market Experiences and Homeownership Decisions*

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Abstract

An extensive literature documents that personally experienced returns disproportionately shape households' expectations and financial decisions. Whether these experiences lead households to make costly financial mistakes is less understood. Using residence histories from the University of California Consumer Credit Panel, we construct person-specific measures of historical county house-price returns linked to residential locations. Moving from the 25th to the 75th percentile of experienced returns predicts an increase in quarterly mortgage entry equivalent to 10.0% of the average entry probability. Higher experienced returns also predict greater mortgage borrowing and subsequent distress: among entrants, moving from the 25th to the 75th percentile of experienced returns predicts an increase in two-year delinquency equivalent to 19.8% of its average probability. In a simple model with rational expectations, households may accept greater delinquency risk when higher experienced returns signal greater future house-price appreciation. Instead, we find that higher experienced returns predict lower subsequent county house-price appreciation. These findings support an experience-based extrapolation mechanism in which optimistic housing beliefs raise mortgage commitments relative to available cash, increasing delinquency risk.

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1 Introduction

Personal experience shapes financial decisions. Classic studies of experience effects show that individuals' past returns influence their willingness to take risk and participate in financial markets (Malmendier and Nagel, 2011; Kaustia and Knüpfer, 2008). These findings raise a further question: can decisions shaped by favorable experiences become costly mistakes? This question is particularly consequential in housing, where an investment often involves substantial borrowing and a long-term commitment to mortgage payments. Favorable housing experiences may encourage households to enter the market and purchase larger homes, but the resulting debt obligations can leave them vulnerable to repayment difficulties. Following households beyond their initial investment decisions therefore provides an opportunity to examine whether the experiences associated with greater participation also predict subsequent financial distress.

In this paper, we study how personal housing experiences relate to mortgage decisions and subsequent repayment. Combining residential histories with administrative credit records, we find that individuals who have experienced higher house-price returns are more likely to enter the mortgage market, borrow larger amounts, and become delinquent afterward. Comparing the 25th and 75th percentiles of experience within each outcome sample, we find an increase in quarterly mortgage entry equivalent to 10.0% of the average entry probability, an 8.66% difference in recorded mortgage borrowing, and an increase in two-year delinquency equivalent to 19.8% of the average delinquency probability. We develop a simple model linking expected appreciation to housing size, debt, and payment risk, and examine its implications using future local prices and wages.

Buying a home combines an investment decision with a commitment to a stream of future payments. A household that expects strong house-price appreciation may be willing to purchase a larger home and take on more mortgage debt. Yet the additional housing wealth may provide little help when a payment comes due and current income is low. The same expectations that encourage participation can therefore leave households more exposed to repayment difficulties. Understanding this connection requires following households beyond the decision to borrow. Our question is whether the housing histories associated with greater mortgage participation also predict

the scale of borrowing and financial distress in the years that follow.

Personal experience provides a natural starting point for this question. Individuals living in the same housing market can have encountered very different price histories because they differ in age and in the places where they have lived. These histories may influence how attractive housing appears even when individuals face similar current market conditions. They can also contain information about future prices or reflect differences in employment and financial resources. We bring together evidence on mortgage choices, subsequent delinquency, and future local economic conditions to assess these explanations and to identify the patterns a model of housing experience must account for.

Our empirical analysis combines the University of California Consumer Credit Panel (UC-CCP) with local house prices and economic conditions. Residential histories allow us to construct individual measures of experienced housing returns, giving greater importance to recent observations. Credit records allow us to follow mortgage participation, recorded borrowing, and subsequent delinquency. The main entry analysis covers adults aged 25–49 from 2010 through the first quarter of 2025. We define entry as a transition from no coded open mortgage in the previous quarter to an open mortgage in the current quarter, including repeat transitions. We then examine borrowing at these transitions and repayment over the following eight quarters. A separate end-of-panel analysis relates experience to mortgage status at each individual's last observed quarter.

The main specifications include county-by-quarter and age fixed effects. County-by-quarter effects absorb housing-market and credit conditions shared by individuals living in the same county at the same time. Age effects account for the common age profile of mortgage participation and repayment. We also control for demographic characteristics, credit use, experienced inflation and local economic growth, and current housing-market conditions. The resulting comparisons relate different personal return histories to different mortgage outcomes within current local markets, conditional on age and observed characteristics. This design is particularly useful because a favorable housing history need not imply that the individual currently lives in a booming market.

An identification challenge remains: residential choices and past local returns may be related to unobserved wealth, employment opportunities, or preferences for housing. We therefore complement

the baseline estimates with an instrumental-variable strategy that uses the component of county experience shared with other counties in the same state. We construct three instruments using equal, inverse-distance, and housing-unit averages of returns in those counties. The instruments strongly predict experienced county returns, and the entry, borrowing, and two-year delinquency estimates remain positive. The identifying assumption is that these broader return histories affect mortgage outcomes through housing experience, conditional on the controls and fixed effects. Shared economic histories and selective migration are relevant to this assumption, so the IV results provide complementary evidence rather than resolving every source of selection.

We find that favorable housing experience is associated with greater mortgage participation. Moving from the 25th to the 75th percentile of experienced county returns in the entry sample is associated with an increase in quarterly entry equivalent to 10.0% of the average entry probability. The relationship is positive in the state-experience and county IV specifications and when housing experience is measured one to four quarters earlier. Estimates by age are largest in the middle age groups. In the end-of-panel analysis, experienced county returns are also positively associated with holding a mortgage at the last observed quarter. Because individuals leave the panel at different times, this outcome captures mortgage status at individual endpoints rather than after a common follow-up period.

Among mortgage entrants, favorable experience is associated with larger mortgage commitments. A move across the borrowing sample's own interquartile range of experienced county returns corresponds to 0.083 log points, or approximately 8.66%, more recorded mortgage borrowing. We obtain a similar positive relationship after dividing the mortgage amount by the current ZIP-area house price. This normalization asks whether borrowing is larger relative to local housing prices. It does not measure the fraction of a particular home's value financed with debt. The two borrowing measures therefore point to the scale of mortgage commitments, the margin emphasized in our model.

The delinquency results show that this pattern extends beyond the initial borrowing decision. We follow 129,209 eligible mortgage transitions by 96,695 individuals with observed delinquency status in each of the next eight quarters. Moving from the 25th to the 75th percentile of experienced

county returns in this sample is associated with an increase in two-year delinquency equivalent to 19.8% of the average delinquency probability. The 95% confidence interval is 8.8% to 30.8% of that average. The positive association appears in the state-experience and IV specifications and with experience measured one to four quarters earlier. The four-year county estimate is also positive, although less precise. These findings concern the conditional relationship: the raw binned association is negative, while adjustment for county-quarter and age effects yields a positive association.

We develop a simple model to connect these findings. A household chooses housing size at a fixed loan-to-value ratio. A larger purchase increases mortgage payments and uses liquid resources for the down payment. Income arrives before repayment, while the proceeds from selling the house become available afterward. Under the model's concavity and interiority conditions, higher expected appreciation raises housing size and debt. Holding initial wealth, loan terms, and the income distribution fixed, it also raises the probability that resources available at repayment fall short of the mortgage payment. The model thus provides a mechanism through which favorable housing expectations can encourage investment while increasing payment risk. The empirical results establish the corresponding pattern across outcomes; they do not quantify the share of the delinquency relationship mediated by larger borrowing.

We then take the model's interpretation to the data by studying subsequent local conditions. An interpretation of the information explanation predicts that favorable housing experience is associated with stronger subsequent appreciation in the transition market, which could explain why individuals with more favorable housing experience are more eager to enter the housing market. We instead find that experienced county returns predict weaker cumulative county house-price appreciation over both two and four years. The corresponding ZIP-price estimates are negative but imprecise. County average weekly wage growth, however, is positively associated with experience at both horizons. Taken together, these six tests are consistent with extrapolation from past housing returns, while leaving room for information about other economic conditions. County wage growth does not measure individual income, and the county-level outcomes require a different fixed-effect structure from the main household regressions. We interpret these tests as evidence on the model's economic mechanism rather than direct measures of individual forecast errors.

Literature Review. Our paper contributes to the literature on experience effects in household finance by connecting personal housing-return histories to both mortgage choices and subsequent repayment. Malmendier and Nagel (2011) show that experienced stock and bond returns predict household portfolio choices and return expectations. Kaustia and Knüpfer (2008) find that investors' own returns on past initial public offerings predict their participation in subsequent offerings. Malmendier and Nagel (2016) document a related role for lifetime inflation experiences in subjective inflation expectations. These findings establish that personal histories can matter for beliefs and financial decisions even when individuals have access to common market information. Malmendier (2021) reviews the evidence and its implications for models of belief formation. We extend this perspective to a setting in which an investment decision creates a continuing payment obligation, allowing us to examine financial outcomes after participation.

A closely related set of papers studies experience in housing and mortgage decisions. Malmendier and Wellsjo (2024) show that past inflation experiences predict homeownership within and across countries and provide survey evidence on the perceived inflation protection offered by housing. Botsch and Malmendier (2020) relate inflation experiences to interest-rate expectations and the choice between fixed- and adjustable-rate mortgages. These studies demonstrate how macroeconomic histories can affect the attractiveness of owning a home and the terms on which households choose to finance it. Our focus is on experienced house-price returns and the sequence from mortgage entry to borrowing and delinquency. Including experienced inflation and local economic growth among the controls helps distinguish this housing-return relationship from other dimensions of individuals' economic histories.

Our residence-based measure also connects to evidence on local experiences, social interactions, and housing expectations. Kuchler and Zafar (2019) find that recent local house-price movements influence expectations about national house prices. Bailey et al. (2018) show that individuals whose geographically distant friends experience greater house-price appreciation are more likely to become homeowners, purchase larger homes, and pay more for a given home. Fang et al. (2025) link individual housing experiences in Dutch survey and administrative data to expectations, forecast errors, and housing choices. Together, these papers show how expectations can reflect information

encountered personally or through social connections. We use residential histories to study mortgage outcomes in administrative records, with subsequent delinquency adding a repayment dimension to this evidence.

Experimental studies provide further evidence that housing expectations influence behavior. Armona et al. (2019) use randomized information about past local prices to study expectation updating and investment in an asset tied to housing returns. Bottan and Perez-Truglia (2025) find that information-induced increases in expected appreciation reduce actual home sales. Liu and Palmer (2026) show that perceived past returns predict experimental real-estate allocations even after conditioning on stated forecasts. These results motivate studying experience and behavior together, while recognizing that an experience measure and an elicited expectation capture different objects. Our contribution is to follow recorded mortgage commitments and repayment outcomes; we do not observe borrowers' forecasts directly.

The borrowing results relate especially closely to Bailey et al. (2019), who study house-price beliefs and mortgage leverage. Their framework distinguishes the choice of housing investment from the choice of financing, and their evidence associates more pessimistic beliefs with higher loan-to-value ratios. Our finding that favorable experience predicts larger mortgage amounts addresses the housing-investment margin. Because a borrower can purchase a larger home without financing a larger fraction of its value, greater mortgage borrowing can coexist with an unchanged or lower loan-to-value ratio. This distinction motivates the fixed-loan-to-value housing-size choice in our model and clarifies the interpretation of the empirical leverage outcomes.

Finally, we connect experience effects to research on mortgage repayment. Campbell and Cocco (2015) model default as a household choice shaped by income, house prices, financial resources, and mortgage terms. Gerardi et al. (2018) document the importance of household employment and financial shocks, and Ganong and Noel (2023) establish a central role for negative life events using linked income and mortgage records. Ganong and Noel (2020) show that short-term payment relief has different effects from reductions in long-term debt, highlighting the importance of liquidity. Our model builds on the distinction between housing wealth and resources available to meet a payment. The closest empirical comparison is Larson et al. (2025), who relate surveyed borrower

expectations to mortgage forbearance during the COVID-19 pandemic. We study residential return histories around mortgage transitions and delinquency in the following two years, complementing their evidence on expectations and pandemic mortgage performance.

The interpretation of these results also relates to models of housing expectations. Glaeser and Nathanson (2017) show how inference from past prices can generate extrapolative beliefs and housing-price dynamics. Kindermann et al. (2026) instead emphasize how owners and renters learn from different information about housing costs. These perspectives underscore that heterogeneous housing expectations can arise through several channels. Our compact model isolates a payment-risk implication of higher expected appreciation, and the future price and wage tests examine observable conditions under which that mechanism operates. The joint evidence motivates a role for experience in mortgage choices without requiring a claim that every difference in beliefs reflects an error.

The remainder of the paper proceeds as follows. Section 2 describes the data and descriptive evidence. Section 3 presents the empirical methodology and results for entry, end-of-panel mortgage status, borrowing, and delinquency, with additional checks in the corresponding appendices. Section 4 develops the model. Section 5 takes its predictions to the price and wage data. Section 6 concludes.

2 Data and variable definitions

We combine quarterly consumer credit records with local housing and economic histories to study mortgage entry, borrowing, and subsequent delinquency. Our entry sample contains 9.77 million person-quarters, with an average quarterly entry rate of 1.84%. Among mortgage transitions with two years of complete follow-up, 8.31% subsequently experience mortgage delinquency. We use the variation in individuals' housing-return histories to study how these experiences relate to their mortgage decisions and repayment outcomes.

To study the role of housing experiences, we need information on the places where individuals have lived, the housing returns in those places, and their mortgage behavior. We obtain the

individual records from the University of California Consumer Credit Panel (UC-CCP), which contains a nationally representative panel of U.S. adults with credit records (California Policy Lab, 2026). The data follow individuals' credit accounts and residential locations over time and provide information on open mortgages, recorded mortgage amounts, and delinquency. We use quarterly records through 2025Q1. Our analytic panel contains 619,839 individuals and 42,196,962 person-quarters, and the main entry regressions cover 2010Q2–2025Q1.

We link individuals' residential ZIP codes to local housing markets using Zillow house-price series (Zillow Research, 2026). These series provide the housing returns used in our experience measures and the current ZIP house prices used as controls. We also use county employment, average weekly wages, and establishment counts from the Quarterly Census of Employment and Wages (U.S. Bureau of Labor Statistics, 2026); median gross rents from the American Community Survey (U.S. Census Bureau, 2026); and the state inflation series of Hazell et al. (2022). These data allow us to account for individuals' broader economic experiences, in addition to their housing experiences.

Our main explanatory variable, E_{it}, summarizes the local housing returns in individual i's residential history through quarter t. We use county-level experienced returns in the baseline and state-level experienced returns as an alternative measure. The history-weighting parameter is $\lambda = 1$, which gives greater weight to more recent returns. Here λ determines how quickly the weights increase with recency: $\lambda = 0$ gives equal weight to available quarters, and larger values place more weight on recent quarters. These weights summarize each individual's past returns; they are distinct from sampling weights and the geographic weights used to construct the instruments. Both measures include the current quarter and are capped at -4% and 5%. They capture the housing returns individuals have experienced, rather than directly measuring their expectations of future appreciation.

Table 1 presents the sample sizes, outcome means, and distribution of county experience. In the entry sample, experienced returns average 0.857%, with a standard deviation of 0.691 percentage points. The 25th and 75th percentiles are 0.466% and 1.275%, respectively. Because the distribution of experience differs across outcome samples, we use the corresponding sample's interquar-

Table 1: Analytic samples and descriptive statistics

A. Samples and outcome means

Sample	Observations	People	Mean
Available panel	42,196,962	619,839	—
Quarterly mortgage entry	9,772,699	402,372	1.843%
End-of-panel mortgage status	293,183	293,183	32.921%
Log mortgage amount	144,265	105,539	12.965
Log(mortgage amount / ZIP price)	144,265	105,539	0.446
Two-year delinquency	129,209	96,695	8.313%
Four-year delinquency	103,825	80,678	11.616%

B. County housing experience by outcome sample (%)

Sample	25th percentile	75th percentile	IQR (pp)
Quarterly mortgage entry	.466	1.275	.810
Borrowing at entry	.489	1.239	.750
Two-year delinquency	.453	1.148	.695
Four-year delinquency	.387	.992	.604

Notes: The entry unit is a person-quarter; borrowing and delinquency are measured at mortgage transitions; the endpoint sample contains one observation per person. Entry and transition samples include ages 25–49, while endpoint ages are 31–59. Binary-outcome means are percentages; borrowing means refer to natural logarithms. Repeat transitions are included. Each delinquency sample requires complete known follow-up over its own horizon. The full panel precedes outcome-specific restrictions.

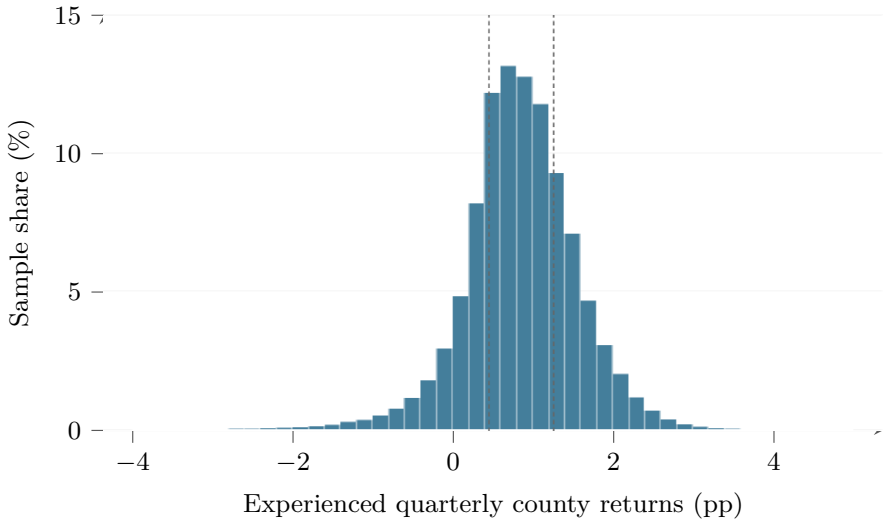
tile range—the difference between the 75th and 25th percentiles—when describing the economic magnitudes of our estimates. For mortgage entry and delinquency, we express these increases as percentages of the corresponding sample's average outcome probability.

Figure 1 shows that experienced county returns are concentrated around positive values but vary substantially across observations.

We measure mortgage entry as a transition from no coded open mortgage in quarter $t-1$ to an open mortgage in quarter t, requiring adjacent calendar quarters. We include repeat transitions and restrict the main entry sample to individuals aged 25–49 who either have no open mortgage in the current quarter or enter in that quarter. Individuals who leave mortgage holding can therefore appear as zero observations. Missing mortgage-open status is coded as no open mortgage before we construct transitions. This measure captures entry into mortgage holding, including repeat entry; it does not identify first home purchases or purchases financed entirely with cash.

To study mortgage holding over a longer period, we also retain one observation per individual from the last quarter in which we observe them. We measure whether the individual has an open

Figure 1: Distribution of experienced county housing returns



Notes: The histogram shows experienced nominal quarterly county house-price returns in the baseline entry sample, ages 25–49. Returns are expressed in percentage points. The vertical dashed lines mark the 25th and 75th percentiles.

mortgage in that quarter and restrict age to 31–59. This sample contains 293,183 individuals, with an average mortgage-holding rate of 32.92%. Since the last observed quarter differs across individuals, this outcome measures mortgage status at the end of observation rather than at a common future horizon.

For borrowing at entry, we use the log recorded mortgage amount and the log of that amount divided by the current ZIP house price. The second measure expresses borrowing relative to local housing values. Unlike a property-level loan-to-value ratio, it can vary with the size or quality of the purchased home relative to other homes in the ZIP, as well as with the financing share. The borrowing sample contains 144,265 transitions by 105,539 individuals aged 25–49 with positive finite mortgage amounts and prices. We do not require subsequent delinquency follow-up for these regressions.

Our main delinquency outcome equals one if an individual experiences mortgage delinquency in any of the eight quarters following entry. We require a known outcome in every quarter of the horizon. A missing delinquency flag is coded zero when an open mortgage is present and remains unknown otherwise; observations whose administrative follow-up ends before the horizon are ex-

cluded. This gives 129,209 transitions by 96,695 individuals, dated 2010Q2–2023Q1. We also study delinquency over sixteen quarters, using a sample of 103,825 transitions by 80,678 individuals with the required follow-up. Since delinquency is measured across an individual's mortgage accounts, it need not refer exclusively to the mortgage recorded at entry. Appendix A.4 describes the follow-up rule and compares it with an earlier outcome definition.

Finally, we control for demographics, credit conditions, economic experiences, and current local housing conditions. Demographics include gender, marital status, and the numbers of adults and children. Credit-card utilization is the account balance divided by its credit limit; the other debt ratios divide balances by recorded account amounts. Appendix A.5 explains the treatment of missing and undefined ratios. We include experienced county employment, wage, and establishment growth, together with inflation experience. Local housing controls include ZIP house-price and rent levels and growth, with indicators for missing rents. House-price growth compares the current ZIP's price with its price four calendar quarters earlier; rent growth uses the interpolated series and four observed records. The baseline measures these controls and housing experience in the current quarter. Appendix A.5 gives the variable transformations and the narrower housing-control set used in the end-of-panel regressions.

3 Empirical analysis

In this section, we study how housing-return experiences relate to mortgage entry, longer-run mortgage holding, borrowing, and subsequent delinquency. We find that individuals with higher experienced returns are more likely to enter mortgage holding, borrow larger amounts, and experience delinquency over the following two years. Within each outcome's sample, a move from the 25th to the 75th percentile of county experience is associated with an increase in quarterly entry equivalent to 10.0% of the average entry probability, 8.66% greater mortgage amounts, and an increase in two-year delinquency equivalent to 19.8% of the average delinquency probability. We first explain our empirical approach and then present the results for each outcome.

A central concern is that housing experiences may be correlated with other determinants of

mortgage decisions. Individuals choose where to live, earlier housing gains may affect their financial resources, and local returns may be measured with error. To address these concerns, we include a rich set of controls and fixed effects and compare the baseline estimates with an instrumental-variable approach based on other counties' return histories. The fixed effects account for current local conditions and age profiles, while the instruments use the component of county experience predicted by broader return movements.

For mortgage entry, borrowing, and delinquency, we estimate the following specification:

$$Y_{it} = \beta E_{it} + X_{it}'\gamma + \delta_{c(i,t),t} + \alpha_{a(i,t)} + \varepsilon_{it}. \tag{1}$$

Here, Y_{it} is the outcome associated with quarter t, E_{it} denotes county- or state-level experienced housing returns, and X_{it} contains the controls described in Section 2. For delinquency, the outcome records events following the mortgage transition in quarter t. We include county-by-quarter fixed effects, $\delta_{c(i,t),t}$, to absorb conditions shared by individuals living in the same county at the same time, including local housing conditions and common credit and labor-market shocks. We also include exact-age fixed effects, $\alpha_{a(i,t)}$, to account for average differences in mortgage behavior over the life cycle. The remaining variation compares individuals facing the same current county market, after accounting for the average age profile, whose earlier housing histories differ.

We estimate linear probability models for the binary outcomes and use logs for the borrowing outcomes. Housing experience and controls are measured at t in the baseline. In the robustness exercises, we lag housing experience and its instrument by one to four quarters while keeping the controls at t. We use multiway clustered standard errors, allowing regression errors to be correlated among observations sharing a county, a quarter, or an age, except in the state-experience entry regression, where we cluster by state, quarter, and age. All coefficient figures report 95% confidence intervals.

For the instrumental-variable estimates, we apply the personal-history weighting rule to returns in other counties within the same state. We construct three instruments using equal, inverse-distance, and housing-unit weights across donor counties. Each instrument enters a separate two-

stage least-squares regression with the same controls and fixed effects as the county baseline. The first stage predicts county experience using the instrument; the second stage relates the instrument-predicted component of experience to the mortgage outcome. This approach reduces reliance on shocks specific to the counties in which an individual has lived while retaining return movements that predict their county experience.

The identifying assumption is that donor-based experience affects mortgage outcomes only through county experience, conditional on the controls and fixed effects. This assumption could fail if shared state shocks, residential sorting, or earlier economic conditions affect mortgage decisions through other channels. In addition, the donor construction substitutes state returns for unavailable donor returns, and these state aggregates can contain an own-county component. We report first-stage statistics to assess instrument relevance and interpret the IV estimates subject to this exclusion restriction. Agreement between the baseline and IV estimates supports the empirical pattern, but does not by itself establish an expectations mechanism.

3.1 Mortgage entry

We begin with the decision to enter mortgage holding. Table 2 reports estimates of Equation (1) for county and state experience, together with the three IV specifications. Across all five columns, higher experienced returns are associated with a greater probability of entry. The county and state estimates are similar in magnitude. All five regressions use the same 9,772,699 person-quarters, including 184,676 observed entry events.

In terms of magnitudes, the county estimate implies that moving from the 25th to the 75th percentile of experience increases quarterly entry by an amount equivalent to 10.0% of the average entry probability, with a 95% confidence interval of 3.3% to 16.8% of that average. The corresponding state-experience estimate is 10.2% of the average entry probability. The three IV estimates imply increases equivalent to 12.1–12.4% of the average entry probability for the same county-experience percentile comparison. Their first-stage clustered Wald statistics range from 1,968 to 2,453, indicating a strong relationship between the instruments and county experience.

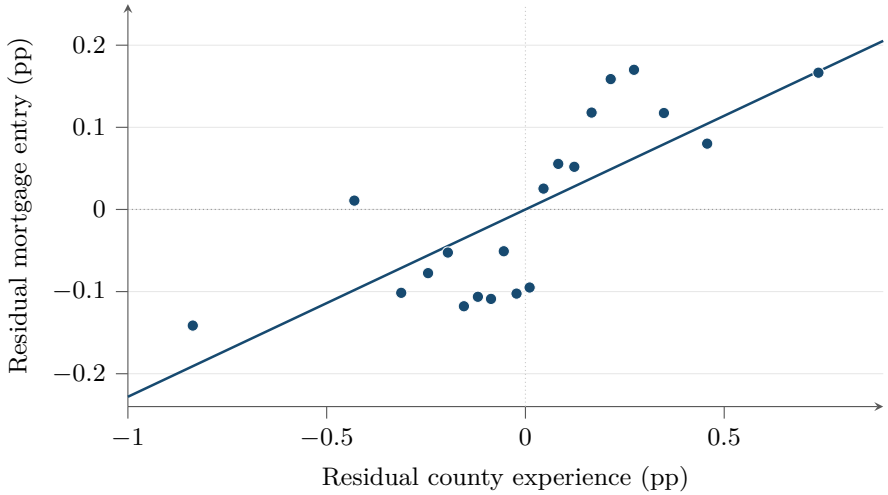
Figure 2 shows an upward-sloping binned relationship after removing the baseline controls and

Table 2: Housing-return experience and quarterly mortgage entry

	County OLS (1)	State OLS (2)	IV: equal (3)	IV: distance (4)	IV: units (5)
Experienced returns	0.228***	0.250***	0.279***	0.275***	0.281***
	(0.075)	(0.085)	(0.096)	(0.093)	(0.094)
Person-quarters	9,772,699	9,772,699	9,772,699	9,772,699	9,772,699
People	402,372	402,372	402,372	402,372	402,372
Entry mean (%)	1.843	1.843	1.843	1.843	1.843
First-stage Wald F	—	—	1967.6	2452.8	2071.5

Notes: The dependent variable equals one for an observed transition from no open mortgage to an open mortgage in adjacent quarters. The sample retains current nonowners and entrants aged 25–49 from 2010Q2 to 2025Q1, including repeat transitions. Coefficients are percentage-point changes in entry per one-percentage-point increase in experienced returns. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County-by-quarter and exact-age fixed effects are included. The IV columns instrument county experience using other same-state counties with equal, inverse-distance, or housing-unit weights. Standard errors in parentheses are clustered separately by county, quarter, and age. The state-experience column instead clusters by state, quarter, and age. Tests use 24 degrees of freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 2: Housing-return experience and mortgage entry

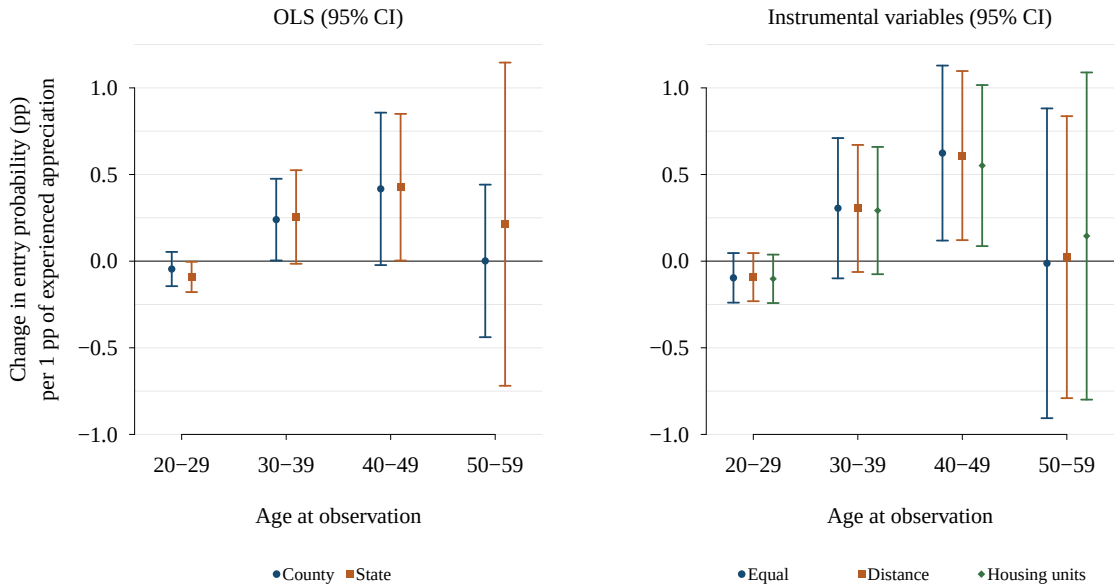


Notes: The figure uses the baseline entry sample of 9,772,699 person-quarters at ages 25–49. Both axes remove the baseline controls and county-by-quarter and exact-age fixed effects. Dots show means within 20 bins of residual county experience. The line uses the county coefficient estimated from individual observations and reported in Table 2; it is not fitted to the bin means. Both axes are expressed in percentage points.

county-by-quarter and age fixed effects, consistent with the positive entry estimates.

To study how the relationship varies over the life cycle, we estimate the specification separately for four age groups. Figure 3 reports these estimates. The county coefficients are close to zero for ages 20–29 and 50–59 and positive for ages 30–39 and 40–49. The point estimate is largest for

Figure 3: Housing-return experience and mortgage entry by age



Notes: The figure reports the percentage-point change in entry probability per one-percentage-point increase in contemporaneous housing-return experience. Bars indicate 95% confidence intervals. All models include the baseline controls, county-by-quarter fixed effects, and exact-age fixed effects within each band. We use multiway clustered standard errors, allowing regression errors to be correlated among observations sharing a county, a quarter, or an age, except state-experience OLS, which clusters by state, quarter, and age. Confidence intervals use 8 degrees of freedom in the youngest band and 9 in the others. Samples differ from the pooled ages-25–49 baseline. Appendix Figure A1 reports experience measured four quarters earlier.

ages 40–49, although its 95% confidence interval includes zero. Thus, the point estimates suggest a concentration in the middle age groups, without establishing a monotone age profile or statistically significant differences between groups.

We further assess the robustness of the entry results by lagging experience and varying the history-weighting parameter. The county estimates remain positive and statistically significant when experience is measured one to four quarters earlier. The estimates are also positive for each value of λ from zero to four, although those for $\lambda = 0$ and 4 are imprecise. Appendix A.1 reports these regressions and the age-specific results using experience at $t - 4$.

Table 3: Housing experience and end-of-panel mortgage status

	County OLS	State OLS	IV: equal	IV: distance	IV: units
	(1)	(2)	(3)	(4)	(5)
Experienced returns	2.855***	2.030	2.467	3.127**	3.752*
	(0.691)	(1.244)	(1.722)	(1.406)	(1.897)
People	293,183	293,183	293,183	293,183	293,183
Mortgage mean (%)	32.921	32.921	32.921	32.921	32.921
First-stage Wald F	—	—	1,479.4	655.1	595.9

Notes: The dependent variable is open-mortgage status in each person's last observed quarter, with endpoint ages restricted to 31–59. Coefficients are percentage-point changes per one-percentage-point increase in experience. Controls include demographics, credit ratios, economic and inflation experiences, and the ZIP house-price level. Separate county, quarter, and age fixed effects are included. The three IV columns use the alternative same-state donor instruments. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 28 degrees of freedom. Standard errors incorporate the reported covariance correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

3.2 End-of-panel mortgage status

We next examine mortgage holding at the end of each individual's observed credit history. For this exercise, we keep one observation per individual from the last quarter in which they appear in the panel. Table 3 shows a positive relationship between county experience and mortgage holding at this endpoint. The county estimate is statistically significant at the 1% level. The average mortgage-holding rate in this sample is 32.92%.

The end-of-panel specification includes separate county, quarter, and age fixed effects, together with demographics, credit conditions, economic experiences, and ZIP house-price levels. Since it does not include county-by-quarter effects, price growth, or rents, it uses a different comparison from the entry regressions. The last observed quarter also differs across individuals, so we interpret this outcome as mortgage participation at the end of observation rather than entry at a common future horizon.

The state and IV estimates are positive, but their precision varies. The state and equal-donor-weight IV estimates have 95% intervals that include zero. The distance-weighted IV estimate is significant at 5%, while the housing-unit-weighted IV estimate is significant at 10% but not 5%. Appendix A.2 reports the results for alternative history weights and lagged experience.

Table 4: Housing experience and borrowing at mortgage entry

	County OLS (1)	State OLS (2)	IV: equal (3)	IV: distance (4)	IV: units (5)
A. Log mortgage amount					
Experienced returns	0.111***	0.140***	0.149***	0.142***	0.153***
	(0.013)	(0.015)	(0.019)	(0.019)	(0.019)
IQR contrast (%)	8.66	10.42	11.80	11.25	12.14
R^2	0.6878	0.6881	0.6877	0.6878	0.6877
B. Log(mortgage amount / ZIP house price)					
Experienced returns	0.105***	0.136***	0.146***	0.138***	0.149***
	(0.014)	(0.015)	(0.021)	(0.019)	(0.020)
IQR contrast (%)	8.19	10.09	11.57	10.92	11.79
R^2	0.6109	0.6113	0.6108	0.6108	0.6107
Transitions	144,265	144,265	144,265	144,265	144,265
People	105,539	105,539	105,539	105,539	105,539
First-stage Wald F	—	—	2,881.6	3,446.7	2,990.3

Notes: The dependent variables are log recorded mortgage amount and log mortgage amount relative to the current ZIP house price. The sample contains mortgage transitions at ages 25–49 with positive finite amounts and prices, including repeat transitions. Coefficients are log-point changes per one-percentage-point increase in experience. The IQR row reports $100[\exp(\widehat{\beta}\Delta E) - 1]$, using the corresponding county or state experience distribution; it measures a percentage difference in the conditional geometric mean. The area-price ratio is not property-level loan-to-value. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County-by-quarter and exact-age fixed effects are included. Each IV column uses the indicated same-state donor instrument. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 24 degrees of freedom. The state-experience standard errors incorporate the reported covariance correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

3.3 Mortgage borrowing

We then study whether individuals with higher experienced returns borrow more when they enter mortgage holding. Table 4 reports the results for log mortgage amount and log mortgage amount relative to current ZIP house prices. The coefficients on county experience are positive and precisely estimated for both outcomes. A one-percentage-point increase in experience is associated with 0.111 log points more mortgage amount and 0.105 log points more borrowing relative to local prices, with standard errors of 0.013 and 0.014, respectively.

The 25th and 75th percentiles of county experience in this sample are 0.489% and 1.239%, giving an interquartile range of 0.750 percentage points. Moving across this range is associated with 0.0830 log points more mortgage amount, or an 8.66% increase in the conditional geometric mean. The corresponding 95% confidence interval is [6.44%, 10.92%]. For the mortgage-to-area-price ratio, the

Table 5: Housing experience and mortgage delinquency within two years

	County OLS (1)	State OLS (2)	IV: equal (3)	IV: distance (4)	IV: units (5)
Experienced returns	2.374***	2.871***	3.174***	3.154***	3.170***
	(0.637)	(0.666)	(0.758)	(0.753)	(0.771)
Transitions	129,209	129,209	129,209	129,209	129,209
People	96,695	96,695	96,695	96,695	96,695
Outcome mean (%)	8.313	8.313	8.313	8.313	8.313
R^2	0.5432	0.5433	0.5431	0.5431	0.5431
First-stage Wald F	—	—	2,848.4	3,269.9	2,832.5

Notes: The dependent variable equals one for any mortgage delinquency in quarters $t+1$ through $t+8$ after entry, requiring a known outcome in every quarter. The sample includes entrants aged 25–49 from 2010Q2 to 2023Q1 and allows repeat transitions. Coefficients are percentage-point changes in delinquency per one-percentage-point increase in experience. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County-by-quarter and exact-age fixed effects are included. The IV columns use the alternative same-state donor instruments. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 24 degrees of freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

interquartile change is 0.0787 log points, or 8.19%, with a 95% interval of [5.90%, 10.52%]. Because the denominator is the ZIP price rather than the purchased property's value, this result can reflect the size or quality of the home as well as the share financed through a mortgage.

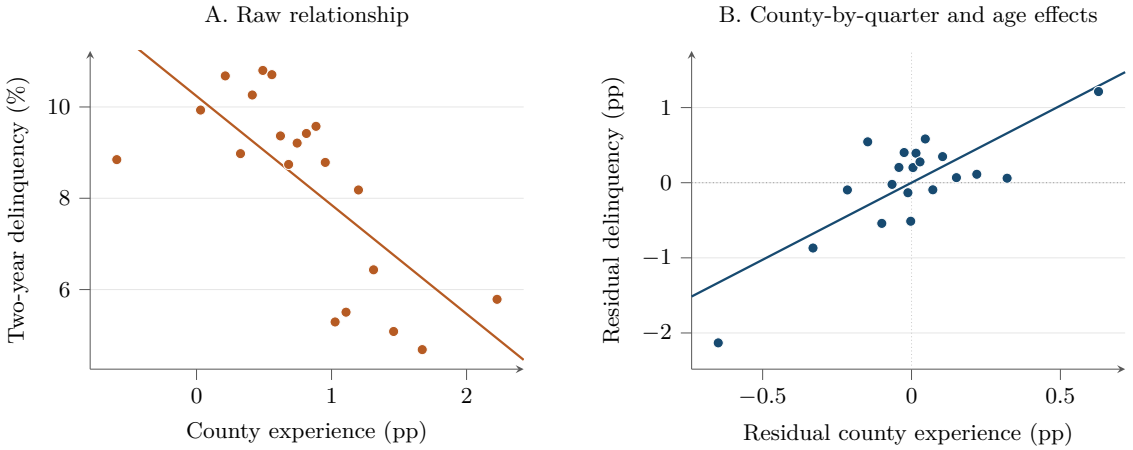
The IV estimates are positive for both outcomes and larger than the county baseline estimates. They imply interquartile increases of 11.25–12.14% in mortgage amount and 10.92–11.79% in the mortgage-to-area-price ratio. Together, these results connect higher experienced returns to a larger scale of mortgage borrowing. They do not separately identify changes in housing consumption and the financing share. Appendix A.3 reports the four-quarter lag and winsorization checks, the magnitude calculations, and the first-stage diagnostics.

3.4 Subsequent mortgage delinquency

Finally, we examine whether experienced returns at entry predict subsequent repayment outcomes. Table 5 shows that individuals with higher experience are more likely to experience mortgage delinquency over the following two years. The county, state, and three IV estimates are positive, with 95% intervals above zero.

In this sample, moving from the 25th to the 75th percentile of experienced county returns is

Figure 4: Raw and adjusted relationships between housing experience and delinquency



Notes: Both panels use the same 129,209 mortgage transitions at ages 25–49 and the two-year delinquency outcome. Dots show means within 20 bins, rebuilt for each specification. Panel A plots the unadjusted relationship; its line is fitted to the 20 bin means. Panel B removes county-by-quarter and exact-age fixed effects from both axes; its line uses the coefficient estimated from individual transitions. The horizontal axes and residual delinquency are in percentage points; unadjusted delinquency is in percent. Appendix Table A9 reports inference and the full-controls comparison. Because the estimation units differ, the slope difference is not a pure fixed-effects decomposition.

associated with an increase in two-year delinquency equivalent to 19.8% of the average delinquency probability, with a 95% confidence interval of 8.8% to 30.8% of that average. The corresponding state-experience estimate is 22.1% of the average probability, and the three IV estimates imply increases equivalent to 26.4–26.5% of the average probability for the county-experience percentile comparison.

The controls and fixed effects matter for the direction of this relationship (Figure 4). The raw binned association between experience and delinquency is negative, while the association becomes positive after county-by-quarter and age adjustment and remains positive with the full set of controls. Appendix A.4 reports these comparisons. The raw line is estimated from bin averages and the adjusted lines from individual observations, so their numerical difference cannot be attributed entirely to adding fixed effects.

We also examine lagged experience and a longer delinquency horizon. The two-year relationship remains positive and statistically significant when experience and its instrument are measured one to four quarters before entry. The county estimate declines from an increase equivalent to 18.3% of

the average two-year delinquency probability with a one-quarter lag to 15.1% with a four-quarter lag, using each specification's own 25th-to-75th percentile comparison. At the four-year horizon, the county estimate implies an increase equivalent to 9.0% of the average four-year delinquency probability for a move from the 25th to the 75th percentile of experience, with a 95% confidence interval that includes zero. The state estimate is significant at 5%, while the three IV estimates are significant at 10% but not 5%. Appendix Tables A7 and A6 report these regressions. Since the longer horizon changes both follow-up eligibility and the distribution of experience, differences across the two horizons do not isolate how the relationship evolves over time.

The results show a common pattern across mortgage entry, borrowing, and delinquency: individuals with more favorable housing-return histories enter mortgage holding more often, borrow more at entry, and subsequently experience more delinquency. These outcomes are measured in related but distinct samples, so they do not establish that borrowing mediates the delinquency relationship. In the next section, we develop a simple model to explain how experience-based expectations can generate these patterns.

4 Theoretical framework

In this section, we develop a simple model linking housing expectations to mortgage borrowing and repayment. Higher expected appreciation increases the household's desired home size, raising both its mortgage payment and the resources committed to the down payment. The resulting decline in available cash increases the probability of a missed payment. Under rational expectations, this response to housing experience requires experience to predict greater appreciation, holding other household circumstances fixed. With extrapolative beliefs, the same mechanism can operate even when actual price prospects remain unchanged.

Housing investment links the composition of household wealth to subsequent financial choices. Cocco (2005) shows how resources committed to housing limit the financial wealth available for portfolio investment, while Campbell and Cocco (2015) studies how mortgage affordability and income risk enter default decisions. We draw on these connections to isolate the effect of perceived

housing gains on the size of mortgage commitments. The two-date setting below holds current prices and loan terms fixed and focuses on home-size choice conditional on purchase.

4.1 Environment

The household chooses home size at date zero and sells the home at the end of date one. It begins with liquid wealth $w > 0$, housing experience e, and a mortgage with fixed loan-to-value ratio $\ell \in (0, 1)$. Normalizing the current price per unit of housing to one, a home of size h requires mortgage borrowing $M = \ell h$ and leaves liquid cash $a = w - (1 - \ell)h$. The household chooses h before observing its date-one income.

At the beginning of date one, the household receives income Y, net of essential spending, and faces a mortgage installment bh, where $b > 0$ is fixed. Income is uniformly distributed between zero and $\bar{y}$, written $Y \sim U[0, \bar{y}]$, and the household correctly perceives this distribution. The household cannot sell the home or obtain short-term borrowing against its future resources before the payment deadline. It therefore misses the installment if income and retained cash are insufficient to pay it in full. The probability of a miss is

$$p_D(h) = \Pr\{Y + a < bh\} = F_Y(Ch - w), \qquad C \equiv b + 1 - \ell > 0, \tag{2}$$

where F_Y is the income distribution. The term C combines the additional payment and the cash used for the additional down payment.

At the end of date one, the household sells the home and settles the remaining debt. An early installment reduces the balance due at settlement; a missed installment becomes arrears and incurs a utility cost $k > 0$. Cash earns no return within date one, and arrears accrue no additional interest over that interval. Sale proceeds and a terminal endowment ensure full repayment, but the endowment cannot be pledged before the installment deadline. Since postponement provides no financial gain and incurs the penalty, the household pays whenever it has sufficient cash. Payment risk therefore arises from a temporary liquidity shortfall. Appendix B sets out the terminal budget.

Utility is linear in consumption and additively separable in housing services, with no discounting.

Let $v(h) = \alpha h - \chi h^2/2$, $\chi > 0$, denote housing benefits net of financing costs. The household perceives expected appreciation $\mu(e) = \mathbb{E}^{\text{subj}}[P_1 - 1 \mid e]$, where P_1 is the terminal price per unit. After dropping terms that do not depend on h, its problem is

$$\max_{h \in \mathcal{H}} \; v(h) + \mu(e)h - kp_D(h). \tag{3}$$

Here $\mathcal{H} = [\underline{h}, \overline{h}]$ is a fixed interval of affordable home sizes satisfying $0 < Ch - w < \bar{y}$ throughout. We consider an interior solution in which the household's optimal home size lies strictly between the minimum and maximum feasible sizes. The down payment is feasible and payment risk lies strictly between zero and one. Linear consumption utility makes expected appreciation the relevant price-belief object, while the uniform income distribution and quadratic housing benefits give a closed-form solution.

4.2 Comparative statics

Higher perceived appreciation makes a larger home more attractive. Within the stated interval, the payment probability is linear in size: $p_D(h) = (Ch - w)/\bar{y}$. The unique interior optimum is

$$h^*(\mu) = \frac{\alpha + \mu - kC/\bar{y}}{\chi}. \tag{4}$$

The household balances housing services and expected appreciation against the financing cost and the expected cost of a missed payment. The latter enters the first-order condition through $kC/\bar{y}$. An increase in perceived appreciation raises the return to choosing a larger home and yields

$$\frac{\partial h^*}{\partial \mu} = \frac{1}{\chi}, \qquad \frac{\partial M^*}{\partial \mu} = \frac{\ell}{\chi}, \qquad \frac{\partial a^*}{\partial \mu} = -\frac{1-\ell}{\chi}, \qquad \frac{\partial p_D(h^*)}{\partial \mu} = \frac{C}{\chi \bar{y}} > 0. \tag{5}$$

The mechanism operates through both sides of the household's liquidity position. A larger property increases the mortgage payment, while its down payment reduces retained cash. More income is therefore needed to meet the installment. The household understands this tradeoff and accepts the higher payment risk because the perceived housing gain has risen. These comparative statics

hold locally with wealth, the income distribution, and financing terms fixed; the appendix gives the interior conditions and the treatment of binding size bounds.

4.3 Expectations and experience

We now consider two ways in which housing experience can affect perceived appreciation. Past price changes may contain information about subsequent returns, as in the evidence on housing-price persistence in Case and Shiller (1989). Let $g(e)$ denote true expected appreciation conditional on experience and the other fixed household circumstances. A household with rational expectations uses $\mu^{\mathrm{RE}}(e) = g(e)$, which implies

$$\frac{dp_D^{\mathrm{RE}}}{de} = \frac{C}{\chi \bar{y}} g'(e). \tag{6}$$

Experience raises payment risk through housing demand in this benchmark when $g'(e) > 0$. The household then chooses a larger mortgage and a greater chance of a missed payment in exchange for higher expected housing gains.

Experience can also shape beliefs through extrapolation. Motivated by the survey evidence in Kuchler and Zafar (2019), suppose that actual expected appreciation is constant at μ_0, while perceived appreciation follows $\mu^{\mathrm{EXP}}(e) = \mu_0 + \eta(e - e_0)$, with $\eta > 0$ and reference experience e_0. In this case,

$$\frac{dp_D^{\mathrm{EXP}}}{de} = \frac{C\eta}{\chi \bar{y}} > 0 \tag{7}$$

even though actual price prospects do not improve. The household's assessment of income risk is unchanged, but a more favorable view of housing gains leads it to make larger commitments. This role for expectations also appears in broader models of housing cycles, such as Kaplan et al. (2020). In our setting, the distinction between informative experience and extrapolation motivates a comparison of experienced returns with subsequent local appreciation. Section 5 combines that comparison with the borrowing and delinquency evidence.

5 Mechanism evidence

We next examine the model's predictions for mortgage commitments and the information contained in housing experience. The positive borrowing and delinquency associations are consistent with higher expected appreciation increasing the scale of housing investment and the risk of a payment shortfall. Favorable experience, however, predicts weaker subsequent county house-price appreciation; the ZIP estimates are also negative, though imprecise. County wage growth is higher. These results support a role for experience-based expectations while indicating that the information conveyed by past housing returns differs across local outcomes.

5.1 Borrowing and repayment

The borrowing results in Section 3 have the sign predicted by equation (5). Moving from the 25th to the 75th percentile of county housing experience in the borrowing sample is associated with 0.083 log points, or 8.66%, more recorded mortgage borrowing. The corresponding contrast in mortgage amount relative to the ZIP-area house price is 0.079 log points, or 8.19%. These borrowing percentages describe differences in the geometric mean implied by the log specification, calculated as $100[\exp(\widehat{\beta}\Delta E) - 1]$. For delinquency, moving from the 25th to the 75th percentile of experience in the delinquency sample is associated with an increase equivalent to 19.8% of the average two-year delinquency probability.

The connection between housing size and financing is central to interpreting these outcomes. As Bailey et al. (2019) emphasize, beliefs can affect both the amount invested in housing and the financing share. For property value V and area price Z, the two components satisfy

$$\log(M/Z) = \log(M/V) + \log(V/Z). \tag{8}$$

The first term is log loan-to-value, and the second captures the value of the purchased property relative to the area price. In our model, a household purchases a larger property at a fixed loan-to-value ratio, increasing both mortgage dollars and mortgage dollars relative to the area price. This is the margin captured by the borrowing predictions. Empirically, the two measures describe the

scale of commitments without separately identifying property-level loan-to-value.

The accompanying rise in delinquency is consistent with these larger commitments reducing the household's capacity to absorb an income shortfall. This connection between payment obligations and available resources is also central to the mortgage model of Campbell and Cocco (2015). Our model isolates the response conditional on purchase, initial resources, and loan terms. The empirical estimates describe related but different borrower samples and an eight-quarter delinquency outcome, so they do not quantify the share of subsequent delinquency attributable to greater borrowing.

5.2 Subsequent local economic outcomes

Equation (6) suggests a further empirical question: do the histories associated with greater borrowing also predict stronger subsequent appreciation? To examine this relationship, we regress future house-price growth in the transition county and ZIP on housing experience at the transition. We also consider county average weekly wage growth, which captures an additional dimension of local economic conditions. Each outcome follows the location at the transition, even if the borrower later moves.

Let $L^j_{g,t}$ be the level of local series j: county house prices, ZIP house prices, or county average weekly wages. For transition i at quarter t, define cumulative growth over $H \in \{8, 16\}$ quarters and estimate

$$G^j_{it,H} \equiv 100 \left(\frac{L^j_{g(i,t),t+H}}{L^j_{g(i,t),t}} - 1 \right) = \beta^j_H e^{\text{pp}}_{it} + X'_{it}\gamma^j_H + \mathcal{F}^j_{it} + u^j_{it,H}, \tag{9}$$

where e^{pp}_{it} is experienced county housing returns in percentage points, X_{it} contains the baseline controls, and $\mathcal{F}^j_{it}$ denotes the fixed effects. We measure cumulative growth from nominal levels over eight or sixteen quarters. Each regression uses the corresponding two- or four-year delinquency sample, subject to availability of the local outcome and required controls. Standard errors are clustered separately by county, age, and quarter.

The fixed effects reflect the geography of each outcome. Since county price and wage growth are common to all borrowers in a transition county-quarter, we include county effects, state-quarter effects, and age effects in those regressions. ZIP price growth varies within counties, allowing us

Table 6: Housing experience and subsequent local outcomes

	County house prices (1)	ZIP house prices (2)	County wages (3)
A. Two-year cumulative growth			
Experienced returns	-1.445^{***}	-0.198	0.362^{***}
	(0.244)	(0.202)	(0.112)
Transitions	128,942	129,171	129,107
B. Four-year cumulative growth			
Experienced returns	-3.336^{***}	-0.454	0.300^{***}
	(0.450)	(0.565)	(0.100)
Transitions	103,590	103,814	103,717
Baseline controls	Yes	Yes	Yes
County effects	Yes	—	Yes
State × quarter effects	Yes	—	Yes
County × quarter effects	—	Yes	—
Age effects	Yes	Yes	Yes

Notes: The dependent variable is cumulative growth in the transition county or ZIP over the indicated horizon, $100(L_{t+H}/L_t - 1)$, with $H = 8$ or 16 quarters. Location is held fixed at the mortgage transition. Coefficients are percentage points of growth per one-percentage-point increase in county housing experience. County wages are average weekly wages for all covered workers and industries. The starting samples are the corresponding two- and four-year delinquency samples. Experience and controls are measured at the transition. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County price and wage regressions include county, state-by-quarter, and age effects; ZIP price regressions include county-by-quarter and age effects. Standard errors in parentheses are clustered separately by county, quarter, and age. Appendix Table A10 reports 95% intervals. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

to retain the county-quarter and age effects from the baseline specification. The county regressions thus use a broader geographic comparison than the delinquency regression, while the ZIP regressions compare outcomes within the same county and quarter.

Table 6 shows that higher experienced returns predict weaker subsequent county appreciation. A one-percentage-point increase in experience is associated with 1.445 percentage points less cumulative appreciation over two years and 3.336 points less over four years. Both estimates are significant at the 1% level. The ZIP coefficients are also negative, at -0.198 and -0.454, but are not statistically distinguishable from zero. These estimates do not support the explanation that favorable histories identify transition counties with stronger subsequent appreciation. The ZIP evidence is less conclusive.

The wage results show a different pattern. A one-percentage-point increase in experience is associated with 0.362 percentage points more cumulative county wage growth over two years and

0.300 points more over four years, both significant at the 1% level. Thus, weaker subsequent appreciation coexists with stronger wage growth. County average wages capture local labor-market conditions, while the earnings and cash available to individual borrowers can follow different paths.

5.3 Interpretation and limitations

Taken together, the results are consistent with an expectations-based account of mortgage choices. More favorable histories are associated with larger commitments and greater subsequent delinquency, even though county appreciation is weaker. In the model, extrapolation generates this combination by increasing desired housing size without requiring an improvement in actual price prospects. The positive wage coefficients also suggest that housing experience can convey information about other local fundamentals.

The comparison concerns realized local outcomes, whereas the model's distinction concerns expected appreciation conditional on the household's information. Moreover, shared future county outcomes are already absorbed by the delinquency regression's county-quarter effects. The county price estimates therefore inform the interpretation of housing experience rather than directly accounting for the within-county-quarter delinquency relationship. Differences in property returns, borrower resources, and information can still affect mortgage choices. Direct evidence on expectations and on how commitments transmit into repayment would help distinguish these channels.

6 Conclusion

This paper studies how personal housing-return histories relate to mortgage participation, borrowing, and subsequent repayment. More favorable experience is associated with greater entry, larger mortgage commitments, and more delinquency over the following two years. A simple model connects borrowing and repayment through the scale of housing investment: higher expected appreciation encourages a larger purchase, which raises payment obligations and reduces retained cash. The finding that favorable experience predicts weaker county appreciation supports a role for experience-based expectations, while stronger county wage growth points to additional information

contained in these histories.

The estimates imply substantial differences in mortgage behavior. Comparing the 25th and 75th percentiles of experience within each outcome's sample gives an increase in quarterly entry equivalent to 10.0% of the average entry probability, 8.66% greater recorded mortgage amounts, and an increase in two-year delinquency equivalent to 19.8% of the average delinquency probability. State-experience and IV estimates have the same signs, and the entry and two-year delinquency relationships persist with lagged experience. These findings extend the evidence on mortgage participation to the commitments households undertake and the repayment outcomes that follow.

A first extension will use movers to distinguish earlier housing histories from conditions in the destination market. Following households across locations allows us to examine whether experiences accumulated before a move continue to predict mortgage choices among people who subsequently face similar local markets. Accounting for the timing and circumstances of moves will be central to separating persistent experience from the financial opportunities that influence residential choice.

We also plan to measure beliefs directly, building on the survey evidence linking housing experience to expectations (Kuchler and Zafar, 2019). Eliciting expected house-price changes alongside residential histories would allow us to examine how those histories shape forecasts and how forecasts relate to mortgage commitments. Comparing expectations with subsequent realizations would help distinguish optimistic assessments from accurate information. Together, the movers analysis and direct belief measurement can clarify how personal housing experience influences the gains households anticipate and the payment obligations they choose.

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A Empirical details and robustness

This appendix presents the additional regressions and variable definitions for Section 3. The positive entry and two-year delinquency relationships remain when housing experience is lagged by up to four quarters. Alternative history weights and the four-year delinquency horizon produce more variation in precision. We organize the results in the same order as the main empirical section.

A.1 Entry

To assess whether the entry results depend on contemporaneous housing experience, we re-estimate the baseline using experience and its instrument at $t-1$ through $t-4$. Table A1 reports the results. We keep all other controls, including economic experiences and local housing conditions, at t. The county, state, and three IV coefficients remain positive and significant at 1% at every lag. The five columns use the same sample within each lag, although the samples can differ across lags.

Table A1: Mortgage entry with lagged housing experience

	County OLS	State OLS	IV: equal	IV: distance	IV: units
	(1)	(2)	(3)	(4)	(5)
Experience at $t-1$	0.230***	0.251***	0.281***	0.277***	0.284***
	(0.073)	(0.083)	(0.093)	(0.091)	(0.092)
Person-quarters	9,772,699	9,772,699	9,772,699	9,772,699	9,772,699
Experience at $t-2$	0.230***	0.248***	0.282***	0.278***	0.285***
	(0.073)	(0.081)	(0.091)	(0.088)	(0.089)
Person-quarters	9,750,980	9,750,980	9,750,980	9,750,980	9,750,980
Experience at $t-3$	0.222***	0.236***	0.273***	0.269***	0.273***
	(0.071)	(0.078)	(0.089)	(0.086)	(0.087)
Person-quarters	9,727,998	9,727,998	9,727,998	9,727,998	9,727,998
Experience at $t-4$	0.214***	0.224***	0.261***	0.259***	0.261***
	(0.069)	(0.076)	(0.087)	(0.085)	(0.086)
Person-quarters	9,703,843	9,703,843	9,703,843	9,703,843	9,703,843

Notes: The dependent variable and sample restrictions follow Table 2. Housing experience and its matching instrument are dated at the indicated lag; all controls remain at t. The five columns use the same eligible sample within a lag, while samples can differ across lags. Coefficients are percentage-point changes in entry per one-percentage-point increase in experience. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County-by-quarter and exact-age fixed effects are included. Standard errors in parentheses are clustered separately by county, quarter, and age. The state-experience column instead clusters by state, quarter, and age. Tests use 24 degrees of freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A2: Mortgage entry with alternative history weights

History parameter λ	0	1	2	3	4
Experienced returns	0.076	0.228***	0.205***	0.157**	0.105
	(0.059)	(0.075)	(0.071)	(0.074)	(0.078)
Person-quarters	9,772,699	9,772,699	9,772,699	9,772,699	9,772,699

Notes: Columns vary the parameter used to summarize county housing-return histories. Larger positive λ places more weight on recent returns; $\lambda = 1$ is the baseline. The sample and controls follow Table 2. Coefficients are percentage-point changes in entry per one-percentage-point increase in experience. County-by-quarter and exact-age fixed effects are included. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 24 degrees of freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

We next vary the parameter that determines the relative importance of recent returns. Table A2 reports county estimates for $\lambda = 0, \ldots, 4$. All five coefficients are positive. With equal history weights, $\lambda = 0$, the estimate is positive but not statistically significant. The coefficients remain significant at 5% for $\lambda = 2$ and 3, but not 4. The positive sign is therefore common across these choices, while the magnitude and precision depend on how the return history is summarized.

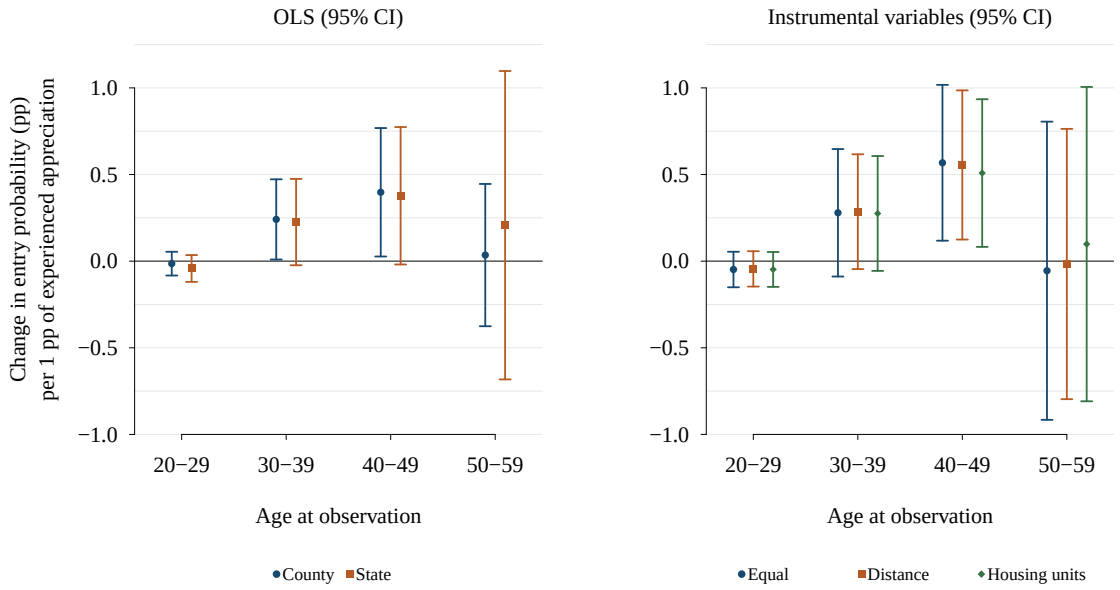
Figure A1 reports the age-specific entry regressions using experience four quarters before the outcome. The county estimate for ages 40–49 is positive, and its 95% confidence interval excludes zero. This differs from the contemporaneous estimate in Figure 3, whose 95% interval includes zero. Both figures have smaller point estimates for the youngest and oldest groups, although they do not establish that the coefficients differ statistically across ages. The entry robustness results reported here use linear probability models.

A.2 End-of-panel mortgage status

For the end-of-panel regressions, we select each individual's final observed quarter and then restrict age to 31–59. We do not replace an ineligible endpoint with an earlier observation. The sample includes both existing mortgage holders and individuals with no observed entry. We include separate county, quarter, and age fixed effects, together with current demographics, credit ratios, economic and inflation experiences, and ZIP house-price levels.

Table A3 reports the results using alternative history weights and one- to four-quarter lags. All specifications contain the same 293,183 individuals. The county coefficients remain positive, but

Figure A1: Mortgage entry by age with experience measured four quarters earlier



Notes: The figure reports the percentage-point change in entry per one-percentage-point increase in housing-return experience at $t-4$, with 95% confidence intervals. All other controls remain at t. Models include county-by-quarter and exact-age fixed effects within each band. Standard errors are clustered separately by county, quarter, and age, except state OLS, which clusters by state, quarter, and age. Confidence intervals use 8 degrees of freedom for ages 20–29 and 9 for each older group. The age-specific samples differ from the pooled ages-25–49 baseline.

decline when we place greater weight on recent returns or lag housing experience. The state and IV coefficients are also positive, with varying precision. Only housing experience and its instrument change across these specifications; the other controls remain measured at the endpoint.

The county and state logit specifications did not converge, so we do not report them as robustness evidence. Table A5 reports the first-stage statistics for the linear IV estimates. The outcome tables note the covariance corrections used in their reported inference.

A.3 Mortgage borrowing

The borrowing regressions include mortgage transitions at ages 25–49 with positive finite mortgage amounts and ZIP prices. We retain repeat transitions and do not require future delinquency follow-up. The ten baseline regressions each contain 144,265 transitions by 105,539 individuals; each model uses its own eligible observations.

Table A3: End-of-panel mortgage status: history weights and lags

	County OLS (1)	State OLS (2)	IV: equal (3)	IV: distance (4)	IV: units (5)
$\lambda = 2$, current	1.922***	1.779*	1.525	2.178**	2.975**
	(0.638)	(0.933)	(1.272)	(0.922)	(1.444)
$\lambda = 3$, current	1.373*	1.440*	1.196	1.750***	2.346**
	(0.774)	(0.715)	(1.118)	(0.576)	(0.918)
$\lambda = 1$, $t - 1$	2.551***	1.501	1.878	2.629*	3.270*
	(0.692)	(1.207)	(1.705)	(1.354)	(1.857)
$\lambda = 1$, $t - 2$	2.404***	1.327	1.699	2.439*	3.094
	(0.709)	(1.234)	(1.745)	(1.381)	(1.893)
$\lambda = 1$, $t - 3$	2.377***	1.276	1.496	2.238	2.855
	(0.735)	(1.292)	(1.805)	(1.458)	(1.981)
$\lambda = 1$, $t - 4$	2.297***	1.121	1.302	2.012	2.701
	(0.731)	(1.340)	(1.710)	(1.434)	(2.011)
People	293,183	293,183	293,183	293,183	293,183

Notes: The dependent variable, sample, controls, and separate county, quarter, and age effects follow Table 3. Only the history parameter or timing of housing experience and its matching instrument changes. Each specification contains 293,183 people. Coefficients are percentage-point changes per one-percentage-point increase in experience. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 28 degrees of freedom. Standard errors incorporate the reported covariance correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

To interpret the magnitudes, let M_{it} denote the recorded mortgage amount and $P_{z(i,t),t}$ the current ZIP price. We use $\log M_{it}$ and $\log M_{it} - \log P_{z(i,t),t}$ as dependent variables. When experience is in decimal units, a coefficient $\widehat{\beta}$ implies a change of $0.01\widehat{\beta}$ log points for a one-percentage-point change in experience. For an experience difference ΔE, the corresponding percentage change in the conditional geometric mean is $100\{\exp(\widehat{\beta}\Delta E) - 1\}$. We transform the confidence-interval endpoints in the same way, treating the experience percentiles as fixed.

The county interquartile change in log mortgage amount is 0.08301, with a 95% interval of [0.06242, 0.10360]. The change in the log mortgage-to-area-price ratio is 0.07868, with an interval of [0.05736, 0.10001]. We exponentiate these changes to obtain the 8.66% and 8.19% magnitudes in the main text. Dividing a log change by the mean log outcome would instead give a normalization in log units, rather than the percentage change in the underlying amount or ratio.

Table A4 examines lagged experience and winsorization. When experience is measured four

Table A4: Borrowing with lagged experience and outcome winsorization

	County OLS	State OLS	IV: equal	IV: distance	IV: units
A. Mortgage amount: experience at $t-4$					
Change in amount (%)	8.815^{***}	11.526^{***}	12.539^{***}	11.935^{***}	12.769^{***}
95% interval	[5.09,12.68]	[6.64,16.64]	[6.41,19.02]	[6.13,18.06]	[6.91,18.95]
Transitions	144,015	144,015	144,015	144,015	144,015

B. Log mortgage amount: current county experience	Baseline	Winsorized at 1st/99th percentiles
Experienced returns	0.11074^{***}	0.10894^{***}
	(0.01331)	(0.01321)
Transitions	144,265	144,265

Notes: Both panels include mortgage transitions at ages 25–49, with the controls and fixed effects in Table 4. Panel A reports the percentage difference in the conditional geometric mean per one-percentage-point increase in experience, with 95% intervals in brackets. Housing experience and its instrument are dated $t-4$; controls remain at t. Panel B reports log-point coefficients for current county experience; the second column winsorizes mortgage amounts at the baseline sample's 1st and 99th percentiles. Standard errors in parentheses are clustered separately by county, quarter, and age; tests use 24 degrees of freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

quarters earlier, the county mortgage-amount estimate implies an 8.815% increase per percentage point of experience, with a 95% interval of [5.086%, 12.676%]. The state and IV estimates also remain positive. Winsorizing log mortgage amount—replacing values below the 1st percentile or above the 99th percentile with the respective cutoff— changes the county coefficient from 0.11074 to 0.10894 log points per percentage point of experience, with standard errors of 0.01331 and 0.01321, respectively. We retain the other controls at the transition quarter in both exercises.

Table A5 reports the first-stage statistics across outcome samples. Each column corresponds to a separate instrument based on equal, inverse-distance, or housing-unit donor weights. The instruments strongly predict county experience in the borrowing regressions, as in the entry and delinquency regressions. These statistics assess relevance; they do not test the exclusion restriction.

A.4 Delinquency outcomes

We construct the two- and four-year delinquency outcomes from the same quarterly definition. Missing mortgage-open status is coded as no open mortgage. A missing delinquency flag is coded zero when an open mortgage is present and remains unknown otherwise. For each horizon, we

Table A5: First-stage relevance across outcome samples

Instrument	Equal	Distance	Housing units
Entry	1967.56	2452.82	2071.53
End-of-panel status	1479.37	655.11	595.89
Mortgage amount / ZIP price	2881.62	3446.72	2990.33
Mortgage amount	2881.62	3446.72	2990.33
Two-year delinquency	2848.42	3269.90	2832.48
Four-year delinquency	2141.25	2342.81	2081.74

Notes: Entries are the single-instrument clustered Wald F statistics for the first stage of each IV regression. Samples, controls, and fixed effects follow the corresponding outcome table. Entry, borrowing, and delinquency use county-by-quarter and age effects; endpoint models use separate county, quarter, and age effects. All IV models cluster separately by county, quarter, and age. These statistics assess instrument relevance, not the exclusion restriction.

require every future calendar quarter to be observed with a known outcome and record whether any quarter has a delinquency. An observed delinquency does not override a missing quarter elsewhere in the horizon. Individuals with administratively incomplete follow-up are excluded rather than assigned a zero outcome.

Table A6 reports the results for delinquency over sixteen quarters. Moving from the 25th to the 75th percentile of experienced county returns is associated with an increase in four-year delinquency equivalent to 9.0% of the average delinquency probability, with a 95% confidence interval of [−2.0%, 19.9%] of that average. Thus, the point estimate remains positive but is less precise than the two-year estimate. The four-year sample applies its own follow-up requirements and fixed-effect singleton exclusions, so it is not a common-sample comparison of the two horizons.

Table A7 reports the two-year regressions with housing experience and its instrument measured one to four quarters earlier. We keep the remaining controls at the transition quarter. All housing coefficients remain positive and significant at 1%. The county sample decreases from 129,209 transitions at the one-quarter lag to 128,971 at the four-quarter lag, so comparisons across lags also reflect small changes in the eligible sample.

We also compare the complete-known-follow-up rule with an earlier definition that records any observed raw delinquency over sixteen quarters and otherwise assigns zero while ignoring missing flags. This alternative still requires observed history through $t+16$ and includes the actual thirteenth lead. It does not assign zero to administratively incomplete follow-up.

Table A6: Housing experience and mortgage delinquency within four years

	County OLS	State OLS	IV: equal	IV: distance	IV: units
	(1)	(2)	(3)	(4)	(5)
Experienced returns	1.725	2.315**	2.251*	2.295*	2.420*
	(1.018)	(1.000)	(1.253)	(1.240)	(1.216)
Transitions	103,825	103,825	103,825	103,825	103,825
People	80,678	80,678	80,678	80,678	80,678
Outcome mean (%)	11.616	11.616	11.616	11.616	11.616
R^2	0.5489	0.5490	0.5489	0.5489	0.5489
First-stage Wald F	—	—	2,141.2	2,342.8	2,081.7

Notes: The dependent variable equals one for any mortgage delinquency in quarters $t+1$ through $t+16$, requiring a known outcome in every quarter. The sample contains entrants aged 25–49 from 2010Q2 to 2021Q1, including repeat transitions. Coefficients are percentage-point changes per one-percentage-point increase in experience. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County-by-quarter and exact-age fixed effects are included. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 24 degrees of freedom. The county experience IQR is 0.604 percentage points. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A7: Two-year mortgage delinquency with lagged housing experience

	County OLS	State OLS	IV: equal	IV: distance	IV: units
	(1)	(2)	(3)	(4)	(5)
Experience at $t-1$	2.212***	2.675***	2.940***	2.932***	2.938***
	(0.623)	(0.644)	(0.734)	(0.728)	(0.746)
Transitions	129,209	129,209	129,209	129,209	129,209
Experience at $t-2$	2.111***	2.540***	2.762***	2.765***	2.770***
	(0.592)	(0.623)	(0.725)	(0.715)	(0.732)
Transitions	129,154	129,154	129,154	129,154	129,154
Experience at $t-3$	2.001***	2.400***	2.609***	2.623***	2.626***
	(0.566)	(0.604)	(0.718)	(0.705)	(0.719)
Transitions	129,092	129,092	129,092	129,092	129,092
Experience at $t-4$	1.851***	2.286***	2.502***	2.514***	2.515***
	(0.538)	(0.573)	(0.689)	(0.678)	(0.689)
Transitions	128,971	128,971	128,971	128,971	128,971

Notes: The dependent variable and sample restrictions follow Table 5. Housing experience and its matching instrument are dated at the indicated lag, while all controls remain at the transition quarter. Each lag uses its own eligible sample. Coefficients are percentage-point changes in delinquency per one-percentage-point increase in experience. Controls include demographics, credit ratios, economic and inflation experiences, and current ZIP house-price and rent controls. County-by-quarter and exact-age fixed effects are included. Standard errors in parentheses are clustered separately by county, quarter, and age. Tests use 24 degrees of freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A8: Earlier four-year delinquency definitions: repeat-transition comparison

	County OLS	State OLS	IV: equal	IV: distance	IV: units
A. Complete known canonical follow-up					
Experienced returns	0.859**	1.189***	1.414***	1.395***	1.335***
	(0.411)	(0.407)	(0.460)	(0.444)	(0.456)
Transitions	122,040	122,040	122,040	122,040	122,040
People	94,373	94,373	94,373	94,373	94,373
B. Ignore missing raw delinquency flags					
Experienced returns	0.922**	1.222***	1.433***	1.421***	1.333***
	(0.411)	(0.399)	(0.466)	(0.451)	(0.457)
Transitions	124,068	124,068	124,068	124,068	124,068
People	95,742	95,742	95,742	95,742	95,742

Notes: These earlier specifications include repeat mortgage transitions at ages 18–49 and a sixteen-quarter horizon. Controls include demographics, credit ratios, and economic and inflation experiences, with county-by-quarter and age fixed effects. Current ZIP price and rent controls are excluded. Panel A requires a known canonical delinquency outcome in every future quarter. Panel B records any observed raw delinquency, otherwise zero while ignoring missing flags, and requires observed history through $t + 16$. Coefficients are percentage-point changes per one-percentage-point increase in experience. Standard errors in parentheses are clustered separately by county, quarter, and age. These are comparisons within the earlier four-year specification. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A8 presents this comparison for an earlier specification using repeat transitions at ages 18–49 and a four-year horizon. The county estimates are positive and statistically significant under both complete known follow-up and the alternative rule. Both specifications include demographics, credit ratios, and economic experiences, without the current ZIP housing and rent controls. On observations eligible under both definitions, the outcomes agree; the difference operates through eligibility. This exercise assesses the earlier four-year outcome convention rather than providing a matched comparison for the current two-year baseline. Earlier delinquency logit and probit specifications did not converge and are not used as robustness evidence.

Finally, Table A9 compares the raw and adjusted relationships between experience and two-year delinquency using the same 129,209 transitions. The raw slope is negative, while the slopes after county-by-quarter and age adjustment and after the full controls are positive. The raw line is estimated from 20 bin means, with equal importance given to each bin and conventional line-fit standard errors. The adjusted lines are estimated from individual observations with three-way clustered standard errors. Since the estimators differ, the change in slopes cannot be attributed entirely to the addition of fixed effects and controls.

Table A9: Raw and adjusted two-year delinquency associations

	Raw binned	Fixed effects	Full controls
	(1)	(2)	(3)
Experienced returns	-2.385^{***}	2.051^{***}	2.374^{***}
	(0.546)	(0.627)	(0.637)
Estimation observations	20 bins	129,209	129,209
County × quarter effects	No	Yes	Yes
Age effects	No	Yes	Yes
Baseline controls	No	No	Yes

Notes: All three specifications describe the same underlying 129,209 mortgage transitions. Coefficients are percentage-point changes in delinquency per one-percentage-point increase in county experience. The raw regression fits an intercept and slope through 20 bin means and uses conventional line-fit standard errors. Columns (2) and (3) use individual transitions, with standard errors clustered separately by county, quarter, and age. Column (2) includes county-by-quarter and age effects; column (3) adds the baseline controls. Because the estimation units differ, the coefficient difference is not a pure fixed-effects decomposition. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.5 Variable transformations and inference

Our demographic controls include the numbers of adults and children, retaining observed zeros, and categorical measures of marital status and gender. The four credit controls divide credit-card balances by limits and student, auto, and unsecured balances by their recorded account amounts. Missing or undefined ratios are assigned one. Infinite ratios remain nonfinite and are excluded when the control is required, while finite negative ratios are retained. These variables are not uniformly capped at one.

We express ZIP house-price levels in units of \$100,000 and rent levels in units of \$1,000. House-price growth compares the current ZIP's price at t with its price at exactly $t - 4$, holding the ZIP fixed for movers. The within-ZIP rent interpolation uses the value four observed rows ahead and the row's position in that sequence; when the forward value is unavailable, the source rent is retained. Rent growth compares with four observed rows earlier. Gaps in the source series mean that four rows need not correspond to four calendar quarters, and the interpolation can use future observations. We set missing rent levels and growth to zero and include separate indicators for their original missingness. The end-of-panel regressions retain only the ZIP price level from this set of housing controls.

The economic-experience controls summarize county employment, average weekly-wage, and

establishment growth, together with state inflation experience. They use the baseline history-weighting parameter and current timing; the inflation construction permits national fallback. The history weights determine how returns at different dates contribute to experience, while the donor weights determine which other counties contribute to each instrument.

Each regression applies its outcome-specific follow-up and complete-case requirements. The borrowing, delinquency, and end-of-panel regressions recursively exclude fixed-effect singletons. The entry regressions retain their complete-case family samples without automatic singleton removal. Clustering treats geography, quarter, and age as three separate dimensions. The baseline ages-25–49 tests use 24 degrees of freedom, the end-of-panel tests use 28, and the age-band figures use 8 or 9, as stated in their notes. Reported p-values are not adjusted for multiple specifications. The regressions do not add a separate individual cluster; an individual who moves can belong to different geographic clusters over time.

B Derivations for the housing-choice model

This appendix derives the household's objective and the comparative statics in Section 4. We first express terminal resources after an early payment or a missed installment, then solve the housing-choice problem. On the specified interval of home sizes, the objective is strictly concave, and higher expected appreciation increases housing size, mortgage borrowing, and payment risk.

B.1 Settlement and the reduced objective

Let $r \geq 0$ be the mortgage interest rate over the full horizon and let $q = bh$ be the early installment, with $0 < b \leq (1 + r)\ell$. Total debt repayment is $(1 + r)M$, including this installment. The terminal endowment T arrives after the installment deadline and cannot support early borrowing. Assume nonnegative resale prices under both true and subjective beliefs, and choose T large enough that terminal consumption is positive for every feasible home size and income realization. Terminal sale and full repayment are required; surrender is not an option in this example.

If the household pays q at the beginning of date one, it carries $Y + a - q$ into the terminal

settlement and owes $(1+r)M-q$. If it misses the installment, it retains $Y+a$ and owes $(1+r)M$. Thus, in either case, terminal consumption is

$$c_1 = T + Y + a + P_1 h - (1+r)M. \tag{10}$$

The installment changes the timing of repayment but leaves total terminal resources unchanged. A miss incurs the utility penalty k. With no return on cash, no additional arrears interest within date one, and no discounting, an affordable payment strictly dominates a voluntary miss. An unaffordable installment becomes arrears and is settled at the terminal date.

Write gross housing-service utility as $s(h) = \widetilde{\alpha}h - \chi h^2/2$. Substituting $M = \ell h$, $a = w-(1-\ell)h$, and $\mathbb{E}^{\text{subj}}[P_1] = 1+\mu$ into expected utility gives

$$\mathbb{E}^{\text{subj}}[c_1 + s(h) - k\mathbf{1}\{Y + a < bh\}] = T + w + \mathbb{E}[Y] + (\widetilde{\alpha} - r\ell + \mu)h - \frac{\chi}{2}h^2 - kp_D(h).$$

Defining $\alpha \equiv \widetilde{\alpha} - r\ell$ yields equation (3). The purchase price is paid through the down payment and mortgage settlement, while the terminal sale returns the home value. A sufficient condition for positive consumption is $T > (1+r)\ell\overline{h}$, because Y, a, and $P_1 h$ are nonnegative throughout the feasible interval.

B.2 Interior restrictions and comparative statics

Choose $0 < \underline{h} < \overline{h} \leq w/(1-\ell)$ such that

$$w < C\underline{h} < C\overline{h} < w + \bar{y}, \qquad C = b + 1 - \ell.$$

These restrictions ensure affordable down payments and an interior payment probability for every $h \in \mathcal{H}$. Uniform income implies $p_D(h) = (Ch - w)/\bar{y}$ there. The first and second derivatives of the objective are

$$W_h = \alpha + \mu - \chi h - \frac{kC}{\bar{y}}, \qquad W_{hh} = -\chi < 0.$$

The unique optimum lies strictly inside $\mathcal{H}$ if

$$\chi \underline{h} < \alpha + \mu - \frac{kC}{\bar{y}} < \chi \overline{h}.$$

Solving $W_h = 0$ gives equation (4); differentiating it and the definitions of M, a, and p_D gives equation (5). The restrictions continue to hold in the neighborhood of beliefs under consideration. A binding size bound makes the response locally zero. On a wider feasible set, the payment probability is $\min\{1, \max\{0, (Ch - w)/\bar{y}\}\}$, with the corresponding boundary regimes treated separately.

With other states fixed, the chain rule gives

$$\frac{dp_D(h^*(\mu(e)))}{de} = \frac{C}{\chi \bar{y}} \mu'(e).$$

Rational expectations set $\mu'(e) = g'(e)$, while the extrapolative rule sets $\mu'(e) = \eta$. When experience contains no information about actual appreciation, $g'(e) = 0$; when it predicts greater appreciation, the rational household also increases its housing commitment and payment risk. The comparison holds the remaining household states fixed. Relating these policy derivatives to a regression among mortgage entrants additionally requires accounting for differences in those states and selection into borrowing.

C Additional results for subsequent local outcomes

This appendix reports the confidence intervals for the local-outcome regressions in Section 5. Higher experienced returns predict lower subsequent county house-price appreciation at both horizons and higher county wage growth. The ZIP house-price coefficients are negative but are not statistically distinguishable from zero.

Table A10: Confidence intervals for subsequent local outcomes

Outcome	Horizon	Estimate	95% confidence interval
County house prices	2 years	-1.445^{***}	$[-1.949, -0.940]$
	4 years	-3.336^{***}	$[-4.265, -2.407]$
ZIP house prices	2 years	-0.198	$[-0.614, 0.218]$
	4 years	-0.454	$[-1.621, 0.712]$
County weekly wages	2 years	0.362^{***}	$[0.132, 0.592]$
	4 years	0.300^{***}	$[0.094, 0.506]$

Notes: The regressions are those in Table 6. Coefficients are percentage points of cumulative outcome growth per one-percentage-point increase in county housing experience. Confidence intervals use the same clustered inference as the main table. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.