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Borrower Expectations and Mortgage Performance: Evidence from the COVID-19 Pandemic

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Abstract

We assess issues related to borrower beliefs and mortgage performance using new individual panel data that simultaneously cover borrower expectations, forbearance status during the COVID-19 pandemic, and a wide array of demographic characteristics. First, we establish the determinants of borrower expectations, with local experiences and those of social networks playing important roles. We then show that households who, at origination, were optimistic about future house price appreciation or pessimistic about the possibility of future unemployment were more likely to enter forbearance in 2020. However, by early 2021, appreciation-optimistic borrowers who were in forbearance were likely to have cured or prepaid their loan, while those who expected unemployment were likely to still be in forbearance. We offer three channels by which expectations affect forbearance behavior: choices of initial loan terms, associations with actual future events, and factors related to belief formation that are also plausibly associated with forbearance. Our findings highlight the crucial role borrower expectations play in both leverage choices and mortgage performance.

Keywords: Behavioral Economics · Employment · Forbearance · Expectations.

JEL Classification: E21, E32, G41, G51, R31.

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1 Introduction

Individual expectations of future house price appreciation are known to be core drivers of behavior in the housing and mortgage markets, including house price dynamics (Case and Shiller, 1988; Glaeser and Nathanson, 2015; Adelino et al., 2018; Kaplan et al., 2020), choices of loan terms (Geanakoplos, 2010; Brueckner et al., 2012, 2016; Bailey et al., 2019), and portfolio decisions (Armona et al., 2019). Despite the clear importance of income shocks in these same modeling frameworks, little is known about the effects of income expectations. Mortgage performance is another relative blind spot; while it is known that expectations drive non-random selection and embedded options in standard mortgage contracts (e.g. Capone and Cunningham, 1992; Brueckner, 2000), few studies have linked explicit measures of individual-level beliefs to mortgage performance.

The COVID-19 pandemic led to a sharp decline in employment and consumer demand (Chetty et al., 2020), stifling the ability of households to make their obligated monthly payments. In response to these events, policy initiatives, largely driven by the Federal Housing Finance Agency (FHFA) and the CARES Act, led to both voluntary and directed expansions of forbearance agreements.[1] These agreements, which typically allow borrowers to pause or reduce their mortgage payments without adverse action by the servicer or lender, rose dramatically in the early COVID-19 period: between January 2020 and May 2020, the share of first-lien loans in forbearance surged from 0.3% to 8.3% (Figure 1). Nearly a year later, in April 2021, the share of borrowers in forbearance had fallen by over half, to 4.1%.

In this paper, we use newly-released data from the National Mortgage Database® (NMDB) and its associated National Survey of Mortgage Originations (NSMO) to explore forbearance behavior during the COVID-19 pandemic. Our data are comprehensive and integrated, allowing us to combine borrower-level demographic, geographic, and loan-level characteristics, house price and income expectations, and mortgage performance at a monthly frequency. These features allow us to isolate plausibly exogenous variation in individual beliefs and trace these effects on loan origination characteristics and loan performance over time.

We use these data to document the drivers of initial borrower expectations before the pandemic began, how expectations drove borrower loan characteristics, and how these two factors

[1] The CARES act is the Coronavirus Aid, Relief, and Economic Security Act of 2020. We describe the COVID-19 forbearance policy setting in greater detail in the next section.

affect forbearance behavior during the pandemic. We offer several main findings. First, prior house price appreciation in an individual's county and housing price weighted-growth from the individual's social network (see Bailey et al., 2018) are important drivers of expectations at origination, conditional on a number of demographic variables, measures of financial sophistication and risk preferences, and fixed effects (see also Redmer, 2019), consistent with prior work (Kuchler and Zafar, 2019; Makridis, 2021).[2] Unemployment expectations at loan origination are much more idiosyncratic, only loosely associated with the social network-weighted unemployment rate, and not the unemployment rate of the borrower's location.

We then turn to analysis of beliefs and mortgage performance. Borrowers who, at origination, expected house prices to *Increase a lot* are 1.7 percentage points (pp) more likely to enter forbearance, whereas those who expect they will *Increase a little* are 1.1pp more likely to enter forbearance, both relative to those who expect house prices to *Remain about the same*. Borrowers who, at origination, expected themselves or their spouse to be at risk of unemployment at some point in the near future were about 2.0pp more likely to enter forbearance, compared to those who did not expect future employment loss. Our estimates are identified by isolating variation within the same state and year, and are remarkably robust, controlling for a wide array of demographic, loan-level, income, and financial sophistication characteristics, including prior same-county house price appreciation. We also control for prior selection of seasoned loans into the national portfolio at the start of the pandemic. The invariance of our estimates to these controls and modeling choices points towards a causal interpretation and the presence of economically meaningful and statistically relevant information contained in borrower expectations.

Next, we establish three mechanisms for this behavior. First, there is a small association between expectations and loan characteristics at origination. Appreciation-optimistic borrowers ("increase a little/a lot" compared to neutral or pessimistic borrowers) have 1.7pp higher debt service-to-income (DTI) ratios and 1.3pp higher loan-to-value (LTV) ratios, indicating effects of expectations on the household balance sheet.[3] Households who expect a layoff ("somewhat or very likely") issue loans with 0.7pp lower LTVs. Overall, appreciation

[2]The NSMO survey is given to borrowers within a year of origination. We use the terms "at origination" or "shortly after origination" interchangeably and in reference to this survey. We also use the terms "layoff expectations" and "unemployment expecations" interchangeably.

[3]This estimate of the effect of appreciation expectations on LTVs is opposite in sign (+) to Bailey et al. (2019).

optimism has a 1.7pp direct effect and 0.2pp indirect effect due to variation in origination DTIs. Because CLTV has a negligible association with forbearance uptake, there is no measurable effect of individual unemployment expectations through the origination characteristics channel. Accordingly, house price expectations serve to amplify forbearance risk due to differences in loan characteristics, while effects of income risk are primarily direct. Additionally, these results show that adverse selection into mortgage characteristics in the vein of Brueckner (1994) and Piskorski and Tchistyi (2010) due to beliefs is present, but fairly small. Our results on expectations are also consistent with Gorton (2010) and Foote et al. (2012a) who emphasize the role of expectations driving an allocation towards securitized and nontraditional mortgage products prior to the financial crisis.

A second mechanism relating the effects of beliefs to forbearance is the association with future events. According to preliminary data from the American Survey of Mortgage Borrowers (ASMB), jointly produced by the FHFA and the Consumer Finance Protection Bureau (CFPB), and fielded between October 2020 and February 2021, 78% of those in forbearance also experienced a job loss or loss in income in the COVID-19 period.[4] While we do not observe the future individual employment experiences of borrowers in our expectations dataset, this additional *ex post* survey evidence strongly suggests that those who expected unemployment may have in fact become unemployed at higher rates than the general population.

The final channel we examine are factors related to expectations formation that are also plausibly related to forbearance. We show that individuals who view housing as a good investment, who identify as being likely to move soon, and those with high levels of financial sophistication are likely to have high appreciation optimism and forbearance uptake. Borrowers who have purchased distressed properties are more likely to have high appreciation expectations, consistent with a speculation channel (Mian and Sufi, 2021). However, borrowers who believe strategic default to be an ethical behavior did not go into forbearance at higher rates, conditional on expectations and other controls. This suggests those in forbearance may not plan on defaulting for strategic reasons at the end of the forbearance period.

[4]See `https://www.consumerfinance.gov/data-research/american-survey-mortgage-borrowers/` for more information on the ASMB.

Finally, we examine the forbearance status of borrowers at the end of our sample, in March 2021, for most of our analysis. A summary estimate of forbearance rates by origination beliefs is shown in Figure 2.[5] Appreciation-optimistic borrowers are no more likely to be in forbearance in March 2021, than those who were not optimistic at origination. These borrowers, on average, entered forbearance at higher rates, but then returned to current status or prepaid their loan in the intervening year at higher rates in a manner that completely offset the initial forbearance effects. On the other hand, borrowers who expect the possibility of future unemployment were more likely to still be in forbearance in 2021. We also find that lower borrower education, purchase loans (versus refinance), and measured risk tolerance are all related to entering and remaining in forbearance. These findings suggest forbearance behavior during the COVID-19 pandemic can be grouped into three main categories: for sophisticated borrowers, as an option to mitigate the possibility of future income risk; as a stop-gap for borrowers planning on moving and/or refinancing; or as a necessity due to loss of income.

Our paper builds on a large literature relating the effects of expectations on real economic activity. Although there has been a recognition since at least Keynes (1936) that expectations matter for explaining business cycle fluctuations, isolating plausibly exogenous variation in micro-data has been difficult. However, an emerging body of work now points towards a causal effect of individuals' economic sentiment on consumption (Gillitzer and Prasad, 2018; Benhabib and Spiegel, 2019; Makridis, 2021). Others have demonstrated how expectations of future house price appreciation are important determinants of house price dynamics (Case and Shiller, 1988; Glaeser and Nathanson, 2015; Adelino et al., 2018; Kaplan et al., 2020), choices of loan terms (Geanakoplos, 2010; Brueckner et al., 2012, 2016; Bailey et al., 2019), and portfolio decisions (Armona et al., 2019). We show that expectations influence mortgage performance as measured by forbearance and largely as a function of leverage choices at the time of origination. This contributes to a theoretical literature on the importance of leverage choices for aggregate fluctuations (Geanakoplos, 2010; Geanakoplos and Wang, 2020).

Our paper is also related with a literature on the effects of foreclosure mitigation policies (Eberly and Krishnamurthy, 2014; Piskorski and Seru, 2018; Campbell et al., 2020). While there is some evidence of strategic motives for default (Guiso et al., 2013), improvements in

[5]Note that the average forbearance rate is lower than Figure 1 due to the NSMO sample having different average characteristics. In Section 7, we estimate partial effects in a regression framework controlling for these factors.

measurement and the scale of data suggest that strategic default, in contrast to the inability to pay, is not prevalent. For example, Gerardi et al. (2017) find that a 10% decline in residual income leads to a 1.1-2.5pp rise in the probability of default. Our paper is most closely related with Cherry et al. (2021) who document a surge in forbearance rates, concentrated in mortgage and student debt, over the COVID-19 pandemic. Moreover, they exploit variation in the conforming loan balance limits to isolate the causal effect of forbearance, finding that it increases by about 25% for loans covered by the mandate. Though COVID-19 is an exogenous shock, moral hazard effects on debt relief are still a concern, as in loan renegotiation efforts (Piskorski and Tchistyi, 2010, 2011; Piskorski et al., 2010), especially because borrowers needed only to attest to hardship without need for verifying documentation. However, our link between forbearance and *ex ante* perceived unemployment risk should be reassuring that borrowers in need of forbearance did seem to receive it.

The structure of the paper is as follows. In Section 2, we establish the institutional setting. Section 3 outlines the data, measurement strategy, and some basic summary statistics. Section 4 begins our empirical strategy, beginning with models of belief formation. Section 5 moves on to estimates of the effects of beliefs on mortgage performance. Section 6 investigates one aspect of the mechanism, the effects of beliefs on loan origination attributes. Section 7 documents determinants of final-period forbearance status for borrowers in the COVID-19 pandemic. Section 8 concludes.

2 Institutional Background

"Forbearance" is an agreement between a loan servicer and a borrower not to take action in response to borrower delinquency of the terms of the loan. These agreements exist in normal times as loss-mitigation strategies for lenders and servicers during times of hardship for a borrower. In response to the COVID-19 pandemic, first the FHFA on March 18, 2020 for Fannie Mae and Freddie Mac, and then the Coronavirus Aid, Relief, and Economic Security (CARES) Act, signed into law on March 27, 2020, for all "federally-backed" mortgages, expanded forbearance eligibility and codified a "consumer right to request forbearance" due to a COVID-19-related hardship (CARES Act, Section 4022). The CARES Act covered all federally-backed loans, defined as those purchased or securitized by Fannie Mae, Freddie Mac, FHA, VA, or FSA/RHS. Sections related to forbearance in the CARES Act are in force for the duration of the President's emergency declaration for the COVID-19 pandemic, which went into effect March 13, 2020.

The CARES Act stipulated that forbearance was guaranteed simply by a borrower fulfilling two conditions: submitting a request to the loan's servicer and affirming a financial hardship due to COVID-19. When in forbearance, scheduled payment amounts could accrue without any penalties, fees, reporting of delinquency to credit repositories, or fear of foreclosure. Loans that were current pre-CARES Act but went into forbearance were to be classified as current rather than delinquent (Section 4021), while loans that we delinquent pre-COVID or for non-COVID hardship-related reasons could not be foreclosed upon. Servicers of loans not covered by the CARES Act often volunteered to grant the same concessions as those mandated by the Act.

The initial forbearance term, as stipulated in the CARES Act, is up to 180 days followed by another 180 extension at the borrower's request, nearly a year in total. On February 25, 2021, the FHFA extended forbearance eligibility for Fannie Mae and Freddie Mac loans for another 6 months. Borrowers can continue making payments during the forbearance period and can cancel forbearance at will. Forbearance periods need not be continuous, however, and can be started, ended, and re-started so long as the total time in forbearance does not exceed these limits. Loans that are originated during the COVID-19 emergency continue to be subject to the forbearance and credit reporting flexibilities afforded by the CARES Act, though not the final 6-month extension afforded to Enterprise loans if they were originated after February 25, 2021.

Due to the perceived low costs of forbearance from the borrower's perspective, and the ease by which forbearance agreements were implemented, the number of loans in forbearance rose dramatically soon after the FHFA policy and the CARES act were implemented. According to the National Mortgage Database (NMDB), described in detail in the next section, the share of first-lien loans in the United States in forbearance rose from 0.3% in January, 2020 to 8.3% in May, 2020 (see Figure 1). By April 2021, the last month in our loan performance sample, the forbearance rate had fallen to 4.1%. Unlike the Great Recession when the delinquency rate on home mortgages grew from 2% to 8%, the rate as reported by credit agencies declined from 3% to 1.8% during the pandemic (Cherry et al., 2021).[6] A primary reason behind the decline in the delinquency rate during the pandemic, rather than surge

[6]Broader definitions of delinquencies, such as in the Mortgage Bankers Association's (MBA) National Delinquency Survey, include both loans classified as delinquent by credit agencies and those in forbearance with borrowers not making payments. The MBA shows rates as high as 8% in 2020, similar to the NMDB forbearance measure.

during the Great Recession, was the provision of forbearance.

The immediate questions then become which borrowers entered forbearance, exited forbearance with full repayment, and who remained in forbearance over a year later in 2021? And specifically, what role did borrower expectations *at origination* play in forbearance uptake? As we show in the following sections, borrower and loan-level attributes that are typically used to explain defaults and prepayments (e.g. LTV, DTI, credit scores) are powerful predictors, in line with early-pandemic results found by McManus and Yannopoulos (2021). But other variables on economic perceptions, financial sophistication, house price and job security expectations, and experiences of socially networked locations also play a crucial role in explaining various aspects of the forbearance experience in the COVID-19 era. Much of these data are available in the National Mortgage Database and the associated National Survey of Mortgage Originations, which we will now describe.

3 Data and Measurement

3.1 Forbearance and Housing Expectations Data

In 2012, the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB) began work on the National Mortgage Database (NMDB) and an associated new quarterly mail survey called the National Survey of Mortgage Originations (NSMO), which serves as our primary research dataset. A significant advantage of NSMO for this article is that it surveys borrowers who have obtained a mortgage within the last six to nine months. These borrowers are likely the most motivated and informed consumers among the overall population of homeowners and their responses, especially concerning expectations, should be more accurate than the general population because they experienced the mortgage process recently.

In 2021, the two agencies released the most recent public-use database covering 26 quarters of NSMO responses from mortgage originations in 2012 through 2019. While the public-use data top-codes or bins data and excludes all geographic and other identifying information, this article draws heavily on an expanded internal government database that relieves these constraints; see Redmer (2019) for early evidence from NSMO relating expected and actual house price appreciation. NSMO contains both survey responses and administrative data from NMDB obtained from a variety of sources including high-quality matches to administrative file records maintained by Fannie Mae, Freddie Mac, the Federal Housing Administration (FHA), the U.S. Department of Veterans Affairs (VA), the Rural Housing Service (RHS), and the Federal Home Loan Banks, which collectively account for over 70 percent of the mortgages in the U.S. Additional NMDB and NSMO information was obtained from other public and proprietary data sources, including deed record filings, HMDA filings, and commercially available servicing databases.

The availability of high-quality administrative data for each sample loan from NMDB means that NSMO does not have to rely on the respondent to provide factual information about the mortgage. Thus, the survey instrument concentrates on obtaining information about the borrowers' knowledge, experience, perceptions, and expectations that are not readily captured anywhere else. The survey asks borrowers about their knowledge of mortgages prior to starting the process, their experience shopping for and closing on a mortgage, their perceptions of the housing market, and their future expectations about house price appreciation and critical household and financial events. The survey also contains demographic, household composition, and other covariate information (e.g., risk preferences and financial sophistication metrics) that is not available in the NMDB. NSMO data matched to the NMDB contains variables drawn from both survey responses and from the NMDB administrative data file, including monthly mortgage performance after origination; see Section 1.1 of the Online Appendix for further details.

To address potential survey non-response bias, NSMO analysis weights are incorporated into all data analysis to account for sampling rate variability that is associated with observables. Non-response bias results when survey respondents differ systematically from non-respondents and at the same time, responses vary. In practice, with a response rate of around one-third of sampled borrowers who completed the survey in each of the 26 waves, NSMO raw survey responses are not quite representative of the borrower population as a whole. Analytic weights assure a distribution among demographic and loan categories that is consistent with borrowers in NMDB. The specific sample of NSMO loans used in all forbearance analysis consists of all loans in the NMDB with a NSMO survey response that were current as of December 2019.

Table 1 documents the relative symmetry between NMDB and the weighted NSMO sample as well as several patterns about forbearance during the COVID-19 pandemic as captured by both NMDB and NSMO. 10.2% of all loans active in NMDB and 9.6% of all loans in the weighted NSMO sample entered forbearance at some point between January 2020 and March 2021. As of March 2021, 28.3% of those NSMO sample loans were still in forbearance, while 48.2% had exited forbearance and were listed as current loans and the remaining 23.5% had been paid off. We will show that those borrowers still in forbearance in March 2021 likely entered forbearance for a different reason (concerns about future employment) than those who had entered but then exited by that point (optimism about house price appreciation).

3.2 Social Network Statistics

In models establishing determinants of expectations, we assess the role social networks play in forming these beliefs. Following the methods of Bailey et al. (2018), we use an extraction of 2019 Facebook data to construct a matrix of friendship ties between each county c and every other county c'. Friendship on Facebook is admittedly a crude proxy for relationship, but it has been a reliable approach to understanding the dissemination of information (e.g. Makridis, 2021). Using these friendship ties, we create a Social Connectedness Index (SCI) for any variable y measured at the county level as a weighted average of other county's values, where weights sum to unity:

$$y_{c,t}^{SCI} = \sum_{c' \neq c} (y_{c',t} \times SCI_{c,c'}/SCI_c) \tag{1}$$

where $SCI_{c,c'}/SCI_c$ denotes the relative share of county c' ties in county c. We exclude the friendship ties between a county and itself to omit any mechanical effects that could emerge.

We calculate SCIs for both house price appreciation and unemployment rates to assess the role social networks play in forming beliefs regarding expected house price appreciation and unemployment. House price indices are annual, county-level repeat-sales indices from Bogin et al. (2019) updated through 2020. These indices have an advantage over other sources of data on housing prices because they have excellent coverage and are constructed using repeat-sales. Unemployment rates are from the Bureau of Labor Statistics' Local Area Unemployment Statistics dataset.

3.3 Descriptive Statistics

Table 2 documents these variables in our sample. We see that roughly 20% of the sample expects that housing prices will increase by a lot, 59% that they will increase by a little, and 18% that they will remain roughly the same. Only 3% believe that housing prices will decrease. Among respondents in forbearance, we see a 5 percentage point higher belief that prices will rise a lot, relative to those not in forbearance. Those in forbearance are also more likely to be self-employed (15% versus 9%), less likely to be White (60% versus 75%), less likely to hold a college degree (57% versus 65%), but no less likely to be married.

Interestingly, we also see that those in forbearance hold slightly less financial sophistication and are more likely to expect that they will be laid off in the upcoming months. Finally, we see that they have a lower credit score (712 versus 744), a higher loan-to-value ratio (81 versus 77), a higher debt-to-income ratio (40 versus 36), and slightly lower rate and cash-out at refinancing. In sum, these descriptive results are consistent with a broader literature about negative selection into default (Gerardi et al., 2013).

Next, Figure 3 explores the share of loans that are in forbearance by the individuals' categorical response for house price and job loss expectations. Starting with Panel (a), we see that the highest share of loans in forbearance are among those who expect that housing prices will increase a lot (9%), a little (7%), no change (6%), and negative (8% with a large standard error). This reflects two potential channels linking forbearance to house price expectations: the most optimistic borrowers may have overestimated their future prospects, and the most pessimistic may have seen trouble coming and borrowed anyway. We will allow for heterogeneous treatment effects when we estimate these relationships more formally, controlling flexibly for observable characteristics.

Turning to Panel (b), there is a monotone relationship between job loss expectations and forbearance: 10% of those who report "very or somewhat likely" for job loss over the next couple of years are in forbearance, relative 8% of those who report "not at all likely." Importantly, these expectations are all taken at the time of origination—not contemporaneously with economic conditions that may correlate with forbearance. Later, we document that expectations may also have a causal effect on forbearance by controlling for a wide array of individual and loan-level features.

To better understand the spatial heterogeneity in forbearance rates and their relationship with expectations across states, Figure 4 provides a heatmap. Starting with Panel (a), some states, such the Dakotas and upper New England, had very low rates of forbearance, at below

3%, whereas others, such as California and Florida, had high rates between 12-15%. One potential explanation behind this pattern is the response to the pandemic: whereas some states had very severe restrictions, which may have worsened the employment decline (and thus ability to pay), other states responded less severely. However, still, there is important heterogeneity, as demonstrated by Florida, which had a high rate of forbearance despite not having severe lockdowns. These settings appear to be driven in large part by their industry composition—that is, Florida's high concentration of leisure and hospitality jobs, which were especially depressed, relative to trend, over the pandemic.

Turning to Panels (b) and (c), we see similarly large heterogeneity, spanning from 58% to 93% of respondents who anticipate positive house price growth in some states and 5.2% to 23% of respondents who anticipate future unemployment in other states. Some states, like Colorado, exhibit both optimism about house prices and pessimism about the labor market, whereas other states, like Arizona, expect high house price growth and low future unemployment. Given the differential exposure to the pandemic across space and the share of jobs that could be done remotely, this cross-sectional variation is important for identification.

4 Determinants of House Price and Job Loss Expectations

4.1 Identification Strategy

In this section, we examine the determinants of house price and job loss expectations. We express expectations in a linear regression framework as a function of local events, events experienced by an individual's expected county-level social network, and individual demographic characteristics that may serve as proxies for heterogeneous preferences or beliefs:

$$e^k_{ict} = \xi_h \Delta h^d_{c,t} + \xi_u u^d_{c,t} + \psi_h \Delta h^{SCI}_{c,t} + \psi_u u^{SCI}_{c,t} + \beta X_{it} + \zeta_s + \lambda_t + \epsilon_{ict} \tag{2}$$

where e^k_{ict} denotes individual i's expectations about $k \in h, u$ (housing or job loss) in county c and quarter t, $\Delta h^d_{c,t}$ denotes year-to-year house price growth, $u^d_{c,t}$ denotes the unemployment rate, $\Delta h^{SCI}_{c,t}$ denotes SCI-weighted housing price growth, $u^{SCI}_{c,t}$ denotes SCI-weighted unemployment, X denotes a vector of individual demographic characteristics, including income and financial controls, and ζ and λ denote state and time fixed effects. Standard errors are clustered at the county-level to allow for correlation of errors in the same area over time.

The identifying assumption in Equation 2 is that variation in individual expectations do not cause fluctuations in county-level house prices and employment, controlling for composition differences across people and focusing on variation within the same state over time. One concern is that individuals with greater optimism also reside within counties with greater house price growth and lower unemployment. Another concern is that expectations influence local demand, particularly in the non-tradables sector. In both cases, there will be upwards bias in our coefficients of interest, causing us to overestimate the role of local conditions. We also implicitly assume that those who have taken out mortgages are representative of the overall population in terms of unobservables; that is, beliefs do not cause selection into our sample. Because optimistic borrowers are more likely to outbid non-optimistic borrowers for housing, this also is likely to cause upward bias in parameters.

We address selection based on observable effects through a granular set of demographic and loan-level controls. In addition to standard demographics (e.g., age, race, marital status, education), we also have access to controls for urban density. For example, we control for whether the borrower is in a CBSA and where in the CBSA the borrower resides, which captures heterogeneity in beliefs due to, for instance, city amenities. We also control for financial knowledge and risk tolerance, which reflect preferences in investment and overall financial sophistication. Moreover, we control for household income at the time of origination and a measure of present liquidity, which reflect internal resources and savings behavior. While none of these controls are perfect by themselves, we show that our estimated coefficients are highly invariant to their inclusion, suggesting that selection effects are unlikely a major threat.

Finally, we control for state and time fixed effects to purge differences in expectations that might also be correlated with time-invariant characteristics of states and heterogeneity in state and national policies. However, state fixed effects could be too coarse, creating concerns that our results reflect a correlation between borrower preferences and unobserved within-state amenities. For example, even within the same state, one county might have access to better amenities (e.g., restaurants or waterfront properties), which could attract borrowers with more optimistic house price beliefs. To address these concerns, our Appendix includes a specification with county fixed effects and the results are indistinguishable.

4.2 Results

Table 3 documents our main results when house price expectations are the outcome. Beginning in column 1, we focus on the raw correlation: a percentage point (pp) rise in network SCI-weighted and local actual house price growth is associated with a 3.6pp and 2.8pp increase respectively in predicted category of house price expectations (among the options *Decrease, Remain about the same, Increase a little, and Increase a lot*) holding unemployment variables constant. We also see that without additional controls, a percentage point increase in network and local unemployment rates have opposite effects holding house price appreciation constant. However, these marginal effects could reflect differences in the composition of loans and cross-sectional state differences. Column 2 subsequently introduces state and origination year fixed effects and controls for whether the borrower is in a core statistical business area (CBSA), exploiting differences among borrowers who originated in the same year and the same state with properties located among common areas of urbanization type. Consistent with theory, we now find that both house price growth and the unemployment rate, together with their network SCI-weighted analogues, have similar qualitative and quantitative gradients on house price expectations.

However, these coefficients could still be biased due to selection effects. Column 3 proceeds by adding a wide array of demographic characteristics, including household income. Column 4 adds proxies for financial sophistication and income stability as a way of mitigating unobserved heterogeneity. While analyzing the determinants of house price appreciation, columns 1 through 4 include all loans with NSMO survey responses, regardless of final loan resolution status. We see almost no change in our point estimates as we layer additional controls between columns 2 and 4, suggesting that there is little margin for selection effects as a source of endogeneity. To show that our smaller forbearance sample generates similar price appreciation determinants to the NSMO sample, column 5 is specified in the same manner as column 4, but only includes loans in the NMDB with a NSMO survey response that were current as of December 2019. Here, we see that a 1pp rise in house price growth and its SCI-weighted equivalent are both associated with a 2.3pp increase in predicted category of house price expectations and a 1pp rise in the unemployment rate and its SCI-weighted equivalent is associated with a 2.9pp decrease and 1.1pp decrease, respectively, in predicted category of house price expectations. These results suggest that the marginal effects are externally valid: they are not driven by variation unique to the COVID-19 pandemic. Furthermore, Appendix Tables A.2 and A.3 show that the results in this section are robust to the alternative functional form assumption of an ordered logit model. For analysis of other NSMO responses, see Appendix Tables A.8 and A.9.

Before continuing, it is noteworthy to take stock of three insights from these results. First, SCI-weighted house price growth and unemployment are more economically significant than their direct county analogues when modeling house price expectations. While the coefficient estimates are not substantially different in the context of housing, increases in the SCI-weighted unemployment rate have over twice as large of a negative effect on house price expectations as the actual county unemployment rate. Second, the SCI-weighted unemployment rate matters slightly more than either house price growth or its SCI-weighted equivalent in explaining house price expectations. Third, our estimates are incredibly robust to the inclusion of different demographic characteristics and dimensions of economic well-being, such as income and financial sophistication. That suggests selection effects are unlikely to be driving the main results; income and financial sophistication are otherwise good proxies for unobserved heterogeneity and if selection were present, the coefficients would change more.

In Table 4, we also document the results when job loss expectations are our outcome variable. As shown in columns 2 through 4, we do not find statistically significant results linking expected job loss with local or SCI-weighted house price growth or the network unemployment rate after controlling for state and origination year fixed effects. While the full NSMO sample shows that local unemployment has a small negative correlation with unemployment expectations, column 5 shows that the relationship is not statistically significant in the smaller forbearance sample of loans. Key variables in forming expectations of future unemployment are race, financial knowledge, employment status (employed, self-employed), and whether the borrower has responded that they have a 3+ month income cushion with which to pay bills in the event of job loss. Within geographies, however, holding these factors constant, individual expectations of future layoffs are largely idiosyncratic.

5 Examining the Effects of Expectations on Forbearance

5.1 Identification Strategy

Having demonstrated that local housing and labor market shocks, together with the role of social networks as propagators of information, influence the formation of expectations (primarily for house price growth), we now ask whether expectations influence the probability of entering forbearance through the regressions:

$$f_{it} = \gamma_h e^h_{it} + \gamma_u e^u_{it} + \alpha D_{it} + \beta X_{it} + \zeta_s + \lambda_t + \epsilon_{it} \tag{3}$$

where f_{it} denotes an indicator for whether an individual is in forbearance, D_{it} denotes a vector of loan-level characteristics, and both e^h_{it} and e^u_{it} denote our measures of expectations on house prices and job loss. Like in Equation 2, we control for individual characteristics and both state and time fixed effects, as well as loan characteristics.

Our identifying variation in Equation 3 comes from comparisons of borrowers who are indistinguishable based on observable demographic and loan-level characteristics, but differ in their underlying expectations about house prices and job loss. Importantly, we present estimates with and without loan-level characteristics to gauge their importance in explaining forbearance outcomes. Our main concern here is that we may fail to control for unobserved heterogeneity that jointly affects selection into the 2020 U.S. mortgage portfolio (vs prior prepayment or default), forbearance during the COVID-19 period, and initial borrower expectations. While it is standard in studies on forbearance to control for demographic characteristics (McManus and Yannopoulos, 2021; Cherry et al., 2021; Fuster et al., 2021; An et al., 2021), to our knowledge, no one has yet to also incorporate loan-level information and other proxies for preferences and abilities, such as risk aversion and financial sophistication, helping us to isolate more fully the causal effects of expectations on mortgage performance outcomes.

5.2 Results

Table 5 documents these results. Starting with column 1, we see that borrowers who believe that house prices will "increase a lot" are 3.3pp more likely to enter forbearance, relative to those who anticipate "no change". We find no statistically significant differences among borrowers reporting only "increase a little" or "decrease by a little/a lot." Moreover, those who anticipate job loss are 2.2pp more likely to enter forbearance. However, like before, these results could reflect unobserved heterogeneity: borrowers who enter forbearance might be negatively selected in other ways too, generating spurious correlation with house price expectations. Column 2 subsequently adds origination year and state fixed effects, attenuating the estimates. Column 3 adds additional loan-level characteristics, including the combined loan-to-value (CLTV) ratio, credit score, and debt-to-income (DTI) ratio, among others. Not surprisingly, higher credit scores are negatively correlated with forbearance, whereas DTI is positively correlated with it.

How robust are these coefficients to the inclusion of additional controls that purge potential selection effects? Column 4 introduces each of the demographic characteristics, including: gender, marital status, age, education, and race. Again, we see statistically indistinguishable results. It is not until column 5 where we insert additional controls for financial sophistication and employment that our estimates change. In particular, we now find that borrowers who anticipate that house prices will "increase a lot" are 1.7pp more likely to enter forbearance in 2020 and those who believe they will "increase a little" are 1.1pp more likely, relative to those who anticipate no change. We see no association among those who believe house prices will "decrease by a little/a lot." Further, expectations of future job loss remain economically and statistically significant and more important than house price expectations. In addition, we see a strong statistically and economically significant association on our new controls: those with financial knowledge are 3.2pp less likely to enter forbearance and those who are self-employed are 4.9pp more likely to enter it.

Finally, columns 6 and 7 provide additional robustness exercises. First, column 6 presents results using a probit estimator, rather than least squares with fixed effects. We find fairly similar marginal effects, although the point estimates on house price expectations decline slightly in magnitude. Second, column 7 presents results after accounting for selection into forbearance using a Heckman probit estimator. Identification in the selection equation comes from the non-linearity of the estimator and a series of variables representing the origination interest rate interacted with origination-year dummy variables. The exclusion restriction for the interest rate - year dummy variables is based on the notion that prepayments and defaults through the end of 2019 are related to refinance pressure from high origination interest rates and differential risk associated with high-interest rate borrowers, and at the same time, high interest rates in the past are not associated with future forbearance activity. We believe this exclusion restriction is satisfied based on the non-significant interest rate estimates once selection has been controlled for in column 7. However, while there is strong evidence of a non-random selection process, this process does not appear to influence the estimates due to the richness of our control set.[7] Although our estimates on house price growth expectations are less statistically significant—likely because our excluded terms to address selection vary at the county, rather than individual, level—they are quantitatively similar.

We also estimate models including other NSMO survey responses, including beliefs regarding strategic default, consequences of default, structure type, and intended use of the property. These estimates are shown in Appendix Table A.10. None of these variables have significant effects on initial forbearance uptake, and all of the expectations variables estimates are nearly identical. One variable of note represents beliefs regarding the ethics of strategic default. This survey question asks "Do you agree or disagree with the following statement: It is okay to default or stop making mortgage payments if it is in the borrower's financial interest" with 6.0% of borrowers responding "Agree". The estimated effect on forbearance is 0.003 with a standard error of 0.009, suggesting that "strategic forbearance", that is, entering forbearance intending to strategically default in the future, is not a contributing factor to the observed high forbearance rate in the COVID-19 pandemic.

These estimates offer several main conclusions. First, expectations at origination strongly influence entry into forbearance: borrowers who are the most optimistic about housing prices are nearly 2 percentage points more likely to enter forbearance, relative to those anticipating no change. Second, job loss expectations are slightly more important than house price expectations. Third, our estimates are highly robust across specifications: despite the potential for bias that would emerge from unobserved heterogeneity, the invariance of our estimates to a wide array of controls suggest there is limited scope for endogeneity. Next, we turn to possible explanations for these large partial effects.

5.3 Discussion

The link between unemployment expectations and forbearance is clear if we make a simple assumption: that borrowers who expected to become unemployed did in fact become unemployed at higher rates in the COVID-19 period. Under this assumption, unemployment expectations led to unemployment which harmed borrowers' ability to repay. These borrow-

[7] We offer a series of models analyzing selection effects in Appendix Table A.6. Selection into the 2020 U.S. mortgage portfolio is determined, to a high degree, by observables, including expectations. However, with the inclusion of demographic and financial controls, the Mills ratio parameter becomes statistically indistinguishable from zero. Our interpretation of these results is that we are adequately controlling for selection effects using our control set in models that do not account for selection, including standard OLS, probit, and logit models. For additional evidence, see Table 7 which shows interest rates to have no significant effect on forbearance outcomes, but important explanatory power in predicting prior terminations.

ers entered forbearance at higher rates. According to preliminary tabulations in the October 2020 - February 2021 American Survey of Mortgage Borrowers, 78% of all borrowers who were in forbearance suffered job loss or reduced income.[8] While this is not direct evidence from our sample of borrowers, it is strongly suggestive that borrowers who expected future unemployment were more likely to face income loss in the COVID-19 period than the general mortgage-holding population.

What is less obvious is how we should attribute the link between house price appreciation expectations and forbearance. Foote et al. (2012b) argue that optimistic house price expectations were the primary drivers behind the loosening of credit standards in the run-up to the Great Recession. In this view, appreciation optimism led to expectations of reduced levels of default and credit losses for all entities involved, including borrowers, lenders, and investors. However, supply-side credit standards are typically tracked by analyzing observable loan-level attributes, and these are controls in the regressions. From the borrower side, expectations can affect both loan terms and then eventual default, typically through expected equity (i.e. expected underwater propensity) (Gerardi et al., 2008). For optimism to have a partial effect on forbearance, conditional on controls, it must have a relation to forbearance through latent borrower characteristics that make a borrower less likely to be able or willing to make their payments.

We argue that there are at least three potential factors causing appreciation expectations to be positively associated with forbearance. For insights, we refer to the existing literature on expectation and belief formation (see Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019; Cocco et al., 2020; Makridis, 2021). We then pair this literature with estimates in the appreciation expectations formation regressions found in Table 2 and Appendix Table A.8 to offer evidence on some plausible channels.

First, borrowers who tend to be more optimistic might also be more likely to speculate and flip homes (Mian and Sufi, 2021). We examine this possibility by including indicators for whether the loan is for an investment or rental property, and if the property purchased was in prior distress. Distressed property purchases are positively associated with appreciation expectations, but investment properties are actually negatively related to expectations. Sec-

[8] Another 5% experienced death, divorce, illness, or disability, while 17% had no stated hardship. This is based on 509 survey respondents, 440 of which were in forbearance. Percentages are survey-weighted to reflect observable attributes in the National Mortgage Database.

ond, borrowers who plan on moving homes have more optimistic appreciation expectations. These individuals might feel less inclined to pay down their mortgage, presumably because prepayment is imminent. Indeed, as we will show in Section 7, positive expectations are associated with prepayment prior to 2020, and they are also associated with forbearance-then-prepayment during the COVID-19 pandemic. There is also additional evidence that household mobility increased dramatically during the COVID-19 pandemic (Davis et al., 2021; Haslag and Weagley, 2021; Liu and Su, 2021). Finally, we suggest that there are certain borrowers who may undertake "precautionary forbearance," that is, they enter into forbearance as an *option* not to make payments. Financial knowledge and financial risk tolerance both positively affect house price expectations with very high-magnitude estimates. It seems plausible that borrowers with high levels of knowledge and risk tolerance are more likely to understand forbearance is an option but not a commitment to violate the initial terms of the mortgage.

6 Selection and Mortgage Market Decisions

What can explain the strong link between expectations and forbearance? Much of the borrower-level survey information we track that is predictive of forbearance is not known to lenders, suggesting the possibility of adverse selection in the vein of Brueckner (1994) and Piskorski and Tchistyi (2010). But through which channels does beliefs exuberance affect mortgage performance? Do beliefs cause borrowers to alter observables, such as leverage (as described by Bailey et al., 2019) or the structure of their household balance sheets, or is the effect of optimism limited to some deeper sorting mechanism that we are unable to observe?

Our estimates of the effect of beliefs on forbearance from Equation 3 are robust to the inclusion of many loan-level and borrower controls, including income. Accordingly, we have already established substantial adverse selection in forbearance from these otherwise unobservable factors. In this section, we find evidence of selection into observable characteristics based on *a priori* beliefs. We show variables such as LTV and DTI include small but important variation due to appreciation optimism and expectations of future individual unemployment risk. This finding has broad implications for mortgage performance models that do not have access to information on borrower beliefs: in traditional mortgage models, assumptions of random assignment of loan-level characteristics may be violated. This may cause bias in traditional estimates linking these variables to mortgage performance, and explain instability of estimates over time found in past studies (An et al., 2012; Kiefer and

Mayock, 2020).

To measure the effect of beliefs on mortgage performance through observables, we link loan characteristics with expectations at the time of origination through regressions of the form:

$$l_{it} = \gamma_h e_{it}^h + \gamma_u e_{it}^u + \beta X_{it} + \zeta_s + \lambda_t + \epsilon_{it} \tag{4}$$

where l_{it} denotes a loan-level characteristic $l \in c, d$ (CLTV or DTI) and our remaining variables are as before. Here, our identifying assumption is that variation in expectations is uncorrelated with selection into different types of loans, conditional on our series of individual demographic characteristics. We then nest these parameters into Equation 3 to estimate the effects of beliefs on forbearance through observables.

6.1 Results

Table 6 documents these results. Columns 1 and 4 shows that there is a strong positive association between borrowers who believe that house prices will "increase a lot" and both the CLTV and DTI ratios. These associations grow stronger after adding all the standard demographic and loan level controls in columns 2 and 5. In particular, we find that those who believe house prices will "increase a lot" have a 1.27pp higher CLTV ratio and a 1.74pp higher DTI ratio. Furthermore, those who believe that house prices will "increase a little" have a slightly stronger association with CLTV of 1.45pp, but a slightly lower association with DTI of 0.95pp. Furthermore, now we find that borrowers who anticipate unemployment have 0.63pp lower CLTV ratios and 0.29pp lower DTI ratios, although the latter is not statistically significant. The (generally) stronger associations reflects the strength of our additional controls and the downwards bias that exists in the raw data. These estimates are similar to quantile regressions found in Appendix Table A.4.

Turning to several of our controls, we find that financial knowledge and risk tolerance are both negatively related with CTLV, as are self-employment, college attainment, age, the 3-month income cushion, and residing in a CBSA. However, being married, male, and Black are all positively associated with CLTV. Finally, columns 3 and 6 show that our results are robust to isolating variation from a subsample of loans from 2019, demonstrating again that our results are not driven by idiosyncracies during the COVID-19 pandemic.

These estimates deserve some discussion relative to Bailey et al. (2019). This paper presents a compelling case that the sign of the relation between LTV and optimism as an empirical tension between a "housing as investment" effect and a "housing as consumption" effect. The investment effect puts positive pressure on the LTV through borrowers seeking to maximize housing returns by maximizing leverage. The consumption effect treats housing as a consumption good to be smoothed intertemporally using debt-financing, with borrowers seeking to minimize the LTV to avoid debt service payments. In their paper, they estimate the optimism effect on LTV to be negative, conditional on a number of borrower-level controls. Here, we are able to estimate the same relation with the addition of other borrower-level controls that were unavailable to Bailey et al. (2019), including financial sophistication, risk tolerance, loan type, and credit score. When controlling for these additional factors, we estimate the sign to be positive. This suggests the estimates from Bailey et al. (2019) may suffer from omitted variable bias, though we admittedly do not include expectations variance terms in our specification. Our results point to the effects of optimism on leverage as an open question, and one that deserves further investigation.

These estimates offer differing mechanisms in the link between expectations and loan origination characteristics. While borrowers choose lower combined leverage at origination when they have an expectation of unemployment in the near future, there is a slight net increase in overall leverage from expectations given the positive correlation between house price expectations and CLTV. Conversely, borrowers appear willing to increase their debt burden when they have an expectation of house price appreciation and this debt burden choice appears unrelated to any expectation of unemployment.

These parameters can be nested into the partial effects of DTI and CLTV found in equation 3 to assess the role expectations play through leverage choice and balance sheet channels. Because the effects on these loan attributes are small, accordingly the effects on forbearance through these channels are small. Beliefs affect CLTV, but the effect of CLTV on forbearance is approximately zero, so there is no effect of beliefs on forbearance through this channel. On the other hand, in Table 5, there is a robust partial 0.1pp effect of DTI on forbearance. Paired with the approximately 1.7pp effect of high appreciation optimism on DTI, this suggests a 0.2pp effect of appreciation optimism on forbearance through changes to DTI. Because there is no effect of unemployment expectations on DTI, this effect is zero.

Overall, considering incidence of forbearance, appreciation optimism has a 1.7pp direct effect and 0.2pp indirect effect due to variation in origination characteristics. There is no measurable effect of individual unemployment expectations through the origination characteristics channel, leaving the 2.0pp direct effect. Accordingly, house price expectations serve to amplify forbearance risk due to differences in loan characteristics, while effects of income risk are primarily direct. These findings also suggest adverse selection into these particular mortgage characteristics based on beliefs is present but small.

7 Determinants of Final Forbearance Status

Given the availability of loan level data one year after forbearance friendly policy implementation, we take the opportunity to explore the forbearance status of borrowers at the end of our sample. As Figure 2 shows, there are still many borrowers in forbearance, but there are important differences among those with varying house price beliefs. For example, the share of borrowers anticipating house price appreciation in forbearance declined from over 6% to 4% between May 2020 and 2021. However, just as many borrowers anticipating a layoff remain in forbearance in 2021, relative to the onset of the pandemic, when compared with the baseline borrower group. These descriptive statistics motivate a deeper investigation into the relationship between final forbearance status and beliefs.

Table 7 regresses indicators for different dimensions of forbearance—(a) in forbearance (as of March, 2021), (b) ever forbearance but now closed, (c) ever forbearance but now current, and (d) terminated prior to 2020 —on house price beliefs and layoff expectations, together with local house price and unemployment rate growth, individual demographics, and loan-level characteristics. Due to low loan counts in buckets a, b, and c, standard errors are higher than in other models, suggesting many estimates to be statistically less precise. Starting with column 1, we see that borrowers who anticipate house price growth are somewhat more likely to still be in forbearance as of March, 2021, relative to those who anticipate no house price growth, as the estimate is positive but with a standard error almost as large. Those who anticipate unemployment are more likely to still be in forbearance with a high degree of statistical likelihood. These borrowers, on average, entered forbearance at higher rates, but then prepaid their loan or returned to current status in the intervening year at higher rates in a manner that completely offset the initial forbearance effects (see "Forbearance Now Closed" and "Forbearance Now Current" columns).

Turning to column 2, we see similar effects for house price appreciation expectations: borrowers with more optimistic attitudes about house prices are more likely to have exited forbearance. However, there is not a statistically significant association between layoff expectations and forbearance now being closed. Finally, column 3 shows a slight positive association between forbearance now current and optimistic beliefs about house prices. Borrowers who expect the possibility of future unemployment were more likely still in forbearance in 2021. Moreover, lower income and not having a 3-month payment cushion at loan origination are both related with entering and remaining in forbearance and at the same time unrelated to exiting forbearance.

The model presented in column 4 is another way of controlling for selection beyond the already-considered Heckman probit models. We can see that both appreciation optimism and expecting to remain employed are associated with terminations prior to the COVID-19 period. In support of the exclusion restriction in the Heckman probit model in Table 5, the interest rate variables are only significant in this category. Many other variables are associated with prior termination, suggesting a rich, non-random selection process.[9]

As it stands through April, 2021, there are still 4.1% of borrowers in forbearance, down from the high of 8.3% in May, 2020. Conditional on other factors, borrowers who are old, not-college educated, Hispanic, Black, have low credit scores, and high DTIs are most likely to still be in forbearance. Due to the prevalence of forbearance directives from the CARES act and the FHFA, loans with government or Enterprise guarantees are more likely to be in forbearance. Those who had low levels of liquid wealth or expectations of a future unemployment spell are also more likely to still be in forbearance, though borrower expectations of future house price appreciation has no partial association at the end of the sample. While borrowers with these characteristics are more likely to be in forbearance, there is a silver lining. The rapid house price appreciation between 2019 and 2021 has led to an *increase* in equity for the average forbearance-status household according to Gerardi et al. (2021). This equity cushion gives borrowers, lenders, servicers, and regulators some breathing room to determine the best path forward for those in forbearance, including stream-lined modifications, refinances, or simply home sales and prepayments of loans.

[9] We also estimate a model describing loan performance status in December, 2019, with each loan assigned "Current", "Prepaid", and "Default or Delinquent". These estimates are shown in Appendix Table A.7. Appreciation expectations are negatively related to default and positively related to prepayment. Unemployment expectations show opposite effects.

8 Conclusion

There is now a large literature about the importance of expectations, especially about housing, for aggregate economic activity. Fluctuations in beliefs, sometimes triggered by local shocks, can generate waves of optimism or pessimism. However, much less research has been done exploiting plausibly exogenous variation in expectations on mortgage performance, which we explore through the lens of the COVID-19 pandemic and the rapid surge in forbearance.

We introduce new individual panel data that simultaneously covers house price and layoff expectations at the time of a borrower's origination, forbearance, and a wide array of individual-level demographic and loan-level characteristics. We begin by decomposing the determinants of house price and layoff expectations as a function of county house price growth and the unemployment rate, together with a measure that exploits variation in house prices and unemployment rates in the social network of each county, controlling for demographic characteristics. Not surprisingly, house price growth (higher unemployment) is associated with greater (lower) house price expectations. However, we find only minor effects on layoff expectations. Importantly, house price growth and the unemployment rate in a county's social network matters at least as much as the local shocks.

We subsequently explore how house price expectations and layoff expectations effect forbearance. We find that borrowers who originated a loan with more optimistic house price expectations are much more likely to enter forbearance (although they are also more likely to exit forbearance in 2021). Furthermore, those who anticipate a layoff are much more likely to enter forbearance. To better understand the mechanism behind these results, we conclude by exploring the relationship between leverage and expectations. We show that greater optimism about house price growth is positively associated with loan-to-value and debt-to-income ratios.

Our analysis opens many new questions for further research. First, more time is needed to explore how these borrowers alter their expectations about house price growth and layoffs as the economy continues to recover from the COVID-19 pandemic and as they exit forbearance. Second, how will borrower expectations lead to different decisions in the mortgage market, especially among those who ultimately decide to move? Third, how might the effects on forbearance on the local economy vary based on borrower expectations and how they feed into local demand? We leave these, and more, for future research.

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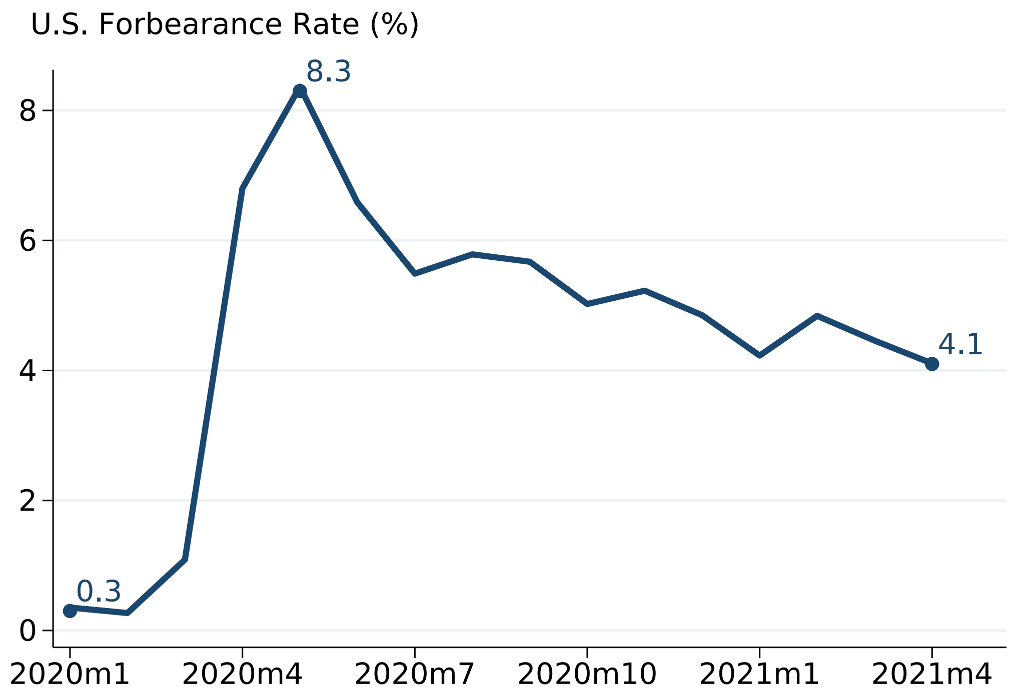
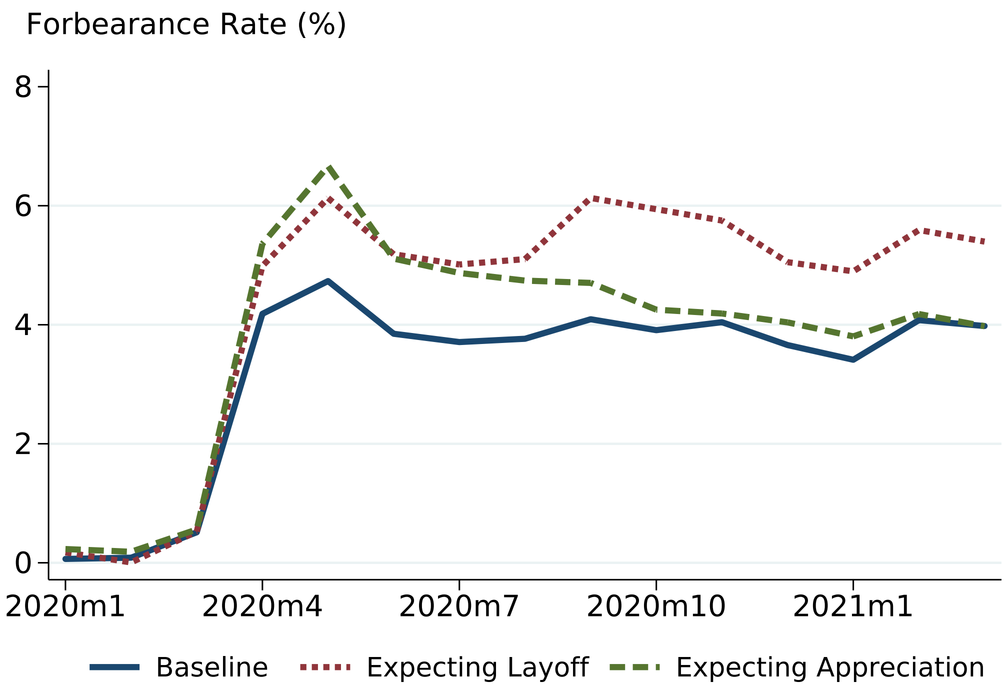
Figure 1: Share of Active Loans in Forbearance



Source: National Mortgage Database.

Notes: The figure plots the share of active loans that were in forbearance as of the particular month.

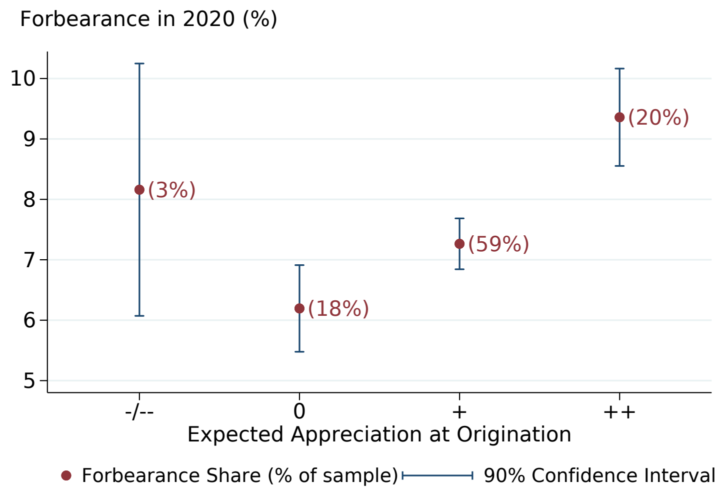
Figure 2: Time Series of Forbearance by Beliefs at Origination



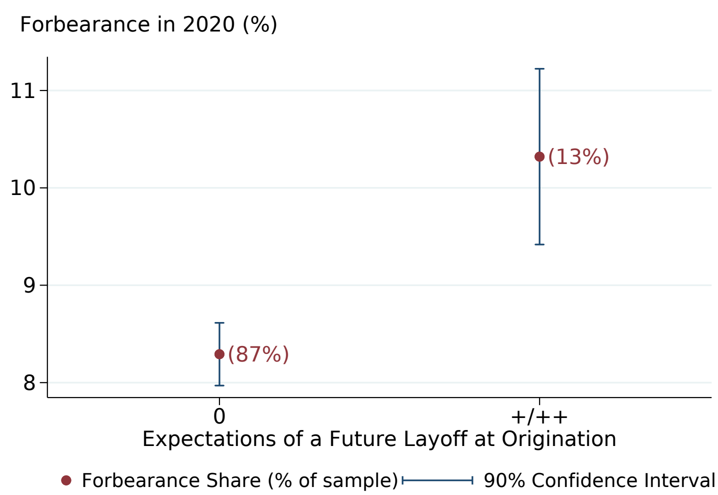
Sources: National Mortgage Database and National Survey of Mortgage Originations.
Notes: The figure plots coefficients from a sequence of monthly regressions of the form: $Forbearance = a + b \times \textit{Appreciation Optimism} + c \times \textit{Unemployment Expectation} + e$. The sample is all loans in the NSMO sample that were active and current as of December, 2019 and still active as of the particular month. *Forbearance* is set equal to one if the loan is in forbearance in the particular month, zero if it is active and not in forbearance. *Appreciation Optimism* is defined at origination based on question 69 in the NSMO survey, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years* set to one if the response is *Increase a lot* or *Increase a little* and zero otherwise. *Unemployment Expectation* is defined based on question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, with *somewhat likely* or *very likely* set to one and zero otherwise. In the figure, *Baseline* is $\hat{a}$, *Expecting Appreciation* is $\hat{a} + \hat{b}$, and *Expecting Unemployment* is $\hat{a} + \hat{c}$, estimated separately in each month.

Figure 3: Share of Loans in Forbearance in 2020, by Beliefs at Origination

(a) House Price Appreciation Expectations



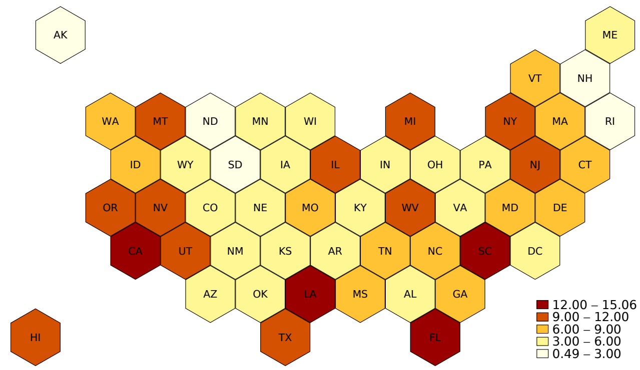
(b) Personal Unemployment Expectations



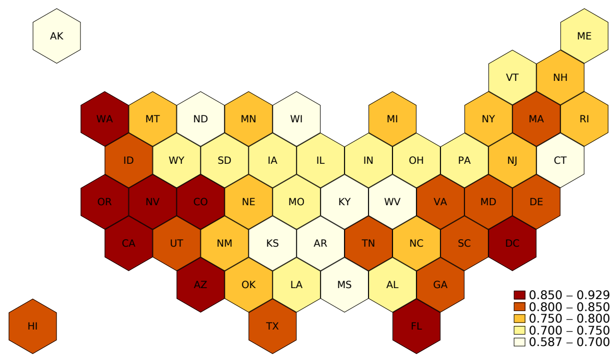
Sources: National Mortgage Database and National Survey of Mortgage Originations.
Notes: The figures present shares of loans in the NMDB with a NSMO survey response that were current in December 2019 and entered forbearance at any point in 2020. Panel (a) shows forbearance by the response to question 69 in the survey, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years.* Possible answers are, *Increase a lot*, assigned "++", *Increase a little*, assigned "+", *Remain about the same*, assigned "0", or *Decrease a little/Decrease a lot*, which are each assigned to "-/–" due to low counts in these cells. Panel (b) shows forbearance by the response to question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, assigned "0" for *not at all likely* and "+/++" for *somewhat likely*, or *very likely*, due to low counts in the "very likely" cell.

Figure 4: Spatial Distribution of Beliefs and Forbearance

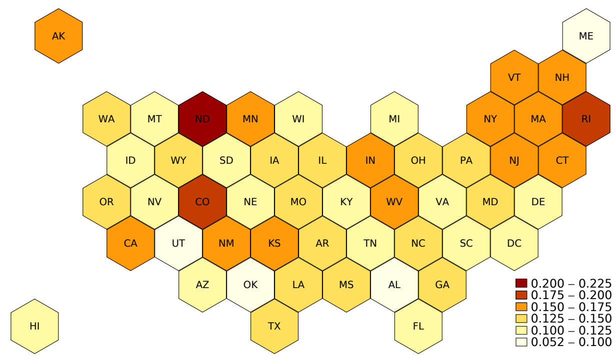
(a) Share in Forbearance in 2020



(b) Share Who Expect Positive Appreciation



(c) Share Who Expect Future Unemployment



Sources: National Mortgage Database and National Survey of Mortgage Originations.

Notes: The figures present: panel (a), shares of loans in the NMDB with a NSMO survey response that were current in December 2019 and entered forbearance at any point in 2020; panel (b), the share of borrowers who responded to question 69 in the survey, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years* with *Increase a lot* or *Increase a little*; and panel (c), the share of borrowers who responded to question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, with *somewhat likely* or *very likely*.

Table 1: Forbearance Statistics through March, 2021

	Count	% of total	% of ever in forbearance
Total NMDB, Active Jan. 2020 through March 2021	3,185,407		
Never in forbearance	2,861,501	89.8%	
Ever in forbearance	323,906	10.2%	
Ever in forbearance in 2020	283,402	8.9%	87.5%
In forbearance, March 2021	107,217	3.4%	33.1%
Exited forbearance, active in March 2021	158,855	5.0%	49.0%
Exited forbearance, closed by March 2021	57,834	1.8%	17.9%
Total NSMO Sample, Current Dec. 2019 (weighted)	24,610		
Never in forbearance	22,236	90.4%	
Ever in forbearance	2,374	9.6%	
Ever in forbearance in 2020	2,109	8.6%	88.8%
In forbearance, March 2021	672	2.7%	28.3%
Exited forbearance, active in March 2021	1,145	4.7%	48.2%
Exited forbearance, closed by March 2021	557	2.3%	23.5%

Sources: National Mortgage Database and National Survey of Mortgage Originations.
Notes: The total count for the NMDB includes all loans active at any point between January 2020 and March 2021. The NSMO sample of loans consists of all loans in the NMDB with a NSMO survey response that were current in December 2019. The NSMO sample is weighted to account for non-response bias and sampling rate variability and then normalized such that the average analytic weight equals 1. The analytic weights generate a distribution among various demographic and loan categories that are consistent with NMDB as a whole. The unweighted "ever in forbearance" fraction is 8.5% in the NSMO sample.

Table 2: Descriptive Statistics by Forbearance Status

	All Current in Dec. 2019		In Forbearance in 2020		Not in Forbearance in 2020	
	Mean	SD	Mean	SD	Mean	Sd
Origination Appreciation Expectations						
Increase a lot	0.2	0.4	0.25	0.43	0.2	0.4
Increase a little	0.59	0.49	0.57	0.5	0.6	0.49
About the same	0.18	0.38	0.15	0.36	0.18	0.38
Decrease a little/a lot	0.03	0.16	0.03	0.16	0.03	0.16
Expect future Unemployment	0.14	0.34	0.16	0.37	0.13	0.34
Appreciation at Origination	5.07	3.53	5.4	3.57	5.04	3.53
Appreciation, Origination-2019	18.96	14.24	18.55	14.13	18.99	14.25
Appreciation, 2019-2020	3.92	2.12	3.8	2.01	3.94	2.13
Network Appreciation at Origination	3.65	1.39	3.87	1.27	3.63	1.4
Unemployment Rate at Origination	4.58	1.82	4.6	1.87	4.58	1.82
Change in U. Rate, 2019-2020	11.07	3.97	11.49	3.99	11.03	3.97
Change in U. Rate, 2020-2021	-8.88	3.94	-8.87	3.96	-8.89	3.94
Network Unemployment Rate	4.96	1.34	4.87	1.23	4.97	1.34
Employed Member of Household	0.5	0.5	0.53	0.5	0.5	0.5
Self-Employed	0.1	0.3	0.15	0.35	0.09	0.29
Household Income	102417	82670	96460	78383	102976	83041
Male	0.56	0.5	0.53	0.5	0.56	0.5
Age	46.31	13.76	43.79	12.62	46.55	13.84
Married	0.66	0.47	0.66	0.47	0.66	0.47
College Graduate	0.64	0.48	0.57	0.5	0.65	0.48
White, non Hispanic	0.74	0.44	0.6	0.49	0.75	0.43
Hispanic (any)	0.13	0.33	0.2	0.4	0.12	0.33
Asian	0.06	0.23	0.08	0.27	0.06	0.23
Black	0.06	0.24	0.11	0.31	0.06	0.23
Other race/eth.	0.02	0.15	0.03	0.17	0.02	0.15
Financial Knowledge	0.69	0.22	0.64	0.23	0.69	0.22
Risk Appetite	0.34	0.27	0.33	0.29	0.35	0.27
Interest Rate at Origination	0.71	0.36	0.65	0.38	0.72	0.36
Spread at Origination	4.06	0.85	4.18	0.71	4.05	0.87
Has 3 Months Reserve	0.22	0.72	0.26	0.58	0.22	0.73
Loan-to-Value ratio	78	20	81	18	77	20
Credit Score	741	64	712	67	744	63
Debt-to-Income ratio	36	12	40	12	36	12
Purchase	0.55	0.5	0.6	0.49	0.54	0.5
Rate/Term Refinance	0.27	0.44	0.23	0.42	0.27	0.44
Cash-out Refinance	0.17	0.38	0.16	0.36	0.17	0.38
Private Backed	0.16	0.37	0.09	0.29	0.17	0.37
Government Backed	0.24	0.43	0.38	0.49	0.23	0.42
Enterprise Backed	0.6	0.49	0.53	0.5	0.6	0.49
Observations	24,610		2,109		22,501	

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year. Network variables are constructed off of the 2019 extraction of the Social Connectedness Index (SCI) where we take $y^{SCI} = \sum_{c' \neq c}(y_{c'} \times SCI_{c,c'}/SCI_c)$ where c denotes the county, $SCI_{c,c}$ denotes the number of friendship ties between county c and c', and $y_{c'}$ denotes either house price growth or the unemployment rate.

Notes: The baseline sample of loans consists of all loans in the NMDB with a NSMO survey response that were current in December, 2019. Reported statistics are based on survey weighted response values.

Table 3: Determinants of House Price Appreciation Expectations at Origination

Dependent Variable: House Price Appreciation Expectations at Origination					
Model	[1]	[2]	[3]	[4]	[5]
Estimator	OLS	OLS	OLS	OLS	OLS
Network Appreciation	0.0364***	0.0276***	0.0268***	0.0268***	0.0234***
	[0.00407]	[0.00609]	[0.00608]	[0.00607]	[0.00780]
County Appreciation	0.0268***	0.0234***	0.0231***	0.0225***	0.0228***
	[0.00135]	[0.00166]	[0.00166]	[0.00165]	[0.00222]
Network Unemployment Rate	0.0101**	-0.0262***	-0.0273***	-0.0296***	-0.0288**
	[0.00491]	[0.00999]	[0.00997]	[0.00986]	[0.0144]
County Unemployment Rate	-0.0188***	-0.0139***	-0.0107***	-0.00833**	-0.0112**
	[0.00338]	[0.00373]	[0.00376]	[0.00370]	[0.00527]
Household Income (ln)			0.0614***	0.0197***	0.0161*
			[0.00721]	[0.00754]	[0.00965]
Male			0.0300***	0.00203	0.0128
			[0.00807]	[0.00822]	[0.0105]
Married			-0.0126	-0.0194*	-0.0238*
			[0.00916]	[0.00999]	[0.0128]
Age			0.000824***	0.000512	0.000522
			[0.000286]	[0.000318]	[0.000415]
College			0.0337***	0.00897	0.0197*
			[0.00898]	[0.00904]	[0.0116]
Hispanic (any)			0.0571***	0.0724***	0.0743***
			[0.0142]	[0.0141]	[0.0182]
Asian			-0.0192	-0.00405	-0.0103
			[0.0178]	[0.0178]	[0.0217]
Black			0.0652***	0.0804***	0.0680***
			[0.0187]	[0.0187]	[0.0235]
Other race			0.0697**	0.0769***	0.112***
			[0.0272]	[0.0270]	[0.0349]
Financial Knowledge				0.214***	0.233***
				[0.0212]	[0.0267]
Financial Risk Tolerance				0.133***	0.114***
				[0.0172]	[0.0220]
Employed Member of HH				0.0144	0.0222*
				[0.00960]	[0.0124]
Self-employed				0.00968	-0.00383
				[0.0135]	[0.0167]
3-month income cushion				0.101***	0.110***
				[0.0121]	[0.0157]
CBSA Outlying (vs non-CBSA)		0.163***	0.155***	0.152***	0.134***
		[0.0265]	[0.0264]	[0.0262]	[0.0335]
CBSA Center-City (vs non-CBSA)		0.195***	0.176***	0.168***	0.156***
		[0.0223]	[0.0222]	[0.0221]	[0.0279]
Origination Year DVs	No	Yes	Yes	Yes	Yes
State DVs	No	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	24,610
R-squared	0.041	0.057	0.063	0.074	0.082

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year. Network variables are constructed off of the 2019 extraction of the Social Connectedness Index (SCI) where we take $y^{SCI} = \sum_{c' \neq c}(y_{c'} \times SCI_{c,c'}/SCI_c)$ where c denotes the county, $SCI_{c,c}$ denotes the number of friendship ties between county c and c', and $y_{c'}$ denotes either house price growth or the unemployment rate.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is set to the NSMO survey response, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years?*. Possible answers are, *Increase a lot*, assigned 3, *Increase a little*, assigned 2, *Remain about the same*, assigned 1, or *Decrease a little/Decrease a lot*, which are each assigned to 0 due to low counts in these cells. The sample in models 1-4 is all loans in the NMDB with a NSMO survey response, and in column 5 is the subsample of loans that were current in December, 2019. Observations weights are normalized within each of these raw samples.

Table 4: Determinants of Individual Unemployment Expectations at Origination

	Dependent Variable: Individual Unemployment Expectations at Origination				
Model	[1]	[2]	[3]	[4]	[5]
Estimator	OLS	OLS	OLS	OLS	OLS
Network Appreciation	-0.00434**	-0.00125	-0.00091	-0.00072	-4.3E-05
	[0.00199]	[0.00278]	[0.00278]	[0.00277]	[0.00363]
County Appreciation	0.000334	0.000454	0.000493	0.000663	0.00115
	[0.000674]	[0.000804]	[0.000803]	[0.000798]	[0.00104]
Network Unemployment Rate	0.00922***	-0.00065	5.55E-05	0.00107	-0.00509
	[0.00241]	[0.00464]	[0.00464]	[0.00463]	[0.00677]
County Unemployment Rate	-0.00028	-0.00306*	-0.00406**	-0.00483***	-0.00217
	[0.00160]	[0.00176]	[0.00177]	[0.00176]	[0.00266]
Employed Member of HH	0.0214***	0.0191***	0.0196***	0.0193***	0.0174***
	[0.00401]	[0.00401]	[0.00492]	[0.00493]	[0.00624]
Household Income (ln)			-0.0169***	-0.0044	-0.0073
			[0.00365]	[0.00380]	[0.00482]
Male			0.00801*	0.0154***	0.00967*
			[0.00411]	[0.00416]	[0.00524]
Married			0.00344	0.00442	0.00289
			[0.00501]	[0.00501]	[0.00630]
Age			-0.000357**	3.75E-05	-0.00018
			[0.000151]	[0.000154]	[0.000200]
College			-0.00936**	-0.00343	0.000868
			[0.00452]	[0.00454]	[0.00571]
Hispanic (any)			0.0141**	0.00938	0.0123
			[0.00707]	[0.00705]	[0.00891]
Asian			0.0279***	0.0239***	0.0318***
			[0.00930]	[0.00927]	[0.0119]
Black			-0.0165**	-0.0221***	-0.0260***
			[0.00795]	[0.00793]	[0.00983]
Other race			0.0204	0.0156	0.0119
			[0.0141]	[0.0141]	[0.0180]
Financial Knowledge				-0.0826***	-0.0805***
				[0.0103]	[0.0131]
Financial Risk Tolerance				0.0146*	0.0117
				[0.00854]	[0.0107]
Self-employed				-0.0128*	-0.0162**
				[0.00669]	[0.00814]
3-month income cushion				-0.0645***	-0.0634***
				[0.00612]	[0.00787]
CBSA Outlying (vs non-CBSA)		0.0159	0.017	0.0177	0.00253
		[0.0126]	[0.0126]	[0.0125]	[0.0158]
CBSA Center-City (vs non-CBSA)		-0.00304	-0.00021	0.00224	-0.00316
		[0.0103]	[0.0103]	[0.0103]	[0.0130]
Origination Year DVs	No	Yes	Yes	Yes	Yes
State DVs	No	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	24,610
R-squared	0.004	0.011	0.013	0.02	0.022

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year. Network variables are constructed off of the 2019 extraction of the Social Connectedness Index (SCI) where we take $y^{SCI} = \sum_{c' \neq c}(y_{c'} \times SCI_{c,c'}/SCI_c)$ where c denotes the county, $SCI_{c,c}$ denotes the number of friendship ties between county c and c', and $y_{c'}$ denotes either house price growth or the unemployment rate.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is set to the NSMO survey response to question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, with *somewhat likely* or *very likely* set to one and zero otherwise. The sample in models 1-4 is all loans in the NMDB with a NSMO survey response, and in column 5 is the subsample of loans that were current in December, 2019. Observations weights are normalized within each of these raw samples.

Table 5: Baseline Results on the Effects of Expectations on Forbearance

	Dependent Variable: Entered Forbearance in 2020						
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Estimator	OLS	OLS	OLS	OLS	OLS	Probit	H. Probit
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	MFX	MFX
Origination Appreciation Expectations (vs *no change)*							
increase a lot	0.0333***	0.0190**	0.0163**	0.0158**	0.0173**	0.0142**	0.0165*
increase a little	0.00899	0.00294	0.00868	0.0106*	0.0114**	0.00940*	0.0109
decrease a little/a lot	0.0118	0.00873	0.00699	0.00543	0.00499	0.00613	0.00735
Expected Unemployment	0.0216***	0.0231***	0.0218***	0.0208***	0.0203***	0.0177***	0.0193***
Change in U. Rate, 2019-2020	0.00226***	0.00258***	0.00210**	0.00218***	0.00214**	0.00189***	0.00207**
Household Income (ln)				0.00938**	0.00932**	0.00941**	0.0115*
Male				-0.00854**	-0.00893**	-0.00743*	-0.00795*
Married				0.0117**	0.0124**	0.0105**	0.0122*
Age				-0.000853***	-0.000771***	-0.000765***	-0.000858***
College				-0.0196***	-0.0179***	-0.0156***	-0.0171***
Hispanic (any)				0.0145*	0.0144*	0.00731	0.00757
Asian				0.0316***	0.0307***	0.0262***	0.0288***
Black				0.0585***	0.0596***	0.0394***	0.0428***
Other race				0.0127	0.0129	0.0127	0.0134
CLTV			5.51E-05	-0.00017	-0.00015	-4E-05	-6.2E-05
Credit Score			-0.000483***	-0.000446***	-0.000428***	-0.000359***	-0.000408***
DTI			0.000952***	0.00110***	0.00104***	0.000952***	0.00107***
Rate/Term Refi (vs Purchase)			-0.0117**	-0.0100*	-0.00945*	-0.00764	-0.00842
Cash-Out Refi (vs Purchase)			-0.0150**	-0.0111*	-0.0101*	-0.00841	-0.00868
Appreciation, Origination-2019			-0.00024	-0.00028	-0.00029	-0.00011	-7.1E-05
Government-backed (vs Private)			0.0281***	0.0297***	0.0309***	0.0341***	0.0367***
Enterprise-backed (vs Private)			0.0577***	0.0567***	0.0585***	0.0516***	0.0586***
Interest Rate at Origination			0.00995*	0.0115**	0.0109**	0.0132**	0.0169
Spread at Origination			-0.00672	-0.00785	-0.00812	-0.0107*	-0.0134
Financial Knowledge					-0.0323***	-0.0257***	-0.0275**
Financial Risk Tolerance					0.00794	0.00542	0.00628
Employed Member of HH					-0.00251	-0.00197	-0.00265
Self-employed					0.0492***	0.0399***	0.0435***
3-month income cushion					-0.00498	-0.00662	-0.00774
CBSA Outlying (vs non-CBSA)		0.00753	0.0072	0.00636	0.00666	0.00837	0.00975
CBSA Center-City (vs non-CBSA)		0.00795	0.0146	0.0106	0.0109	0.0123	0.0142
Origination Year DVs	No	Yes	Yes	Yes	Yes	Yes	Yes
State DVs	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,610	24,610	24,610	24,610	24,610	24,610	37,881
R-squared	0.003	0.02	0.047	0.053	0.056		

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year.

Notes: Robust standard errors omitted from table for brevity, but available upon request. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The sample in models 1-6 is all loans in the NMDB with a NSMO survey response that were current in December, 2019. In model 7, it is all loans with reported status (24,610 current plus 13,271 loans in the selection equation, see Appendix Table A.6 for full selection model estimates). Observations weights are normalized within each of these raw samples.

Table 6: Determinants of Leverage and Debt Burden

Model	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable	CLTV	CLTV	CLTV	DTI	DTI	DTI
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Expectations (NSMO) (vs *no change)*						
increase a lot	1.190***	1.266***	0.761*	1.308***	1.739***	1.643***
	[0.377]	[0.339]	[0.428]	[0.232]	[0.216]	[0.274]
increase a little	0.436	1.448***	1.185***	-0.155	0.954***	0.909***
	[0.315]	[0.282]	[0.349]	[0.198]	[0.183]	[0.226]
decrease a little/a lot	0.998	0.862	0.82	1.069**	0.785	0.832
	[0.820]	[0.749]	[1.071]	[0.532]	[0.479]	[0.667]
Expected Unemployment	-0.0888	-0.633**	-0.692*	-0.0249	-0.29	-0.329
	[0.312]	[0.278]	[0.364]	[0.213]	[0.193]	[0.247]
Household Income (ln)		1.333***	1.377***		-7.675***	-7.484***
		[0.208]	[0.257]		[0.155]	[0.194]
Male		1.316***	1.233***		-0.0985	-0.0872
		[0.198]	[0.248]		[0.130]	[0.166]
Married		0.586**	0.346		1.725***	1.713***
		[0.246]	[0.308]		[0.159]	[0.202]
Age		-0.346***	-0.353***		0.0649***	0.0653***
		[0.00852]	[0.0108]		[0.00547]	[0.00709]
College		-0.913***	-1.177***		0.873***	0.826***
		[0.221]	[0.278]		[0.147]	[0.188]
Hispanic (any)		1.722***	2.170***		1.130***	1.265***
		[0.314]	[0.382]		[0.208]	[0.267]
Asian		-4.383***	-3.731***		1.363***	1.604***
		[0.412]	[0.507]		[0.248]	[0.315]
Black		4.859***	5.236***		1.889***	1.814***
		[0.426]	[0.529]		[0.282]	[0.345]
Other race		1.972***	2.209**		0.15	0.0774
		[0.732]	[0.952]		[0.426]	[0.573]
Financial Knowledge		-2.483***	-2.977***		2.600***	2.680***
		[0.522]	[0.657]		[0.334]	[0.420]
Financial Risk Tolerance		-1.896***	-1.364***		0.878***	0.972***
		[0.400]	[0.502]		[0.267]	[0.331]
Employed Member of HH		0.0899	0.144		0.568***	0.586***
		[0.228]	[0.285]		[0.149]	[0.191]
Self-employed		-2.747***	-2.389***		2.047***	2.022***
		[0.348]	[0.428]		[0.234]	[0.295]
3-month income cushion		-4.291***	-3.519***		-1.368***	-1.393***
		[0.296]	[0.376]		[0.191]	[0.243]
Rate/Term Refi		-9.021***	-9.485***		-0.363**	-0.229
		[0.249]	[0.313]		[0.163]	[0.215]
Cash-Out Refi		-10.68***	-11.37***		-1.221***	-1.163***
		[0.271]	[0.343]		[0.169]	[0.210]
Credit Score		-0.0575***	-0.0581***		-0.0346***	-0.0337***
		[0.00194]	[0.00249]		[0.00118]	[0.00150]
CBSA Outlying (vs non-CBSA)	2.780***	2.572***	1.001	0.534	1.525***	1.304***
	[0.758]	[0.687]	[0.850]	[0.435]	[0.408]	[0.502]
CBSA Center-City (vs non-CBSA)	1.354**	1.325**	0.316	-0.259	1.510***	1.441***
	[0.665]	[0.614]	[0.748]	[0.359]	[0.344]	[0.412]
Origination Year DVs	Yes	Yes	Yes	Yes	Yes	Yes
State DVs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,088	40,088	24,610	40,088	40,088	24,610
R-squared	0.036	0.262	0.289	0.019	0.203	0.196

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. Robust standard errors omitted from table for brevity, but available upon request. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample in models 1,2, 4 and 5 is all loans in the NMDB with a NSMO survey response, and in columns 3 and 6 is the subsample of loans that were current in December, 2019. Observations weights are normalized within each of these raw samples.

Table 7: Forbearance Outcomes through March, 2021

Multinomial logit model, outcome in column (vs current, never in forbearance). SE in bracket.

Outcome	Still in Forbearance		Forbearance then Closed		Forbearance then Current		Terminate prior to 2020	
Origination Appreciation Expectations (vs *no change*)								
increase a lot	0.159	[0.156]	0.197	[0.129]	0.281	[0.188]	0.216***	[0.0467]
increase a little	0.0152	[0.131]	0.181	[0.111]	0.186	[0.165]	0.139***	[0.0387]
decrease a little/a lot	0.543**	[0.249]	0.131	[0.253]	-0.579	[0.421]	0.129	[0.0906]
Expect a layoff	0.444***	[0.120]	0.0359	[0.106]	0.288**	[0.141]	-0.0914**	[0.0399]
Change in U. Rate, 2019-2020	0.152***	[0.0290]	0.108***	[0.0245]	0.179***	[0.0300]	0.00124	[0.00964]
Change in U. Rate, 2020-2021	0.174***	[0.0308]	0.0947***	[0.0260]	0.176***	[0.0312]	0.00837	[0.00971]
Appreciation, 2019-2020	-0.0333	[0.0203]	-0.0470**	[0.0183]	0.000221	[0.0260]	-0.00923	[0.00689]
Appreciation, Origination-2019	0.000266	[0.00423]	0.00451	[0.00356]	0.0204***	[0.00534]	0.0158***	[0.00117]
Household Income (ln)	-0.0755	[0.0986]	0.018	[0.0803]	0.315***	[0.107]	0.228***	[0.0285]
Male	-0.152	[0.0950]	-0.0967	[0.0780]	-0.0667	[0.107]	0.0673**	[0.0286]
Married	0.142	[0.111]	0.159*	[0.0929]	0.0919	[0.128]	0.161***	[0.0349]
Age	-0.00795**	[0.00377]	-0.00727**	[0.00308]	-0.0186***	[0.00430]	-0.00255**	[0.00120]
College	-0.403***	[0.104]	-0.142	[0.0877]	-0.141	[0.121]	0.0153	[0.0311]
Hispanic (any)	0.192	[0.131]	0.195*	[0.109]	0.0734	[0.150]	-0.0728	[0.0468]
Asian	0.340*	[0.204]	0.460***	[0.149]	0.253	[0.205]	-0.00548	[0.0603]
Black	0.806***	[0.140]	0.442***	[0.136]	0.0893	[0.203]	-0.202***	[0.0603]
Other race	-0.163	[0.342]	0.3	[0.213]	0.0696	[0.322]	-0.0935	[0.0938]
CLTV	-0.00292	[0.00334]	-0.00205	[0.00231]	0.0036	[0.00345]	-0.00477***	[0.000870]
Credit Score	-0.00682***	[0.000809]	-0.00569***	[0.000610]	-0.00306***	[0.000921]	-0.00181***	[0.000262]
DTI	0.00821**	[0.00389]	0.00903***	[0.00322]	0.0218***	[0.00385]	0.00415***	[0.00121]
Rate/Term Refi (vs Purchase)	-0.540***	[0.125]	-0.14	[0.0965]	0.000579	[0.137]	0.00722	[0.0344]
Cash-Out Refi (vs Purchase)	-0.203	[0.137]	-0.128	[0.105]	-0.0859	[0.155]	0.184***	[0.0396]
Government-backed (vs Private)	0.725***	[0.176]	0.505***	[0.135]	0.655***	[0.197]	-0.174***	[0.0388]
Enterprise-backed (vs Private)	1.150***	[0.194]	0.717***	[0.158]	0.739***	[0.216]	0.349***	[0.0502]
Interest Rate at Origination	0.095	[0.103]	0.0845	[0.0876]	-0.0306	[0.120]	0.539***	[0.0334]
Spread at Origination	0.0638	[0.126]	0.0187	[0.103]	-0.0145	[0.147]	-0.385***	[0.0380]
Financial Knowledge	-0.2	[0.235]	-0.453**	[0.188]	-0.328	[0.259]	0.252***	[0.0711]
Financial Risk Tolerance	0.326*	[0.191]	-0.00165	[0.158]	0.0548	[0.208]	0.0717	[0.0575]
Employed Member of HH	0.0228	[0.109]	-0.0196	[0.0909]	-0.0691	[0.123]	-0.107***	[0.0327]
Self-employed	0.563***	[0.140]	0.587***	[0.112]	0.537***	[0.148]	-0.126**	[0.0490]
3-month income cushion	-0.21	[0.133]	0.0257	[0.115]	-0.11	[0.148]	-0.0667	[0.0416]
Origination Year	-0.0188	[0.0338]	0.0143	[0.0299]	0.233***	[0.0446]	-0.353***	[0.0100]
CBSA Outlying (vs non-CBSA)	0.23	[0.324]	0.126	[0.245]	0.702	[0.435]	0.0858	[0.0859]
CBSA Center-City (vs non-CBSA)	0.262	[0.274]	0.0637	[0.216]	0.704*	[0.394]	0.114	[0.0737]
Total Observations	37,881							
Outcome Count (weighted, 23,118 base)	777		1,201		584		12,201	
Outcome Count (unweighted, 22,931 base)	643		1,028		517		12,762	

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response that have servicer reporting in December 2019. Estimates are from a single survey-weighted multinomial logit model, with five outcomes (vs current in March 2021 and never in forbearance) in each column. Outcome counts are weighted based on normalized weights from the 37,881 observation sample, giving 25,680 weighted observations for loans current in December, 2019, versus the 24,610 raw count in other tables.

A.1 Online Appendix

1.1 Supplement to Data and Measurement

Several variables incorporated in this analysis are derived from survey responses compiled from 30 waves of the National Survey of Mortgage Originations. Exact question numbers in different survey waves varied slightly. The reference to any question number in this analysis is based on the numbering in NSMO survey waves 29 and 30, which includes the most recent printing of the survey as of the publishing of this analysis. We have the following variables as controls in our main specification:

Financial Knowledge *(Source: National Survey of Mortgage Originations)*: Respondents are asked a series of questions regarding their financial knowledge both 1) prior to beginning the mortgage origination process (**NSMO Question 05**) and 2) after they completed the origination process (**NSMO Question 56**).

NSMO Question 05 asks: *When you began the process of getting this mortgage, how familiar were you (and any cosigners) with each of the following:*

a) The different types of mortgages available.

b) The mortgage process.

c) The down payment required to qualify for a mortgage.

d) The income required to qualify for a mortgage.

e) Your credit history or credit score.

g) The money needed at closing.

NSMO Question 56 asks: *How well could you explain to someone the...*

a) Process of taking out a mortgage.

b) Difference between a fixed- and adjustable-rate mortgage.

c) Difference between a prime and a subprime loan.

d) Difference between a mortgage interest rate and its APR.

e) Amortization of a loan.

Possible answers to each of these questions are, *Very, Somewhat, Not at All*.

The **Financial Knowledge** variable is an equally weighted linear combination of the responses to these two series of questions, with a *Very* response receiving 2 points, a *Somewhat* response receiving 1 point, and a *Not at All* response receiving 0 points. Therefore, a respondent with all *Very* responses would have a maximum **Financial Knowledge** score of 22 and a respondent with all *Not at All* responses would have a minimum **Financial Knowledge** score of 0.

Financial Risk Tolerance *(Source: National Survey of Mortgage Originations)*: **NSMO Question 89** asks: *Which one of the following statements best describes the amount of risk you are willing to take when you save or make investments?* Possible answers to this question are, *Take substantial financial risks expecting to earn substantial returns, Take above-average financial risks expecting to earn above-average returns, Take average financial risks expecting to earn average returns, Not willing to take financial risks.* The binary **Financial Risk Tolerance** variable takes a value of 1 when the respondent selects *Take substantial financial risks...* or *Take above-average financial risks...* and 0 otherwise.

3-month income cushion *(Source: National Survey of Mortgage Originations)*: **NSMO Question 96a** asks: *If your household faced an unexpected personal financial crisis in the next couple of years, how likely is it you could pay your bills for the next 3 months without borrowing?* Possible answers to this question are, *Very, Somewhat, Not at All.* The binary **3-month income cushion** variable takes a value of 1 when the respondent selects *Very* or *Somewhat* and 0 otherwise.

Expected Unemployment *(Source: National Survey of Mortgage Originations)*: **NSMO**

Question 95c asks: *How likely is it that in the next couple of years you (or your spouse/partner) will face a layoff, unemployment, or forced reduction in hours?* Possible answers to this question are, *Very, Somewhat, Not at All.* The binary **Expected Unemployment** variable takes a value of 1 when the respondent selects *Very* or *Somewhat* and 0 otherwise.

Future Move Likely *(Source: National Survey of Mortgage Originations)*: **NSMO Question 71b** asks: *How likely is it that in the next couple of years you will move but keep this property?* Possible answers to this question are, *Very, Somewhat, Not at All.* The binary **Future Move Likely** variable takes a value of 1 when the respondent selects *Very* or *Somewhat* and 0 otherwise.

Invest in other Real Estate *(Source: National Survey of Mortgage Originations)*: **NSMO Question 88d** asks: *Does anyone in your household have investment real estate?* Possible answers to this question are, *Yes or No.*

Belief Home is Good Investment *(Source: National Survey of Mortgage Originations)*: **NSMO Question 90a** asks: *Do you agree or disagree that owning a home is a good financial investment?* Possible answers to this question are, *Agree or Disagree.*

Belief in Default Consequences *(Source: National Survey of Mortgage Originations)*: **NSMO Question 90d** asks: *Do you agree or disagree that late payments will lower your credit rating?* Possible answers to this question are, *Agree or Disagree.*

Strategic Default Ethical *(Source: National Survey of Mortgage Originations)*: **NSMO Question 90f** asks: *Do you agree or disagree that it is okay to default or stop making mortgage payments if it is in the borrower's financial interest?* Possible answers to this question are, *Agree or Disagree.*

Purchased Distressed Property *(Source: National Survey of Mortgage Originations)*: **NSMO Question 59** asks: *Which one of the following best describes how you acquire this property?* Among a long list of possible answers to this question are, the binary **Purchased Distressed Property** variable takes a value of 1 when the respondent selects *Purchased a foreclosed property from a bank, investor, or government agency* or *Purchased a 'short sale' property from the previous owner* and 0 otherwise.

Single-family *(Source: National Survey of Mortgage Originations)*: **NSMO Question 60** asks: *Which one of the following best describes this property?* Among a long list of possible answers to this question are, the binary **Single-family** variable takes a value of 1 when the respondent selects *Single-family detached house* and 0 otherwise.

Renting out All or Part of Unit *(Source: National Survey of Mortgage Originations)*: **NSMO Question 63** asks: *Do you rent out all or any portion of this property?* Possible answers to this question are, *Yes or No.*

Property is Investment or Rental *(Source: National Survey of Mortgage Originations)*: **NSMO Question 66** asks: *Which one of the following best describes how you use this property?* Among a long list of possible answers to this question are, the binary **Property is Investment or Rental** variable takes a value of 1 when the respondent selects *Seasonal or second home* or *Rental or investment property* and 0 otherwise.

Table A.1: Loan Performance Status, NSMO sample (raw counts), December 2019

Raw Status	Counts	% of Total
D30-D179	275	0.7%
D180+	29	0.1%
Negative resolution (i.e. Default)	205	0.5%
Prepaid	12,762	31.8%
Current	24,610	61.4%
Opened	83	0.2%
In database but not opened yet	527	1.3%
Performance gap	21	0.1%
Opened but performance not started	1,555	3.9%
Performance suppressed by servicer	21	0.1%
Total	40,088	

Mapped December 2019 Status	Counts	% of Loans with reporting by servicer
Default/Delinquent	509	1.3%
Prepaid	12,762	33.7%
Current	24,610	65.0%
Performance unknown/not started	2,207	
Total reported by servicer	37,881	

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.

Table A.2: Determinants of House Price Appreciation Expectations at Origination, Ordinal Logit Models

	Dependent Variable: House Price Appreciation Expectations at Origination				
Model	[1]	[2]	[3]	[4]	[5]
Estimator	O. Logit	O. Logit	O. Logit	O. Logit	O. Logit
Estimate	Log-Odds	Log-Odds	Log-Odds	Log-Odds	Log-Odds
Network Appreciation	0.114***	0.0817***	0.0806***	0.0812***	0.0720***
	-0.0117	[0.0177]	[0.0177]	[0.0177]	[0.0231]
County Appreciation	0.0770***	0.0671***	0.0662***	0.0646***	0.0673***
	-0.00384	[0.00477]	[0.00478]	[0.00479]	[0.00650]
Network Unemployment Rate	0.0338**	-0.0806***	-0.0831***	-0.0887***	-0.0848**
	-0.014	[0.0289]	[0.0289]	[0.0288]	[0.0424]
County Unemployment Rate	-0.0582***	-0.0423***	-0.0341***	-0.0282***	-0.0360**
	-0.00963	[0.0109]	[0.0110]	[0.0109]	[0.0154]
Household Income (ln)			0.172***	0.0523**	0.042
			[0.0207]	[0.0219]	[0.0282]
Male			0.0912***	0.00877	0.0442
			[0.0236]	[0.0241]	[0.0310]
Married			-0.0432	-0.0631**	-0.0737**
			[0.0266]	[0.0292]	[0.0375]
Age			0.00220***	0.0013	0.00129
			[0.000840]	[0.000939]	[0.00123]
College			0.0995***	0.0276	0.0595*
			[0.0263]	[0.0267]	[0.0344]
Hispanic (any)			0.210***	0.255***	0.261***
			[0.0418]	[0.0420]	[0.0548]
Asian			-0.0428	0.00114	-0.0226
			[0.0521]	[0.0523]	[0.0652]
Black			0.260***	0.307***	0.266***
			[0.0575]	[0.0575]	[0.0730]
Other race			0.213***	0.237***	0.346***
			[0.0815]	[0.0816]	[0.109]
Financial Knowledge				0.630***	0.697***
				[0.0627]	[0.0802]
Financial Risk Tolerance				0.409***	0.347***
				[0.0514]	[0.0668]
Employed Member of HH				0.0393	0.0608*
				[0.0278]	[0.0360]
Self-employed				0.0275	-0.0149
				[0.0394]	[0.0489]
3-month income cushion				0.278***	0.314***
				[0.0356]	[0.0467]
CBSA Outlying (vs non-CBSA)		0.483***	0.465***	0.458***	0.427***
		[0.0748]	[0.0747]	[0.0746]	[0.0969]
CBSA Center-City (vs non-CBSA)		0.580***	0.526***	0.504***	0.481***
		[0.0622]	[0.0622]	[0.0620]	[0.0794]
Origination Year DVs	No	Yes	Yes	Yes	Yes
State DVs	No	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	40,088
Pseudo R-Squared	0.0209	0.0209	0.0302	0.033	0.0388

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year. Network variables are constructed off of the 2019 extraction of the Social Connectedness Index (SCI) where we take $y^{SCI} = \sum_{c' \neq c}(y_{c'} \times SCI_{c,c'}/SCI_c)$ where c denotes the county, $SCI_{c,c}$ denotes the number of friendship ties between county c and c', and $y_{c'}$ denotes either house price growth or the unemployment rate.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is set to the NSMO survey response, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years?*. Possible answers are, *Increase a lot*, assigned 3, *Increase a little*, assigned 2, *Remain about the same*, assigned 1, or *Decrease a little/Decrease a lot*, which are each assigned to 0 due to low counts in these cells. The sample is all loans in the NMDB with a NSMO survey response. Estimates are based on survey-weighted values.

Table A.3: Determinants of Individual Unemployment Expectations at Origination, Ordinal Logit Models

	Dependent Variable: Individual Unemployment Expectations at Origination				
Model	[1]	[2]	[3]	[4]	[5]
Estimator	O. Logit	O. Logit	O. Logit	O. Logit	O. Logit
Estimate	Log-Odds	Log-Odds	Log-Odds	Log-Odds	Log-Odds
Network Appreciation	-0.0391**	-0.0124	-0.00905	-0.00718	-0.00352
	[0.0153]	[0.0235]	[0.0234]	[0.0234]	[0.0315]
County Appreciation	0.00387	0.00385	0.00401	0.00535	0.00949
	[0.00529]	[0.00652]	[0.00649]	[0.00650]	[0.00855]
Network Unemployment Rate	0.0686***	-0.0018	0.00418	0.0121	-0.0384
	[0.0180]	[0.0359]	[0.0360]	[0.0359]	[0.0563]
County Unemployment Rate	-0.00222	-0.0253*	-0.0339**	-0.0399***	-0.0202
	[0.0123]	[0.0141]	[0.0144]	[0.0143]	[0.0215]
Employed Member of HH	0.176***	0.157***	0.162***	0.161***	0.153***
	[0.0329]	[0.0331]	[0.0408]	[0.0411]	[0.0541]
Household Income (ln)			-0.141***	-0.0394	-0.0665
			[0.0308]	[0.0326]	[0.0431]
Male			0.0659*	0.127***	0.0822*
			[0.0340]	[0.0348]	[0.0453]
Married			0.0296	0.0354	0.0229
			[0.0421]	[0.0423]	[0.0551]
Age			-0.00306**	0.000142	-0.00184
			[0.00126]	[0.00130]	[0.00174]
College			-0.0774**	-0.0289	0.00573
			[0.0370]	[0.0375]	[0.0494]
Hispanic (any)			0.111**	0.0729	0.102
			[0.0547]	[0.0550]	[0.0723]
Asian			0.209***	0.178***	0.239***
			[0.0667]	[0.0672]	[0.0868]
Black			-0.151**	-0.196***	-0.243**
			[0.0749]	[0.0751]	[0.101]
Other race			0.163	0.124	0.11
			[0.107]	[0.108]	[0.147]
Financial Knowledge				-0.672***	-0.678***
				[0.0822]	[0.108]
Financial Risk Tolerance				0.119*	0.102
				[0.0699]	[0.0918]
Self-employed				-0.109*	-0.144*
				[0.0600]	[0.0781]
3-month income cushion				-0.506***	-0.513***
				[0.0460]	[0.0609]
CBSA Outlying (vs non-CBSA)		0.134	0.145	0.15	0.0215
		[0.107]	[0.107]	[0.107]	[0.138]
CBSA Center-City (vs non-CBSA)		-0.0219	0.00299	0.0229	-0.0296
		[0.0911]	[0.0911]	[0.0913]	[0.114]
Origination Year DVs	No	Yes	Yes	Yes	Yes
State DVs	No	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	24,610
Pseudo R-Squared	0.00438	0.0128	0.0154	0.0246	0.0266

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year. Network variables are constructed off of the 2019 extraction of the Social Connectedness Index (SCI) where we take $y^{SCI} = \sum_{c' \neq c}(y_{c'} \times SCI_{c,c'}/SCI_c)$ where c denotes the county, $SCI_{c,c}$ denotes the number of friendship ties between county c and c', and $y_{c'}$ denotes either house price growth or the unemployment rate.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is set to the NSMO survey response to question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, with *somewhat likely* or *very likely* set to one and zero otherwise. The sample is all loans in the NMDB with a NSMO survey response. Estimates are based on survey-weighted values.

Table A.4: Determinants of Leverage and Debt Burden, Quantile Regressions

	Dependent Variable: Variable shown in Column					
Model	[1]	[2]	[3]	[4]	[5]	[6]
Estimator	Q. Reg.	Q. Reg.	Q. Reg.	Q. Reg.	Q. Reg.	Q. Reg.
Dep. Variable	CLTV	CLTV	CLTV	DTI	DTI	DTI
Quantile Value	65	80	93	28	36	43
increase a lot	1.587***	1.011***	0.795***	2.424***	2.034***	1.516***
	[0.377]	[0.257]	[0.222]	[0.209]	[0.181]	[0.180]
increase a little	1.603***	1.050***	0.490***	1.452***	1.207***	0.725***
	[0.316]	[0.216]	[0.186]	[0.176]	[0.152]	[0.151]
decrease a little/a lot	-0.159	1.210**	0.404	0.0852	0.855**	0.554*
	[0.698]	[0.476]	[0.411]	[0.388]	[0.335]	[0.333]
Expected Unemployment	-0.472	-0.542**	-0.549***	-0.788***	-0.634***	-0.393**
	[0.325]	[0.221]	[0.191]	[0.180]	[0.156]	[0.155]
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Borrower/Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Origination Year DVs	Yes	Yes	Yes	Yes	Yes	Yes
State DVs	Yes	Yes	Yes	Yes	Yes	Yes
CC/Outlying DVs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	40,088	40,088
Pseudo R-Squared	0.20	0.19	0.16	0.13	0.12	0.09

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.

Notes: Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response that were active in December, 2019. Estimates are based on survey-weighted values.

Table A.5: The Effects of Expectations on Forbearance, Alternative Controls

	Dependent Variable: Entered Forbearance in 2020						
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Label	Baseline	State × Urban	State × Year	County FEs	SDR	OpenTable	NAICS
Origination Appreciation Expectations (vs *no change)*							
increase a lot	0.0169***	0.0170***	0.0167***	0.0137**	0.0173***	0.0199**	0.0149***
	[0.00569]	[0.00569]	[0.00575]	[0.00615]	[0.00576]	[0.00953]	[0.00570]
increase a little	0.0118***	0.0120***	0.0116***	0.0109**	0.0118***	0.0107	0.0105**
	[0.00431]	[0.00432]	[0.00436]	[0.00472]	[0.00436]	[0.00789]	[0.00432]
decrease a little/a lot	0.00881	0.00894	0.00767	0.00427	0.00962	-0.00011	0.00877
	[0.0114]	[0.0114]	[0.0115]	[0.0122]	[0.0117]	[0.0190]	[0.0114]
Expected Unemployment	0.0203***	0.0207***	0.0203***	0.0208***	0.0196***	0.0131*	0.0195***
	[0.00533]	[0.00533]	[0.00538]	[0.00570]	[0.00536]	[0.00783]	[0.00533]
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower/Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origination Year DVs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State DVs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CC/Outlying DVs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x CC/Outlying DVs	No	Yes	No	No	No	No	No
State x Year DVs	No	No	Yes	No	No	No	No
County DVs	No	No	No	Yes	No	No	No
Stressed Default Rate	No	No	No	No	Yes	No	No
OpenTable Control	No	No	No	No	No	Yes	No
NAICS (2-digit) sector shares (2019)	No	No	No	No	No	No	Yes

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.
Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response that have servicer reporting in December 2019. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The Open Table variable is the drop in reservations between August 2019 and August 2020 in percentage terms for a particular CBSA. NAICS 2-digit sector shares are annual values from the 2019 Quarterly Census of Employment and Wages, produced by the Bureau of Labor Statistics. The Stressed Default Rate is the counterfactual lifetime default rate as if the loan were a new origination in 2007, as described by Larson (2021). Estimates are based on survey-weighted values.

Table A.6: The Effects of Expectations on Forbearance, Models with Selection

	Dependent Variable: Entered Forbearance in 2020							
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Estimator	OLS	Probit	H. Probit	H. Probit	H. Probit	H. Probit	OLS	Probit
Main Estimate	$\hat{\beta}$	MFX	MFX	MFX	MFX	MFX	$\hat{\beta}$	MFX
Origination Appreciation Expectations (vs *no change*)								
increase a lot	0.0333***	0.0322***	0.0379***	0.00849*	0.0135*	0.0165*	0.0173**	0.0142**
increase a little	0.00899	0.0094	0.0121*	0.000529	0.00725	0.0109	0.0114**	0.00940*
decrease a little/a lot	0.0118	0.0125	0.016	0.00492	0.00804	0.00735	0.00499	0.00613
Expected Unemployment	0.0216***	0.0203***	0.0237***	0.0151***	0.0198***	0.0193***	0.0203***	0.0177***
ρ			-0.186***	-0.199***	-0.0936	-0.0793		
Demographic Controls	No	No	No	No	No	Yes	Yes	Yes
Borrower/Loan Controls	No	No	No	No	Yes	Yes	Yes	Yes
Origination Year DVs	No	No	No	Yes	Yes	Yes	Yes	Yes
State DVs	No	No	No	Yes	Yes	Yes	Yes	Yes
CC/Outlying DVs	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	24,610	24,610	24,610	24,610	24,610	24,610	24,610	24,610
Observations (weighted)	24,610	24,610	25,046	25,046	25,046	25,046	24,610	24,610
Selection Estimate	None	None	Log-Odds	Log-Odds	Log-Odds	Log-Odds	None	None
Origination Appreciation Expectations (vs *no change*)								
increase a lot			-0.208***	-0.145***	-0.127***	-0.101***		
increase a little			-0.124***	-0.0857***	-0.0959***	-0.0670***		
decrease a little/a lot			-0.100*	-0.0778	-0.0784	-0.0792		
Expected Unemployment			0.0400*	0.0445*	0.0505**	0.0467**		
All other controls in Main Estimate			Yes	Yes	Yes	Yes		
Interest Rate X 2012 Origination			-1.513*	-1.481*	-1.707*	-1.714*		
Interest Rate X 2013 Origination			-0.107***	-0.0992***	-0.227***	-0.237***		
Interest Rate X 2014 Origination			-0.0755***	-0.0729***	-0.258***	-0.267***		
Interest Rate X 2015 Origination			-0.137***	-0.130***	-0.310***	-0.325***		
Interest Rate X 2016 Origination			-0.176***	-0.173***	-0.344***	-0.356***		
Interest Rate X 2017 Origination			-0.124***	-0.115***	-0.305***	-0.310***		
Interest Rate X 2018 Origination			-0.0362	-0.0396	-0.220***	-0.218***		
Interest Rate X 2019 Origination			-0.202***	-0.210***	-0.383***	-0.383***		
Selection Wald χ^2			12.92	14.91	1.147	0.815		
Selection p-value			3.24E-04	0.000113	0.284	0.367		
Non-Selected			13,271	13,271	13,271	13,271		
Non-Selected (weighted)			12,835	12,835	12,835	12,835		

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response that have servicer reporting in December 2019. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. Identification in selection equation provided by both origination interest rate interacted with origination year and the nonlinearity of the estimate. Estimates are based on survey-weighted values.

Table A.7: The Effects of Expectations on Outcomes Prior to COVID Era

Multinomial logit model, outcome in column (vs current in December 2019)

Outcome	Default/Delinquent	Prepay
Origination Appreciation Expectations (vs *no change)*		
increase a lot	-0.0138	0.186***
	[0.168]	[0.0467]
increase a little	-0.215	0.125***
	[0.137]	[0.0385]
decrease a little/a lot	0.298	0.117
	[0.275]	[0.0889]
Expected Unemployment	0.161	-0.0946**
	[0.141]	[0.0392]
Demographic Controls	Yes	
Loan-Level Controls	Yes	
Finance/Employment Controls	Yes	
Origination Year DVs	Yes	
State DVs	Yes	
CC/Outlying DVs	Yes	
Observations	37,881	
Outcome (weighted, 25,045 base)	509	12,762
Outcome (unweighted, 24,610 base)	634	12,200

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.
Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response that have servicer reporting on or before December 2019. Estimates are based on survey-weighted values.

Table A.8: Determinants of Individual House Price Appreciation Expectations at Origination, Additional NSMO Variables

	Dependent Variable: Individual House Price Appreciation Expectations at Origination									
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Network Appreciation	0.0259***	0.0261***	0.0267***	0.0267***	0.0269***	0.0267***	0.0268***	0.0268***	0.0268***	0.0266***
	[0.00604]	[0.00604]	[0.00606]	[0.00607]	[0.00607]	[0.00607]	[0.00607]	[0.00607]	[0.00607]	[0.00607]
County Appreciation	0.0223***	0.0224***	0.0224***	0.0225***	0.0225***	0.0225***	0.0224***	0.0225***	0.0225***	0.0225***
	[0.00165]	[0.00165]	[0.00165]	[0.00165]	[0.00165]	[0.00165]	[0.00165]	[0.00165]	[0.00165]	[0.00165]
Network Unemployment Rate	-0.0285***	-0.0281***	-0.0296***	-0.0296***	-0.0295***	-0.0297***	-0.0297***	-0.0296***	-0.0298***	-0.0300***
	[0.00979]	[0.00980]	[0.00985]	[0.00986]	[0.00986]	[0.00987]	[0.00987]	[0.00986]	[0.00986]	[0.00986]
County Unemployment Rate	-0.00817**	-0.00852**	-0.00851**	-0.00825**	-0.00834**	-0.00831**	-0.00847**	-0.00831**	-0.00823**	-0.00776**
	[0.00367]	[0.00367]	[0.00369]	[0.00370]	[0.00369]	[0.00370]	[0.00370]	[0.00370]	[0.00369]	[0.00369]
Belief Home is Good Investment	0.308***	0.308***								
	[0.0223]	[0.0223]								
Future Move Likely	0.0425***		0.0398***							
	[0.0106]		[0.0104]							
Invest in other Real Estate	-0.0102			-0.0138						
	[0.0108]			[0.0101]						
Belief in Default Consequences	-0.0225				-0.0218					
	[0.0164]				[0.0164]					
Strategic Default Ethical	-0.00699					-0.0172				
	[0.0175]					[0.0176]				
Purchased Distressed Property	0.0493**						0.0476**			
	[0.0236]						[0.0239]			
Single-family Home	-0.00125							-0.00214		
	[0.0114]							[0.0111]		
Renting out All or Part of Unit	0.0192								-0.0167	
	[0.0203]								[0.0153]	
Property is Investment or Rental	-0.0635***									-0.0483***
	[0.0195]									[0.0146]
Standard controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	40,088	40,088	40,088	40,088	40,088	40,088
R-squared	0.083	0.081	0.075	0.074	0.074	0.074	0.074	0.074	0.074	0.074

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.
Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response. Estimates are based on survey-weighted values. "Standard controls" include all borrower, demographic, financial sophistication, and dummy variables found in Table 3.

Table A.9: Determinants of Individual Unemployment Expectations at Origination, Additional NSMO Variables

	Dependent Variable: Individual Unemployment Expectations at Origination									
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Network Appreciation	-0.000550	-0.000536	-0.000838	-0.000722	-0.000806	-0.000479	-0.000724	-0.000795	-0.000704	-0.000704
	[0.00276]	[0.00277]	[0.00276]	[0.00277]	[0.00277]	[0.00278]	[0.00277]	[0.00277]	[0.00277]	[0.00277]
County Appreciation	0.000454	0.000674	0.000558	0.000663	0.000677	0.000520	0.000670	0.000654	0.000640	0.000660
	[0.000793]	[0.000796]	[0.000795]	[0.000798]	[0.000798]	[0.000797]	[0.000798]	[0.000798]	[0.000798]	[0.000798]
Network Unemployment Rate	0.00105	0.000658	0.00110	0.00107	0.00102	0.00137	0.00108	0.00107	0.00123	0.00112
	[0.00461]	[0.00461]	[0.00462]	[0.00463]	[0.00463]	[0.00464]	[0.00463]	[0.00463]	[0.00462]	[0.00463]
County Unemployment Rate	-0.00505***	-0.00478***	-0.00509***	-0.00483***	-0.00482***	-0.00490***	-0.00482***	-0.00479***	-0.00492***	-0.00490***
	[0.00175]	[0.00175]	[0.00176]	[0.00176]	[0.00176]	[0.00176]	[0.00176]	[0.00176]	[0.00176]	[0.00176]
Employed Member of HH	0.0213***	0.0202***	0.0207***	0.0193***	0.0193***	0.0191***	0.0193***	0.0195***	0.0192***	0.0192***
	[0.00490]	[0.00492]	[0.00492]	[0.00493]	[0.00493]	[0.00492]	[0.00493]	[0.00493]	[0.00493]	[0.00493]
Belief Home is Good Investment	-0.0828***	-0.0877***								
	[0.0121]	[0.0121]								
Future Move Likely	0.0537***		0.0551***							
	[0.00545]		[0.00542]							
Invest in other Real Estate	-0.00635			-0.000103						
	[0.00550]			[0.00521]						
Belief in Default Consequences	0.0122				0.0127*					
	[0.00764]				[0.00765]					
Strategic Default Ethical	0.0763***					0.0830***				
	[0.0100]					[0.0101]				
Purchased Distressed Property	-0.00549						-0.00372			
	[0.0137]						[0.0137]			
Single-family Home	0.00182							-0.00684		
	[0.00592]							[0.00577]		
Renting out All or Part of Unit	0.0159								0.0168**	
	[0.0109]								[0.00835]	
Property is Investment or Rental	-0.00772									0.00589
	[0.0103]									[0.00795]
Standard controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,088	40,088	40,088	40,088	40,088	40,088	40,088	40,088	40,088	40,088
R-squared	0.030	0.023	0.024	0.020	0.020	0.024	0.020	0.020	0.020	0.020

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data.

Notes: Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample of loans consists of all loans in the NMDB with a NSMO survey response. Estimates are based on survey-weighted values. “Standard controls” include all borrower, demographic, financial sophistication, and dummy variables found in Table 4.

Table A.10: Effects of Expectations on Forbearance, Additional NSMO Variables

	Dependent Variable: Individual Unemployment Expectations at Origination									
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Expectations (NSMO) (vs *no change)*										
decrease a little/a lot	0.0172**	0.0171**	0.0171**	0.0173**	0.0173**	0.0173**	0.0173**	0.0173**	0.0173**	0.0174**
	[0.00753]	[0.00754]	[0.00751]	[0.00752]	[0.00752]	[0.00752]	[0.00753]	[0.00752]	[0.00752]	[0.00751]
increase a little	0.0113**	0.0113**	0.0113**	0.0114**	0.0114**	0.0115**	0.0114**	0.0114**	0.0114**	0.0115**
	[0.00572]	[0.00571]	[0.00571]	[0.00571]	[0.00571]	[0.00571]	[0.00571]	[0.00571]	[0.00571]	[0.00570]
increase a lot	0.00563	0.00544	0.00478	0.00499	0.00502	0.00493	0.00500	0.00499	0.00499	0.00512
	[0.0140]	[0.0141]	[0.0140]	[0.0140]	[0.0140]	[0.0140]	[0.0140]	[0.0140]	[0.0140]	[0.0140]
Expected Unemployment	0.0200***	0.0204***	0.0200***	0.0203***	0.0203***	0.0201***	0.0203***	0.0203***	0.0203***	0.0203***
	[0.00664]	[0.00659]	[0.00662]	[0.00659]	[0.00659]	[0.00660]	[0.00659]	[0.00659]	[0.00659]	[0.00659]
Belief Home is Good Investment	0.00675	0.00673								
	[0.0104]	[0.0103]								
Future Move Likely	0.00309		0.00334							
	[0.00588]		[0.00576]							
Invest in other Real Estate	8.09e-05			0.00118						
	[0.00568]			[0.00553]						
Belief in Default Consequences	0.00182				0.00224					
	[0.00842]				[0.00839]					
Strategic Default Ethical	0.00349					0.00323				
	[0.00924]					[0.00923]				
Purchased Distressed Property	-0.00432						-0.00379			
	[0.0141]						[0.0141]			
Single-family Home	-0.000224							-0.000881		
	[0.00603]							[0.00589]		
Renting out All or Part of Unit	-0.00587								0.000348	
	[0.0106]								[0.00829]	
Property is Investment or Rental	0.00901									0.00583
	[0.0102]									[0.00802]
Standard controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,610	24,610	24,610	24,610	24,610	24,610	24,610	24,610	24,610	24,610
R-squared	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The sample is all loans in the NMDB with a NSMO survey response that were current in December, 2019. Estimates are based on survey-weighted values. "Standard controls" include all borrower, demographic, loal-level, financial sophistication, and dummy variables found in Table 5.