highly inconvenient and the consumer is more likely to exit the market entirely rather than obtain a jumbo loan. In contrast, when γ_i is low, jumbo loans are relatively convenient and the consumer is more likely to remain in the market. That is, γ_i governs the missing mass of borrowers whose ideal loan size is jumbo, but because jumbo loans are inconvenient and conforming loans are too small, decide to exit the market entirely. Observe from Figure 7A that there is indeed a missing mass of jumbo borrowers: the density of mortgages drops discontinuously above the conforming loan limit in excess of the bunching at the limit. That is, consumers value the convenience of conforming mortgages. Put another way, holding market size constant on the extensive margin, γ_i governs the relative market shares of conforming and jumbo mortgages, with a high γ_i leading to relatively more conforming loans. Consequently, the average level of γ_i is identified from the relative market shares of conforming and jumbo loans holding overall market shares fixed, while γ_i's covariance with income and house price is identified based on how these relative market shares vary with wage and house prices in the data.

The last micro-moment we match is the income difference between borrowers exactly at the conforming loan limit and those nearby (see Figure 7B). Intuitively, the larger the income spike at the discontinuity, the less sensitive the higher-income population is to taking a mortgage which is smaller than ideal. This moment aids in identifying the correlation between income and preferences for a jumbo mortgage, i.e., the structure of the correlation in the random coefficients.

Model Fit: Targeted Moments and Simulated Responses to Real Policy Changes

We estimate the model over the period 2010–2015. The demand parameter estimates are shown in Table 5. By construction, the model fits market shares data. The model also fits the size distribution of mortgages in the data quite well. Figure 8B shows the model replicates the average amount of bunching at the conforming loan limit generated by our model. Figure 8A shows that the model can replicate the qualitatively bunching patterns across markets and does well in quantitatively matching the extent of bunching. We overestimate the extent of bunching in the markets with the most bunching. Intuitively, these are markets with the highest demand for jumbo mortgages. The difference between data and model estimates is likely due to approximating the desired loan size with a log-normal distribution. Markets in which desired loan sizes are large will also be high variance, so the log-normal distribution will put a lot of mass to the right.

We also examine the fit of the model by confronting it with actual policy changes. We exploit changes to conforming loan limits over time in the U.S. mortgage market between 2007 and 2016. We compute market outcomes using model estimates, and compare model-predicted changes to those from the data. The main variables of interest at the level of county and origination year are jumbo origination share (*%Jumbo*), bank origination share (*%Bank*), and the mass of borrowers at conforming limit cutoff (*%AtCutoff*). The main explanatory variable captures the change in conforming limit in a given county in a given year. We measure increases as the percentage difference between the conforming loan limit in year *t* in county *c* and the conforming loan limit in 2007 for the same county *c*:

$$LimitIncrease_{ct} = \frac{Limit_{ct}}{Limit_{c2007}} - 1$$