The Effects of Place on Economic Inequality

by

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To *Ajja* and *Amamma* – Ramachandra and Sharada Rao; to *Daji* and *Maa* – Navinkant and Vamila Desai

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ABSTRACT

This dissertation examines the relationship between local labor and housing market disparities and inter-generational wealth inequality in the United States. It consists of papers that collectively contribute to our understanding of how variations in labor markets, housing markets, and wealth accumulation interact to shape wealth inequality dynamics.

The first paper, **"The Intergenerational Wealth Effects of Local Labor and Housing Markets Markets in the United States"** employs an event-study style analysis to investigate the impact of local labor and housing market disparities on inter-generational wealth inequality from 1999 to 2019. The findings reveal that individuals who grew up in areas with robust labor markets and homeowner parents have, on average, a net worth that is $45,000 higher as adults. The increase in wealth is attributed to factors such as entry into homeownership and greater intergenerational transfers. Additionally, the study shows that variations in local market growth account for nearly 40% of the wealth inequality increase among the bottom 90% of U.S. households. This outcome is primarily driven by bequest concerns, leading households in growing areas to save disproportionately more.

The second paper, **"The Effect of Local Labor and Housing Markets on Household Wealth in the United States"** complements the first, and focuses on exploring the influence of local labor markets on household-level wealth in the United States between 1980 and 2019. Three key findings are established: First,

labor demand has driven house prices to rise significantly more between 1999 and 2019 compared to the period between 1980 and 1999. Second, areas experiencing high labor demand tend to have limited housing supply, exacerbating the housing market challenges. Third, households residing in high labor demand areas accumulate an additional $43,000 in net worth, primarily driven by housing wealth. In contrast, the impact of better labor markets on wealth accumulation is only associated with a $17,000 increase in wealth between 1980 and 1999. These findings underscore the importance of considering the spatial distribution of labor market growth and its interaction with local housing markets in understanding U.S. wealth inequality dynamics.

Collectively, these papers contribute to our understanding of the complex dynamics between local labor markets, housing markets, wealth accumulation, and inter-generational wealth inequality in the United States. The findings highlight the importance of considering the spatial dimension of labor market growth and its interaction with housing markets when examining wealth disparities and economic mobility.

CHAPTER I

The Intergenerational Wealth Effects of Local Labor and Housing Markets Markets in the United States

1.1 Introduction

The recent increase in wealth inequality within the United States has led to debates about its extent and causes both within economics and public policy. The public debate on the topic has focused on the top 1% (Saez and Zucman [2016]) of the population, while paying relatively little attention to the wealth of the bottom 90%. It is important to consider these groups separately because their wealth portfolios are dramatically different – while the wealth of the top 1% consists primarily of stock holdings and business wealth, that of the bottom 90% is dominated by housing.[1] A home is also the most important asset passed down generations, which makes changes in housing wealth especially salient for the intergenerational persistence in wealth.

Meanwhile, local markets across the U.S. have been diverging away from each other: between 1999 and 2019, the Detroit metro area has seen real wages decline by 2%, while real house prices have decreased by 12.5%; on the other hand, the San Francisco metro area has seen real wages increase by 50%, and real house prices

[1] To be sure, these measures typically do not include Social Security or pension wealth, which is a future transfers in the life of a working household that has not yet been accounted for.

increase by 99%.[2] These trends, in turn, affect the wealth holdings of households experiencing them. For homeowners in these areas, they affect their housing wealth as well. In order to understand the distribution and persistence of wealth within the bottom 90% of households, it is important to understand how trends in local markets across the U.S. shape the wealth of households living in them and how they are able to pass on these advantages to their children.

In this paper, I quantify the extent to which the local labor markets experienced by parents shape their children's wealth and affect wealth inequality across the United States between 1999 and 2019. How is this dynamic mediated by parental homeownership? Specifically, I build an intergenerational dataset of households in the U.S. using the Panel Study of Income Dynamics (PSID).[3], and augment it with measures of labor market growth in the parent's area of residence before the child splits off to form her own household. Local labor markets are defined as Core Based Statistical Areas (CBSAs), and their strength is measured using the County Business Patterns (CBP) dataset.[4] Using this, I follow children after they split-off and study their wealth accumulation, focusing on how this differs according to the local labor market experienced by her parents as well as parental homeownership. I find that children of parents who experienced better labor markets do, in fact, accumulate more wealth, but only if the parents were *homeowners*. Among this population, those whose parents were homeowners in *inelastic* housing markets (i.e., where housing is difficult to build) show the greatest increase in net worth. Children of renter parents do not show a significant response in their wealth accumulation, and if anything, are negatively affected.

[2]Henceforth, metro areas are implied when cities are referred to by name.

[3]The PSID has been the primary data source in the literature on wealth mobility (Mazumder [2018]) It is the only household level survey in the United States that collects data on the wealth of households over time, links across generations, and observes the area in which the parents and children live.

[4]The reason for this is explained in Section 1.2.

These results have direct consequences for the welfare of children. I find that there is a positive, anticipatory increase in consumption for the children of homeowner parents from better labor markets compared to those from worse ones. This underscores the salience of these markets for children's well-being in later life.

How are these children able to accumulate greater wealth? Upon investigating mediating factors such as gift receipt, labor income, and child homeownership, I find that there is a significant increase in monetary gifts received by the children of homeowning parents, help received to pay the downpayment on a house, as well as their homeownership rates. However, there is no differential trend in their labor earnings, which points to the importance of parental transfers instead of labor market benefits of wealthier parents.

In order to quantify some of the channels through which these divergent patterns might affect wealth inequality, I build a parsimonious, multi-region, general equilibrium modeling framework of local labor and housing markets with homeownership and location choice where households leave bequests that include their home. I find that the dispersion in local labor market growth across the U.S. is responsible for about 40% of the increase in wealth inequality among the bottom 90% of households between 1999 and 2019. Primarily, this is because households in the model care about leaving bequests to their kids, and treat these bequests as luxury goods: if their local labor market does well, they have an additional incentive to save more and, if they are homeowners, consume more housing. On the other hand, the pass through of the growth in local labor markets to house prices accounts for only about 8% of the increase. In an alternate model where I force all households to be renters, I find that wealth inequality would increase by only 40% as much as it did in this period.

The paper consists of two parts – the empirics and the model. In the first part, I use data from the CBP and PSID to provide some baseline empirical facts about the association between the local labor markets experienced by parents with the wealth accumulation of their children, and how this is mediated by parental homeownership. Specifically, I focus on the child's wealth accumulation from the time of her split off from the parent's household, and study how this varies according to the labor market growth in the parent's area in the ten years prior to splitoff. If a child splits off from her Detroit parents in 1999, she is assigned the labor market growth in Detroit between 1989 and 1999. How does this child accumulate wealth over time as she interacts with the market herself? Further, how do the accumulation patterns change if her parents were homeowners or renters?

I use an event study style specification to answer these questions, and compare children who split off from parents when local labor markets were doing great (one standard deviation above average) versus not-so-great. The "event" I study is the child splitting off, and the shock in question is a shift-share measure of labor demand growth in the parent's area of residence. To fix ideas about the regression, one can think of the comparison between two children who split off from parents in Detroit – but one split off in 1999, when the Detroit metro area was doing relatively well, and the other right in the aftermath of the Great Recession in 2009, by which point the area had declined dramatically.

It is important to break these estimates by parental homeownership. Since the effects of local labor markets spill over into housing markets, they can also have distinct effects depending on whether the parents owner their home. I do this by performing a "triple difference" version of the previous regression by explicitly accounting for an interaction between parental homeownership and local labor demand growth.

I find that a significant association between parental local labor market growth and the net worth of children after they have split off, but the direction and magnitude depends crucially on parental homeownership. Specifically, twenty years after splitting off[5], children who grew up in one standard deviation better labor markets have a higher net worth by almost \$45,000 if their parents were homeowners. On the other hand, the children of renter parents show no statistically significant effect, with the point estimate being negative. This suggests that the effects of local labor and housing markets on cost of living and housing wealth are particularly salient for the parent.

Homeownership is correlated with various co-variates including occupation, age profiles, etc. How can we be sure that the results are driven by the increases in housing wealth as opposed to parental preference to own? I address this question by comparing the outcomes of children who grew up in markets with a low versus high elasticity of housing supply. The elasticity captures how difficult it is to build new housing in an area, and so a growth in local labor markets should lead to much larger increases in house prices when the supply elasticity of housing is low (like in the San Francisco metro area). In this way, we can compare two children whose parents both experienced better labor markets, but one of whom experienced a much larger increase in the value of their home. I find that the association between parental labor markets and their child's wealth accumulation is driven by those parents who live in areas with a low house supply elasticity. This lends additional support to the argument that the increase in child wealth is due to an increase in the housing wealth of parents.

[5]When these children are on average 45 years of age.

The data also allows for investigating the association between the components of net worth (non-housing or housing, assets or debt) of the child and parental labor markets. I find that better parental labor markets are associated with an increase in the non-housing wealth of the child of about $35,000 and with an increase in housing wealth of about $10,000. Again, this is only true for the children of homeowner parents.

I also provide evidence that the association between the child's wealth accumulation and parental labor markets is driven by the increase in the housing wealth of the parent as opposed to preferences for being a homeowner or some other unobservables that might affect entry homeownership (such as a higher propensity to save). I do this by considering the subset of children whose parents were homeowners, and splitting them according to whether the housing supply in the area was highly elastic (such as in Indianapolis) or not (such as in San Francisco). I find that the association between the child's wealth and parental labor markets is strongest in low-elasticity housing markets (where the pass through of labor markets into house prices is presumably the highest), lending support to the argument that it isn't parental homeownership per se that drives the child's wealth accumulation, but rather increases in the housing wealth of the parent.

Parents engaging in wealth transfers play an important role in mediating the persistence of wealth. Upon investigating mediating channels (inheritances and gifts, help with downpayment on a home, homeownership, labor income) that point towards how these child households are able to accumulate wealth, I find evidence for direct transfers. Specifically, I find that for the children of homeowner parents, a 1 standard deviation better labor market when growing up is associated with an increase in inheritances of gift receipt by almost $15,000. It is also associated with an increase in homeownership rates by about 5 percentage points, and an increase in the likelihood of parents helping with the downpayment for a house by about 4 percentage points. Surprisingly, there is no effect on the labor income of children. In this way, there is a direct link across generations in how the advantages of wealth persist: parents are directly able to help children by giving them gifts or leaving them inheritances, and also by helping pay the downpayment for a home, easing entry into homeownership.

Finally, there is also some evidence for anticipatory effects of these transfers in the child's consumption-related expenditures. I find that there is a positive association of about $5,000 per year between better parental labor markets and the child's consumption immediately following splitoff, although this association disappears in time as the wealth transfers kick in around 14-20 years post-splitoff. This is consistent with the children of homeowners from better labor markets anticipating a transfer and increasing consumption in early adulthood, while the children of homeowners from worse labor markets catch up only later in life.

These divergent trends in wealth accumulation also have implications for the level of wealth inequality across the U.S., especially that of the bottom 90%.[6] However, the empirics present many channels that might affect inequality – local labor and housing markets, intergenerational transfers, homeownership, geographic mobility – and it is hard to disentangle them using just the data. In order to make a first pass at quantifying some of these channels, I build a parsimonious model in general equilibrium with multiple areas, each with its own labor and housing markets, where households can choose homeownership and location and leave bequests to their children in the form of their home (if owners) and a risk free asset. The model, which

[6] Appendix A.1 provides descriptive evidence of the increase in wealth inequality in this population.

I view as an accounting or modeling framework, is a first pass at quantifying the results in the data.

In the model, local labor and housing markets are intrinsically linked because households live and work in the same area, and parents have preferences to leave bequests to their kids. These bequests include the value of the home if they are homeowners. The key mechanism is that bequests, in the model, are a luxury good for parents (this follows work by De Nardi [2004] and Straub [2019]), and so increase disproportionately with an increase in income. As different areas grow at different rates, parents in the fastest growing areas have the most incentives to save more, and, if they are homeowners, to consume disproportionately more housing (since in the model, homeowners leave their home to their kids). This leads to a disproportionate increase in bequests among parents in the fastest growing areas, exacerbating wealth inequality.

The model is calibrated to the U.S. economy for the bottom 90% of households in 1999 as the initial equilibrium. Next, I calculate local increases in productivity in each local area between 1999 and 2019, feed this into the calibrated model, and solve for the final equilibrium. The main exercise is to compare initial and final equilibria in terms of their wealth distributions under different assumptions.

The model generates an increase in wealth inequality between 1999 and 2019 of 0.05 points of the wealth Gini of the bottom 90% of households (the wealth Gini increases from 0.46 to 0.51), which is 72% of the increase observed in the data. I also conduct various quantification exercises to measure how much channels mentioned above contribute to the rise in wealth inequality in this period. I find that the dispersion in labor market growth across areas, i.e., the fact that certain areas grow more than others, is responsible for about 0.02 points (40%) of the increase in the wealth Gini; however, heterogeneity in local house supply elasticities only accounts for a rise of 0.003 points (8%). Shutting off labor mobility would increase inequality by an additional 0.008 points (13%). Finally, an alternate version of the model which does not allow for homeownership would only increase wealth inequality by 0.02 points of the Gini, or about 40% as much as in the main model.

Related Literature This research is broadly related to three strands in the economics literature.

First, it relates to the analysis of local labor and housing markets. The mechanism of labor market shocks leading to house price declines has been studied extensively in the literature in the context of spatial equilibrium. Rosen [1979] and Roback [1982] analyze the optimal choice of location when areas differ by amenities. Spatial equilibrium models have been the foundation of many subsequent papers that also look at differences in wages and amenities across areas to study inequality in real wages (Topel [1986], Moretti [2013], Diamond [2016], Notowidigdo [2011], Zabek [2017]).

I add to this literature by explicitly considering the role of homeownership within local markets. My findings indicate that the fact that some of the people living in an area own their residence is quantitatively relevant in determining how they react to labor market shocks, particularly in terms of the wealth accumulation of their children.

Second, this paper relates to the literature on the documentation, determinants, and causes of wealth inequality. Important papers in this literature include Saez and Zucman [2016] (the importance of taxation in determining the wealth shares of the top 1%), and Moll et al. [2021] (automation and wealth inequality). Other studies, such as Fisher et al. [2022] and Killewald et al. [2017], document the increase in wealth inequality in the United States. The closest analysis to this paper is Greaney [2020], who also looks at the role of local labor and housing markets in determining wealth inequality in the long run. However, my analysis focuses on direct measurements of wealth and its intergenerational persistence. Further, my model focuses on the key mechanism of parental transfers to children, which are treated as luxury goods, as opposed to the model in Greaney [2020], which does not include any non-homotheticity in wealth accumulation. Finally, my model is also set in general equilibrium, while Greaney [2020] takes interest rates as fixed. I add to this literature by considering the role of local markets, homeownership and intergenerational wealth accumulation.

Third, the paper relates to the literature on intergenerational transfers, which has found an important role for homeownership. Ownership increases lifetime savings, facilitates wealth transfers to younger generations, and makes it more likely that children will become homeowners themselves (Engelhardt and Mayer [1998], Spilerman and Wolff [2012], Brandsaas [2021]). The effects of local labor markets can also persist across generations. Meanwhile, effects of increases in housing wealth include an increase in the child's college attendance [Lovenheim, 2011] and education [Killewald et al., 2017]. Gale and Scholz [1994] argue that almost 50% of accumulated wealth is accounted for by intergenerational transfers, and up to 90% of wealth transfers come from parents or grandparents [Wolff and Gittleman, 2014]. An extensive literature also shows that the transmission of physical and human capital from parents to children is a very important determinant of households' wealth and earnings ability.[7] To the best of my knowledge, this paper is the first to study a unique channel of

[7] See, among others, Becker and Tomes [1986] Kotlikoff and Summers [1981], De Nardi [2004], Pfeffer and Killewald [2019]).

intergenerational pass through: local labor markets that parents experience when the child is growing up.[8]

The paper proceeds as follows. Section 1.2 introduces the data used in the paper; Section 1.3 decomposes the change in mean wealth between 1999 and 2019 into coming from homeowner or renter households, and Section 1.4 presents the main empirical results of the paper. Section 1.5 introduces the model of local labor and housing markets to quantify various channels that might affect wealth inequality, and Section 1.6 concludes.

1.2 Data

I use two main data sources for the empirical analysis presented in this paper. The first is the County Business Patterns (CBP) dataset, which I use to construct measures of local labor market growth in areas. The second is the Panel Study of Income Dynamics, which is a panel of households followed over time and space, and linked across generations. Both these sources are describes in detail below.

1.2.1 County Business Patterns (CBP)

The County Business Patterns (CBP), released publicly by the United States Census Bureau is a dataset that reports industry level employment and annual payrolls in the United States at the county, Meteropolitan Statistical Area (MSA), and state levels. For the various analyses in this paper, I use the county level data and aggregate these up to the level of Core Based Statistical Areas (CBSAs), which are collection of counties meant to capture larger areas in which people live and work. I define local areas as Core Based Statistical Areas (CBSAs) because they capture

[8]Daysal et al. [2022] looks at how increases in housing wealth of parents when their child is growing up affects the housing wealth of the child as an adult. They find that there is a large pass through to housing wealth that is driven through a transmission of preferences, but the effect is sensitive to when the parents experience the increase in housing wealth.

urban centers where households live and work. They consist of groups of counties. I do this by using a county-to-CBSA crosswalk, with county specific weights used to capture the relative importance of each county to the CBSA in terms of population. CBSAs are similar to Metropolitan Statistical Areas, but also include smaller urban areas (defined as Micropolitan Statistical Areas) which lets me capture more households in the data. On the other hand, Commuting Zones, the other most commonly used definition of local markets, include rural areas as well as urban areas. Since my focus is on aggregate markets in *urban* areas, CZs are not appropriate in my context.

I use the CBP data in both the empirical and the modeling part of the paper. First, I use employment changes over time to define the shift-share labor demand growth that forms the main measure of local labor markets. In particular, I collect employment by industry (I use the 3-digit 2012 NAICS industry classifications) in each area between 1984 and 2017. These statistics, as mentioned previously, are aggregated up to the CBSA level. I provide more details about calculating the measure of labor demand growth by area in Section 1.4.

Second, I calculate total employment for the 100 largest areas by population size in the CBP. These employment numbers are used to calculate employment shares, which in turn discipline the model I build in Section 1.5.

1.2.2 Panel Study of Income Dynamics (PSID)

The Panel Study of Income Dynamics (PSID) is a household survey that began in 1968, and in 2017 collected data for about 9,000 households. It was a yearly survey until 1999, at which point it became biennial. It asks interviewees detailed questions about housing, wealth, employment, and mobility, and follows families over time and even across generations.

This is the primary source of data for this paper. The richness of the PSID makes it particularly amenable to answering questions about wealth and the labor market, since it contains details not only about (self-reported) home values and income, but also about the wealth portfolio of households. The PSID first asked about wealth in 1984, and then once every five years until 1999, after which every interview wave has collects this information. This makes the PSID particularly useful in exploring wealth dynamics, since we are able to follow the same households over time as they interact with the labor market, save, purchase housing stock, and so on.

Crucially for this paper, the PSID also follows the children of families that are interviewed. This makes it possible to observe not just the wealth of families who live in a particular labor market, but also the impact this potentially has on their children's wealth.

It should be noted that information about wealth portfolios is available at the household level, and is asked to the "household head", or "reference person" (RP). So, the unit of analysis in this paper will be the household, and not individuals. The specific wealth variables I consider are:

1. Wealth with home equity: total net worth, calculated as the sum of all assets minus all debt.

2. Wealth without home equity: the sum of all other forms of wealth, including cash, bonds, sums in checking and savings accounts, etc. minus all outstanding debt.

3. Home equity: calculated as self reported home value minus all outstanding mortgages on the house.

4. Assets: The total value of all assets, including cash, owned by the household.

5. Debt: The total value of all debt owed by the household.

Note that these measures of wealth include retirement wealth in IRA accounts. However, they do not include other sources of wealth such as pensions or Social Security, because these are not "owned" by the household yet. In principle, it is possible to calculate future Social Security wealth based on current income, but this is not reflective of life cycle income patterns, which is what determines Social Security returns. This matters because a household might change its consumption and savings behavior in the present given future sources of wealth. In other words, all forms of wealth could potentially be fungible across the life cycle. However, given the difficulty in estimating retirement wealth more completely, I only use wealth in IRA accounts in my measures.

On the other hand, there is a debate about whether IRA accounts constitute wealth that is bequeathable or spendable by households. I therefore include a robustness check in Appendix A.4 and show that my results are robust to excluding wealth in IRA accounts.

In addition to these, I use the vast array of household level characteristics that the PSID is known for, including measures of family income, employment, race, age profiles, number of children, marital status, etc.

In order to construct the intergenerational dataset, I use the parent IDs provided by the PSID. Splitoff indicators are also available to track household members who move away from the main interview family and will be subsequently counted as a separate household. Crucially, the PSID also collects the reason for the splitoff happening, and I am able to use this information to identify children leaving home as opposed to, for example, a couple who separate or divorce. With this, I am able to identify households who splitoff from 1999 onwards, and since the PSID collects data biennially after this point, I collect this information every two years. On average, I find that about 500 families splitoff from their parents in the PSID data every interview wave.

I also define a new variable – years from splitoff – which allows me to pool the data together consistently capture years from the "event" of the splitoff. This means that the regressions I run pool children who splitoff in different years according to this new variable, i.e., it doesn't matter whether a child splits off in, say, 1999 or 2003, what matters is the number of years since the split off happened.

2013 Family Rosters and Transfers Module

I complement the data in the previous section with the 2013 Family Rosters and Transfers Module, which was a supplement to the 2013 wave of the PSID and asked families if they had received help from their parents since turning 18. Specifically, they ask if the respondents received help with paying for a home (downpayment assistance), for college, or any other finances.

I focus on downpayment assistance and help with other finances. The primary reason to not look at education is because split offs are defined by the PSID as occurring after education is complete, and so this would not be an outcome to study in this particular paper. A rich literature exists, as discussed in the introduction, on the effects of housing wealth on college attendance and quality.

I merge this dataset with the main PSID interview in 2013. This means that any analysis using this data would only use information on households who split off before 2013, but nevertheless it provides a natural complement to other results on how parental wealth is useful for children.

1.2.3 Final Dataset

Finally, the two datasets are merged to create the final dataset I use for the empirical analyses in the paper. All variables that contain monetary measures (such as house prices, income, or wealth) are deflated to 2019 prices using the Consumer Price Index for Urban Consumers provided by the Bureau of Labor Statistics. [9] I also rely on the fact that the PSID also collects information about the location of households, although this isn't made publicly available (except at the state level). However, the restricted version of the dataset does contain this information.

I merge the labor demand growth calculated with the CBP data into the PSID data based on the location of the parent that the child has split off from. For instance, if a child splits off from a parent who lives in the Detroit metro area in 1999, then this child is assigned the labor demand growth in Detroit in 1999. I explain the specifics of why this is done in Section 1.4.

1.2.4 Descriptive Statistics about the Sample

It is useful to consider where households are splitting off from, and when. Table 1.1 provides the number of households in the main sample that split off each year between 1999 and 2017. Since 2019 is the last year I observe households, I limit the collection of splitoffs to occur before this time, i.e., by 2017. Of course, households are still observed in 2019, and the regressions use the wealth of households in 2019 as well.

Table 1.1 shows that there are roughly 250 families in the PSID who split off from their parents each year. Of these, roughly 70% splitoff from homeowner parents and the rest split off from renter parents. These families are interviewed yearly unless they drop out of the PSID interviews.

[9] The data can be accessed at http://www.bls.gov/cpi/data.htm.

In total, between 1999 and 2019, this yields 13,443 household x time data points for the main regression. Unfortunately, PSID restrictions about reporting summary statistics or presenting maps for geographic areas finer than the state level prevent me from plotting the spatial distribution of the sample. I use longitudinal weights provided by the PSID for all regressions, which makes the data nationally representative.

Table 1.1: Number of Splitoffs by Year

Year of Splitoff	**N**
1999	193
2001	220
2003	281
2005	265
2007	291
2009	298
2011	311
2013	279
2015	255
2017	197
Total	**2590**

This table presents the number of splitoff households per year in the PSID data between 1999 and 2017. Since the 2019 round is the last interview wave available, I take the latest splitoff information until 2017. However, households are still observed in 2019.

In the next section, I provide more descriptive evidence on the wealth distributions of households in the sample in 1999 and 2019 (the start and end of the sample), and how they differ between homeowners and renters.

1.3 The Wealth of Owners and Renters Over Time: A Decomposition

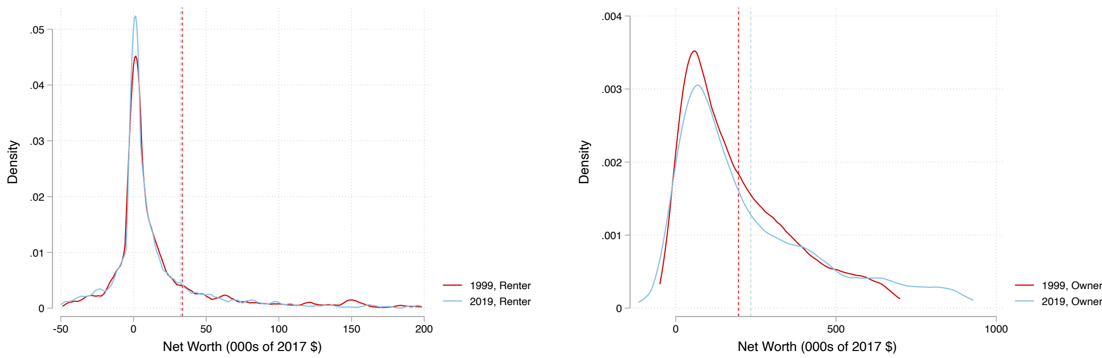
The mean level of wealth in the United States among the bottom 90% of households increased between 1999 and 2019. Using the Panel Study of Income Dynamics (PSID), I find that among this group, the average net worth (including home equity) was $142,299[10] in 1999. This went up to $168,022 by 2019, a real increase of almost

[10] All prices are in real 2017 dollars.

Figure 1.1: Distribution of Wealth of Renters and Homeowners in 1999 and 2019

(a) Renters

(b) Owners



This figure presents the wealth distribution of the bottom 90% of households in 1999 and 2019. The left panel shows the distribution of renters, and the right panel shows the distribution of homeowners. The wealth of owners, as expected, is much higher than the wealth of renters. However, while the wealth of renters has barely moved, and if anything slightly decreased between 1999 and 2019, the wealth of homeowners has gone up considerably.

$26,000.

Figure 1.1 presents the wealth distribution of the bottom 90% of households in 1999 and 2019. The left panel shows the distribution of renters, and the right panel shows the distribution of homeowners. The wealth of owners, as expected, is much higher than the wealth of renters. However, while the wealth of renters has barely moved, and if anything slightly decreased between 1999 and 2019, the wealth of homeowners has gone up considerably.

Given the importance of housing wealth in the wealth portfolio of these households, it is useful to decompose the change in mean wealth as coming from homeowners or renters. However, the homeownership rate has also changed in this time span, which makes it harder to see how much of the increase in mean wealth overall is due to each group. Therefore, I decompose the change in mean wealth between 1999 and 2019 as coming from three components: the change in the wealth of homeowners and renters respectively, keeping ownership rates constant, and the change in the ownership rate, keeping the wealth difference between owners and renters constant.

Specifically, we can write the change in mean wealth between 1999 and 2019, $\Delta\bar{W} = \bar{W_{2019}} - \bar{W_{1999}}$ as:

$$\begin{aligned}
\bar{W}_0 &= \frac{1}{N}\sum_{i=0}^{N} W_{i,0} \\
&= \frac{N_{R,0}}{N}\frac{1}{N_{R,0}}\sum_{i=1}^{N_{R,0}} W_{i,R,0} + \frac{N_{O,0}}{N}\frac{1}{N_{O,0}}\sum_{i=1}^{N_{O,0}} W_{i,O,0}
\end{aligned}$$

We can further define $Q_{R,1} = N_{R,1}/N$ as the proportion of renters in period 1, $Q_{O,1} = N_{O,1}/N$ as the proportion of owners, and ΔQ_O as the change in the fraction of owners over time. Assuming N is constant over time,

$$N_{R,0} + N_{O,0} = N = N_{R,1} + N_{O,1} \implies \Delta Q_R = -\Delta Q_O$$

We can now rewrite the difference in mean wealth between period 1 and period 2:

$$\Delta\bar{W} = \bar{W}_1 - \bar{W}_0 \tag{1.1}$$

$$\begin{aligned}
&= \left(Q_{R,1}\frac{1}{N_{R,1}}\sum_{i=1}^{N_{R,1}} W_{i,R,1} + Q_{O,1}\frac{1}{N_{O,1}}\sum_{i=1}^{N_{O,1}} W_{i,O,1}\right) - \\
&\quad \left(Q_{R,0}\frac{1}{N_{R,0}}\sum_{i=1}^{N_{R,0}} W_{i,R,0} + Q_{O,0}\frac{1}{N_{O,0}}\sum_{i=1}^{N_{O,0}} W_{i,O,0}\right)
\end{aligned} \tag{1.2}$$

$$= Q_{R,0}\Delta\bar{W_R} + Q_{O,0}\Delta\bar{W_O} + \Delta Q_O(\bar{W_{O,1}} - \bar{W_{R,1}}) \tag{1.3}$$

where ΔW_R is the change in the average wealth of renters between periods 0 and 1, and ΔW_O is the same statistic for the wealth of owners. Notice that in the last equation, these changes are weighted by the proportion of renters and owners in the first period. In other words, it's the contribution of the mean changes in rental and owner wealth keeping constant the proportion of renters and owners. The final

Table 1.2: Mean Wealth for Bottom 90% Households in PSID (in 000s of 2017 dollars)

	1999	**2019**
Owners	\$192,648	\$246,161
Renters	\$43,618	\$42,606
All	\$142,299	\$168,022
Ownership	0.662	0.616

term of equation (1.3) is the change in the proportion of owners multiplied by the difference between the mean wealth of owners and renters in the final period.

To aid interpretation, we can divide both sides of the last equation (equation (1.3)) by the left hand side to get:

$$1 = \frac{Q_{O,0}\Delta \bar{W_O}}{\Delta \bar{W}} + \frac{Q_{R,0}\Delta \bar{W_R}}{\Delta \bar{W}} + \Delta Q_{O,0}\frac{(\bar{W_{R,1}} - \bar{W_{O,1}})}{\Delta \bar{W}} \tag{1.4}$$

The first term on the right hand side captures the mean change in the wealth of owners over time, keeping constant the ownership rate. The second term captures a similar change in the mean wealth of renters, keeping constant the ownership rate. The third term is the change in the ownership rate, keeping constant the difference in the mean wealth of owners and renters. Table 1.2 provides the moments of the wealth distribution needed for the calculation using household level PSID data in 1999 and 2019.

Plugging in the numbers, I find that:

(1.5)

$$1 = \underbrace{(1.377)}_{\text{Due to change in wealth of owners}} + \underbrace{(-0.0133)}_{\text{Due to change in wealth of renters}} + \underbrace{(-0.364)}_{\text{Due to change in ownership rate}}$$

The calculations reveal that almost the entirety of the change in means between 1999 and 2019 has come from the wealth of homeowners and the fact that homeownership rates have declined. The wealth of renters, on the other hand, is barely responsible for the change in means.

This indicates that homeowners and renters had dramatically different dynamics of wealth over this time period, and while one group increased their wealth, the other group stagnated. Ownership rates decreased, which means that more people are excluded from future gains in housing wealth.

1.4 The Effects of Local Labor Markets on Intergenerational Wealth

The effects of local labor markets can persist across generations. To measure how strong this association is, I examine the wealth accumulation of children as they split off from their parents and form their own households, and how this differs according to the labor markets that their parents experienced before they split off. Through this, I am able to establish some facts about the wealth accumulation patterns of the children of parents who experience good versus bad labor markets as the child is growing up.

I run an event study style analysis to get at these questions, with the "event" being the child splitting off, and the shock in question being the shift share measure of labor demand growth in the area of residence of the parent as described in the previous section. Here, we are comparing the children who split off from a parent who experienced one standard deviation better labor markets relative to other parents, at each point in time after splitting off. However, note that this isn't a conventional event study because as such, there is no "pre" period since the household wealth of the child is not observed before split-off.[11] It is worth noting that there is a "first stage" of this regression in the background, where the local labor markets of parents

[11] Technically, I do observe kids before they split-off, but since they are counted as being part of their parents' household, and wealth is only measured in the PSID at the household level, I can only observe their parents' wealth.

affect the *parent's* income and wealth. The implicit question is: how is the increase in their wealth associated with an increase in their children's wealth?

I also perform a triple difference version of the same regression by adding an interaction term between the labor demand shock and parental homeownership. One might suspect that local labor market growth might have dramatically different effects on the wealth of parents who own versus those who do not, since local labor market demand affects local house prices. Through this channel, an increase in labor demand will lead to increases in rent and also in housing wealth. The first effect here hurts renters; the second effect benefits homeowners. Therefore, this regression allows me to examine whether the association of parental labor markets with children's wealth differs by parental homeownership.

1.4.1 Measuring Local Labor Market Growth

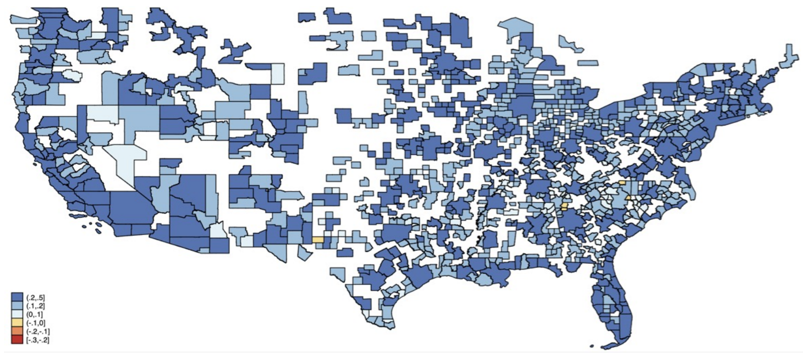
Before presenting the regressions I estimate, it is important to define the measure of parental labor market growth that I use. Motivated by the literature (for instance Notowidigdo [2011] and Zabek [2017]), I construct local employment shift share shocks in the spirit of Bartik [1991] to measure changes in local labor demand. The shift-share shock, as illustrated in Goldsmith-Pinkham et al. [2020], takes the changes in national industrial employment and projects them onto the CBSA-level employment shares. These capture local changes in labor demand because they capture national level trends in industries, which are then weighted by the share of that industry in the area. Finally, this term is aggregated over industries. Specifically, I use employment shares for 3-digit 2012 NAICS private industries, and then project them onto leave-one-out national industry growth rates for the relevant time period.

In the main regression specification, I calculate labor market growth in the ten years prior to the child splitting off. This is done for several reasons. First, the paper studies wealth accumulation of children right after they split off from their parents, and so it is natural to consider labor market growth until this point. Second, I observe split offs every two years in the PSID data, which means that there are cohorts that split off in 1999, 2001, and so on, and the shock under consideration must be consistent across these cohorts. For instance, there is an argument to be made for defining labor market growth in periods such as the Great Recession or the Volcker recession since these are economically meaningful events, but this leads to an inconsistency in timing: consider two children splitting off, one in 2013 and one in 2017. If the labor market growth under consideration is the Great Recession, then the parents of the child splitting off in 2013 have had four years to recover from the recession while the other set of parents have had eight. On the other hand, measuring labor market growth in the ten years prior to the split off might be arbitrary in terms of national economic conditions, but standardizes the time period where local markets affect parental wealth in the lead up to an economically meaningful event in the lifecycle of a parent: the split-off of their child to form her own household. However, I conduct additional analyses by varying the timing of the labor demand growth under consideration to be in the first ten years of the child's life, or when the child is between 8 and 18 years old. The results from these regressions are discussed in Appendix A.5.

Further, Goldsmith-Pinkham et al. [2020] show that the exogeneity of the shift-share instrument comes from employment shares, and not from the national level growth rates. To partially alleviate this concern, I take employment shares in an area five years prior to the growth period. For instance, I take employment shares in an area from 1984 if the labor market growth period goes from 1989 to 1999.

Specifically, I define parent's labor market growth as $\Delta\theta^{par}_{j,T}$, for a parent in CBSA

Figure 1.2: Spatial Distribution of Labor Demand Growth Between 1989 and 1999



This figure plots labor demand growth between 1989 and 1999 across the United States. We see that most areas grew very strongly in this time period. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

j at time of the child splitting off, T as:

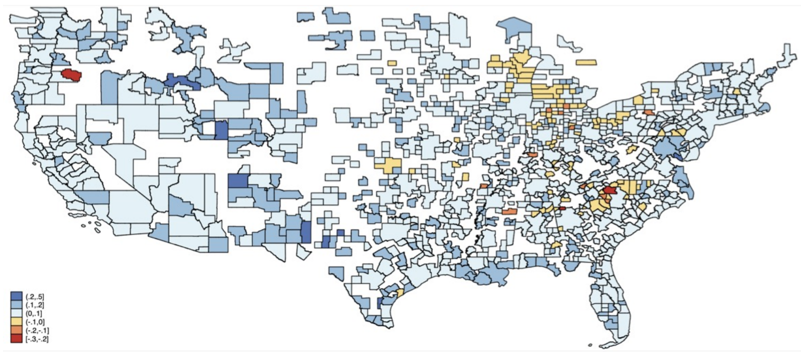
$$\Delta\theta^{par}_{j,T} = \underbrace{\sum_{k\in ind}}_{\text{summing over industries}} \underbrace{\left(\frac{L_{k,-j,T} - L_{k,-j,t-l}}{L_{k,-j,T-l}}\right)}_{\text{national growth rate}} \underbrace{\frac{L_{k,j,T-l-5}}{L_{j,T-l-5}}}_{\text{share of industry in area}} \tag{1.6}$$

where k is industry, and l is the length of the labor market period under consideration. Further, I also "standardize" the shocks by demeaning them and dividing by the standard deviation – this aids interpretation, as now the shock can be measured in standard deviation units. in words, $\Delta\theta^{par}_{j,T}$ captures how parental labor markets grow due to local labor demand.

In practice, how are these Bartik measures spread across the United States? Figures 1.2 and 1.3 present the spatial distribution of labor market growth between 1989 and 1999 and between 2001 and 2011. Between 1989 and 1999, most areas experienced strong growth in their labor markets. However, this slow down between 2001 and 2011, mostly due to the Great Recession. In fact, many areas in this period, particularly in the Midwest, experienced negative labor demand growth. These figures are presented in greater detail in Appendix A.7.

The main idea is to examine differences in children's outcomes T onwards accord-

Figure 1.3: Spatial Distribution of Labor Demand Growth Between 2001 and 2011



This figure plots labor demand growth between 2001 and 2011 across the United States. We see a greater heterogeneity in growth in this period, primarily due to the heterogeneous effects of the Great Recession. Areas in the so-called Rust Belt particularly did poorly in this time period. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

ing to the parent's labor market condition at T. In the next section, I formalize the notion of these regressions.

1.4.2 Regression Framework

Once households are assigned the labor market growth of the parent, I regress this measure of parental labor market growth on the child's household wealth. It is useful to think about the regression as an event study regression of sorts. The event here is the child splitting off to form her own household, and the shock in question is the labor demand growth in the parent's area of residence in the ten years prior to splitoff. The identification of the effect of the labor market growth, then, is through difference-in-differences. The regressions I run are of the form, where T is the time of splitoff and j is the area of residence of the parent:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \ \mathbf{x} \ \Delta\theta^{\text{par}}_{j,T}) + \beta_4 X_{ijt} + \beta_5 X^{par}_{T} + \epsilon_{ijt} \tag{1.7}$$

where:

- Y_{ijt}: child's household level outcome.
- μ_{t-T}: indicator for years since splitoff
- X_{ijt}: child's household characteristics
- $\Delta\theta^{\text{par}}_{j,T}$: strength of parent's labor market at splitoff.
- X^{par}_{T}: parent's household characteristics at splitoff.

All regressions include year and parental area fixed effects. $\beta_{2,t-T}$ is the effect of a 1 standard deviation increase in the strength of the parental labor market on the mean wealth of children $t - T$ years from splitoff. The outcomes I examine include several measures of wealth, income, homeownership, and home values.

It is important to note that I do *not* include income, homeownership, or area of the child's residence as part of the control variables in this regression. The omission stems from the fact that these are plausible mechanisms through which parental labor markets might impact a child's wealth. Including these covariates would effectively "shut off" a channel through which parental labor markets might affect a child's wealth. For instance, there are a host of ways an increase in parental wealth can be invested in a child's education, which in turn leads to higher income and wealth. However, the purpose of this regression is to measure the "total effect" of an increase in parental labor markets, for which it is necessary to omit these intermediating channels. However, I run separate regressions to investigate the relative importance of these channels in Section 1.4.6.

All regressions are run using longitudinal weights provided by the PSID. These are meant to make the data nationally representative. I also cluster standard errors at the parental area (or area where the household grew up) level.

Finally, I Winsorize the wealth data at the 1st and 99th percentile. The Winsorization is important because the wealth data in particular contains outliers that ideally should not have a disproportionate effect on the estimate, and is particularly important in this case because wealth is also allowed to be negative (this is why I cannot simply take logs). Winsorizing the data essentially means top and bottom-coding the data – it means I do not lose the outlier observations, but rather just top-code them to ensure that the effects I estimate are not unduly influenced by children who have millions of dollars in wealth. In practice, the top percentile of wealth in the data is about $1.5 million, and the bottom percentile is at $150,000 of debt, i.e., -$150,000 of wealth.

Concerns with Causal Inference

The event study regression is designed to capture the association between parental labor markets and a child's wealth accumulation after splitting off from her parents. Given the burgeoning literature on issues with causal identification through difference-in-differences designs (Goodman-Bacon [2021], Callaway et al. [2021]), and causal identification with shift-share instruments (Goldsmith-Pinkham et al. [2020], Borusyak et al. [2022]), it must be stressed that the results in this paper should not be interpreted as strictly causal.

However, in this section, I address some concerns with causal inference that these literatures have raised. Identification of this regression is through difference-in-differences, which means that the labor demand growth in the area of the parent prior to splitoff must be exogenous. Recall that the labor demand shock has a shift-share construction, where I take national level growth rates by industry over the ten years before splitoff and interact them with industry shares fifteen years before splitoff. Given what we know of shift-shares from Goldsmith-Pinkham et al. [2020], it must be that the industry mix in an area from fifteen years before splitoff is uncorrelated with any unobservables that might affect a child's wealth accumulation after accounting for observable controls.

Something that goes against this assumption might be the following: if San Francisco was always a technology hub even before the IT boom, then it might attract certain kinds of parents into the area, who in turn bring up their children in a particular way that is relevant for their wealth accumulation – for instance, by emphasizing saving more. In this case, the labor demand shock captures not only the area doing well, but also the fact that parents in these areas just bring up their children differently. It could also be that the area a child grows up in matters for other reasons, such as the opportunities she is exposed to in the area.

To address these kinds of endogeneity issues, I add parental area fixed effects to my estimation. Adding these removes the time-invariant characteristics of people moving into an area due to it's industry mix in the past. I am now comparing children of parents who split off when labor market growth was one standard deviation higher to kids who grew up in the same area but split off when times weren't as great.

Further, it also removes the effects of that an area could have that are specific to that area. For instance, if house prices are always high in San Francisco, the parental area fixed effect will remove this level difference. Of course, there can still be variation in house prices in an area over time, which the fixed effect does not absorb, and this variation over time is a useful source of underlying variation.

There could also be endogeneity concerns about the timing of the split-off event with respect to the demographics of the children, although it isn't clear which direction this would do. Would the children of richer parents split-off earlier or later? This assumption is tested in Appendix A.8.

Finally, it is useful to understand the "first-stage" of the effects the paper is interested in, i.e., do parental labor markets affect the outcomes of the parents themselves? This is investigated in Appendix A.6.

Heterogeneity of Results by Parental Homeownership

The total effects of local labor markets on parental wealth can be summarized in two parts: one, there is a "real wage" effect, a la Moretti [2013], which is the the direct effect of the labor markets on savings, net of increases in cost of living; two, there is a housing wealth effect, which is the general equilibrium effect of local labor markets on housing values, which directly affects homeowners but not renters.

To get at the importance of the latter, I perform a triple difference estimation by including an interaction of the labor demand growth with parental homeownership:

$$
\begin{aligned}
(1.8)\quad Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \text{ x } \Delta\theta^{\text{par}}_{j,T}) \\
+ \beta_3(\mu_{t-T} \text{ x } \Delta\theta^{\text{par}}_{j,T} \text{ x } \text{Own}^{\text{par}}) + \beta_4 X_{ijt} + \beta_5 X^{par}_{T} + \epsilon_{ijt}
\end{aligned}
$$

This "differences out" the real wage effect of labor markets, since the renters soak that term up. Of course, to interpret these results as causal, one would have to believe that renters are a good comparison group to owners after having added all the fixed effects and controls. This is likely not true, and I therefore refrain from interpreting the results of this regression as strictly causal in terms of being the causal effect of an increase in homeowner parents' home equity.

However, the exercise is still useful because it allows us to look at heterogeneity in the effect of labor markets by parental homeownership. This shows the relative importance of looking at these two groups of parents – homeowners and renters – and who is better able to pass on the advantages of local labor markets to their children. It is also useful because in many cases, the total association might be hiding this heterogeneity, and performing the triple difference estimation allows us to uncover differential effects.

1.4.3 Effect on Wealth Portfolio of Splitoff Households

In this section, I present results from the difference-in-difference regression in equation 1.4.2 and the triple difference regression in equation 1.4.2 on a variety of wealth measures. Instead of presenting tables with the regression results, I plot them so that they are easy to interpret and visualize. The coefficients that the point estimates on the figures are calculated from are available in Appendix A.2.

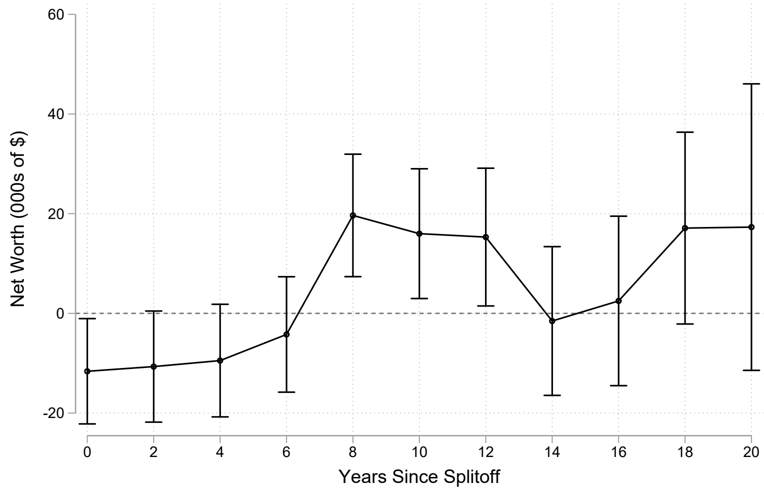
For each outcome, I calculate the association of a 1 standard deviation increase in the strength of parental labor markets with the outcome every year from splitoff, separately by parental homeownership. At the end of the sample, I observe children who have been splitoff from their parents for 20 years, although there is only one such cohort – the households who split off in 1999. This is also the reason that standard error bars keep getting larger the further away from split off one is.

Net Worth

First, I focus on net worth of the household, which is the total amount of assets owned by the household minus all the debt they owe. The results are plotted in Figure 1.4. I find that overall, although there is an upward trend in wealth, the effect of the labor demand growth is not significantly positive for all time periods. By the end of the sample period, i.e., twenty years after splitoff, a 1 s.d. better parental labor market is associated with an increase of about $20,000 of net worth.

However, Figure 1.5 shows that this masks substantial heterogeneity in the pat-

Figure 1.4: Association of Better Parental Labor Markets with Child's Net Worth



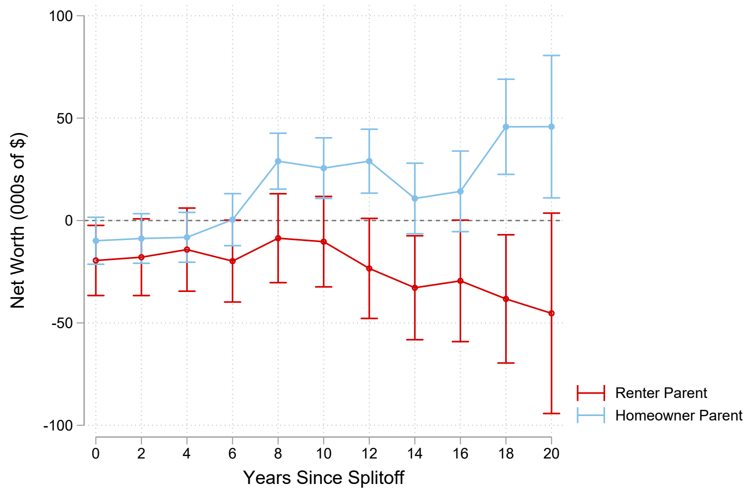
This figure presents the association of a 1 s.d. increase in parental labor market growth with the net worth of a child, t years after splitting off. There is no significant pattern of associations between parental labor market growth and wealth accumulation overall, although in general the association is positive. Twenty years after splitoff, children who grew up in better local labor markets have on average \$20,000 higher net worth.

terns of wealth accumulation in terms of parental homeownership. Children of homeowner parents accumulate much more wealth than their renter parent counterparts: a 1 s.d. better parental labor market for the children of homeowner parents is associated with an increase in their wealth by \$45,800, on average, 20 years after splitoff. For the children of renter parents, this number is -\$43,312 (although this is not statistically significant at the 5% level.)

The point estimates in this figure can be backed out by summing across the relevant coefficients in Table 1.4.7 in Appendix A.2. For instance, the association of a 1 s.d. increase in local labor markets with the net worth of the children of homeowning parents, 20 years after splitoff, is calculated as $-19.508 - 25.804 + 9.631 + 81.503 = 45.8$, i.e., \$45,800. The same point estimate for the children of renter parents would be $-19.508 - 25.804 = -45.312$, i.e., -\$43,312.

Several trends stand out. Most notably, for the children of homeowner parents, the association of parental labor markets with child net worth gets significantly positive

Figure 1.5: Association of Better Parental Labor Markets with Child's Net Worth by Parental Tenancy



This figure presents the association of a 1 s.d. increase in parental labor market growth with the net worth (without home equity) of a child, t years after splitting off. There is no significant association between parental labor market growth and wealth accumulation overall, as seen in Figure 1.4. However, this masks substantial heterogeneity by parental homeownership. Twenty years after split-off, children of homeowning parents who split off when the parental area was doing better have $45,000 higher net worth.

starting about eight years after splitoff, and stays positive, rising to $45,800 after twenty years. However, the same associations for the children of renter parents are, if anything, negative in the later periods. It is difficult to empirical ascertain why this is. However, it is theoretically possible that, given the rise in house prices that often follow strong labor markets, renter parents might face a higher real increase in their rent. While homeowners also face a rise in the cost of living, they are hedged against the increase in rents (or user costs) because their property is appreciating. In this way, rising labor markets could *hurt* renters in terms of wealth accumulation. I provide this hypothesis as a plausible explanation that is consistent with the facts. However, there isn't enough data to prove or disprove this theory.

Net Worth without Home Equity

It is useful to investigate what part of the wealth portfolio of the child is driving these effects. To do this, I break down the net worth of the child as consisting of a non-housing part, and a housing part. The latter is simply home equity (calculated as home value minus outstanding mortgage), and the former is everything but home equity.

Figure 1.6 plots the association of a 1 s.d. better parental labor market with the non-housing wealth of the child, split by parental homeownership. This figure closely follows Figure 1.5. 20 years from split off, a 1 s.d. better parental labor market is associated with a higher net worth of almost \$35,000. This association is positive only for the children of homeowner parents. If anything, the non-housing wealth of the children of renter parents have a negative association with better parental labor markets, just like in the previous section.

This is important because it shows that the benefits of local markets that accrue to *homeowner* parents show up in the non-housing part of the child's wealth portfolio. This wealth is liquid, and so has direct implications for the child's welfare.

Twenty years after split of, the \$35,000 represents about 63% of the overall increase in net worth (\$45,000) for the children of homeowner parents.

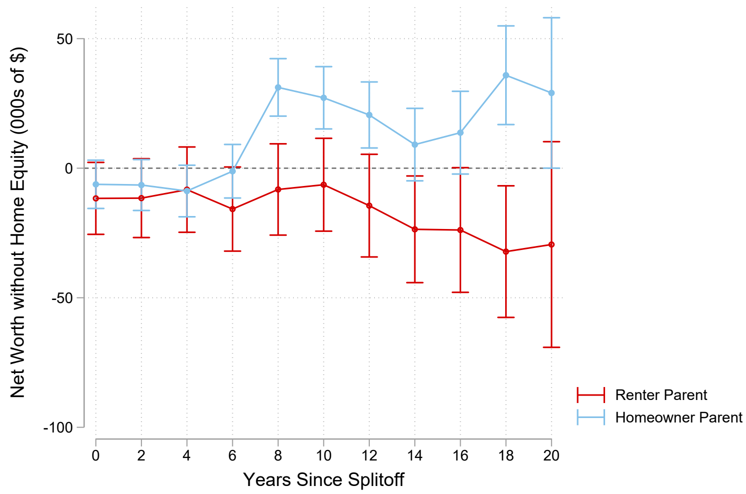
Home Equity

The other major part of a household's wealth portfolio is housing wealth. This is calculated as home value minues the outstanding mortgage on a household has. By definition, the housing wealth of renter households is zero.

Figure 1.7 presents the association of 1 s.d. better parental labor markets with the home equity of their children, split by parental homeownership. We see that twenty years on, 1 s.d. better parental labor markets are associated with a \$10,000 increase in home equity for the children of homeowner parents. Children of renter parents, if anything, are worse off.

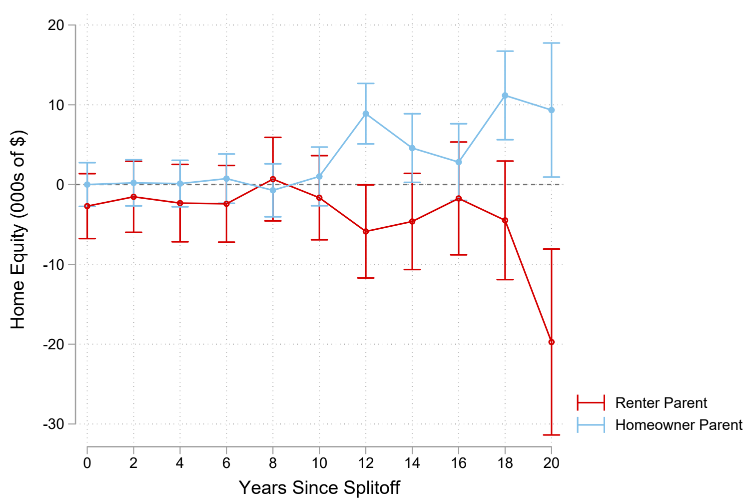
However, these results include both renter and homeowner children. As discussed

Figure 1.6: Association of Better Parental Labor Markets with Child's Net Worth (without Home Equity)



This figure presents the association of a 1 s.d. increase in parental labor market growth with the net worth (without home equity) of a child, t years after splitting off. There is no significant association between parental labor market growth and wealth accumulation overall, as seen in the left panel. However, this masks substantial heterogeneity by parental homeownership, as revealed in the right panel. Twenty years after split-off, children of homeowning parents who split off when the parental area was doing better have \$35,000 more non-housing wealth.

Figure 1.7: Association of Better Parental Labor Markets with Child's Home Equity

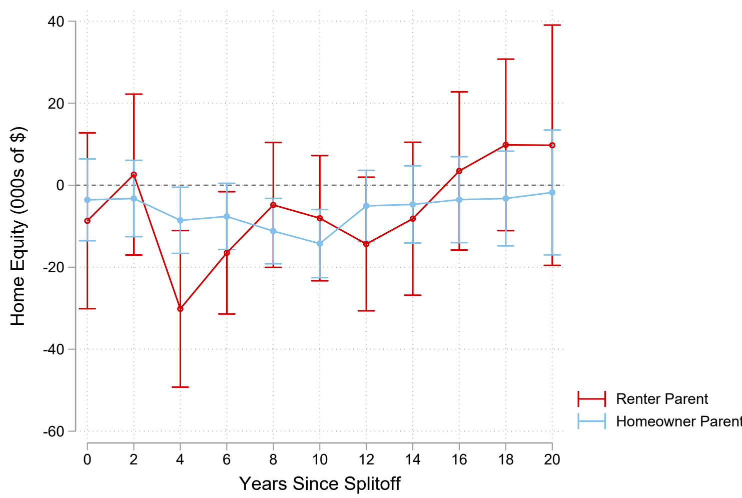


This figure presents the association of a 1 s.d. increase in parental labor market growth with the home equity of a child, t years after splitting off. Twenty years after split-off, children of homeowning parents who split off when the parental area was doing better have \$10,000 more of housing wealth.

above, home equity is zero for renter children. So, I run another analysis considering only homeowner children to see how much the selection into homeownership affects the results. The estimates from this regression are plotted in Figure 1.8. They show that all the results from Figure 1.7 were being driven by selection into homeowners.

Conditional on the child being a homeowner, there is no association between better parental labor markets and the child's home equity. In other words, the children of homeowners are not buying more expensive homes, but are more likely to be homeowners themselves. This result is confirmed in the next section when I examine intermediating outcomes that could affect child wealth.

Figure 1.8: Association of Better Parental Labor Markets with Child's Home Equity (only Owners)



This figure presents the association of a 1 s.d. increase in parental labor market growth with the home equity of a child, t years after splitting off. Only children who own a home are considered in this regression. Twenty years after split-off, children of homeowning parents who split off when the parental area was doing better do not have more of housing wealth. In contrast to the previous figure (Fig. 1.7), conditional on owning a home, there is no effect on home equity.

1.4.4 The Importance of Parental Homeownership

The evidence provided thus far establishes a significant link between parental homeownership and an increase in the child's net worth, yet it remains unclear what it is about parental homeownership that influences a child's wealth accumulation. For instance, parents' preference for ownership over renting could be proxying for their financial literacy or saving behavior. Such unobserved characteristics may be key to understanding the connection between parental homeownership and the child's wealth growth. On the flip side, a child's wealth may hinge on the capital gains from the parent's property which are then passed down to the child in the form of wealth transfers. Each of these theories yields different insights about the sources and persistence of a child's wealth accumulation, leading to distinct policy implications. In this section, I attempt to tease apart these various elements.

Interaction with House Supply Elasticity

I begin by considering the heterogeneity in wealth accumulation among the children of homeowner parents in terms of the area that they owned their home in. Specifically, I split these children according to whether they grew up in areas with a high elasticity of housing supply (like Indianapolis) or a low one (like San Francisco). The idea is as follows. Suppose San Francisco and Indianapolis experience the same growth in local labor demand. This leads to similar increases in housing demand in the two areas. However, Indianapolis has a high elasticity of housing supply, which means that house prices don't increase as much as in San Francisco for the same increase in demand. In turn, the extent of the increase in home equity is limited for parents living in areas with a high supply elasticity of housing.

Comparing the children of two homeowners, one growing up in a high supply elasticity area and the other in a low supply elasticity one, allows us to fix parental preferences for homeownership (since both parents are owners) and investigate directly the effect of an increase in housing wealth that follows from a strong labor market. In this way, estimating the regression in equation 1.4.2 with an additional interaction term that captures the elasticity of housing supply where the child grew up isolates the effect of an increase in parental housing wealth on the child's wealth accumulation. The regression I estimate, for the subset of children whose parents were homeowners, is:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T}) + \beta_3(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T} \textbf{ x } \text{Elasticity}^{\text{par}}) + \beta_4 X_{ijt} + \beta_5 X^{par}_{T} + \epsilon_{ijt} \tag{1.9}$$

A potential drawback of this approach is that preferences to own might be area specific – for instance, households that prefer to own in San Francisco vs. Indianapolis might also be different along unobserved characteristics such as saving behaviors and financial savvy. Unfortunately, I am not able to disentangle location specific and unobserved characteristics of homeowning parents. Nevertheless, the results from this estimate help us decompose the association seen in Figure 1.5 into coming from parents in low vs. high supply elasticity areas, which in turn determines the extent of increases in home equity these parents experienced.

The results from this estimation can be found in Figure 1.9. This figure shows that the children of homeowners from low supply elasticity areas like San Francisco are able to accumulate much more wealth compared to children from low supply elasticity areas like Indianapolis. This supports the theory that increases in the parent's home equity is a salient predictor of a child's wealth accumulation patterns.

Length of Parental Homeownership

A second aspect that provides suggestive evidence is the length of parental homeownership. Recall that in the baseline specification, we are concerned with labor market growth in the parent's area of residence in the ten years before splitoff, and parental homeownership is measured at the end of that period. However, not all parents were homeowners for the entirety of that period. In theory, those who were homeowners for a shorter time get lower capital gains in terms of their house price

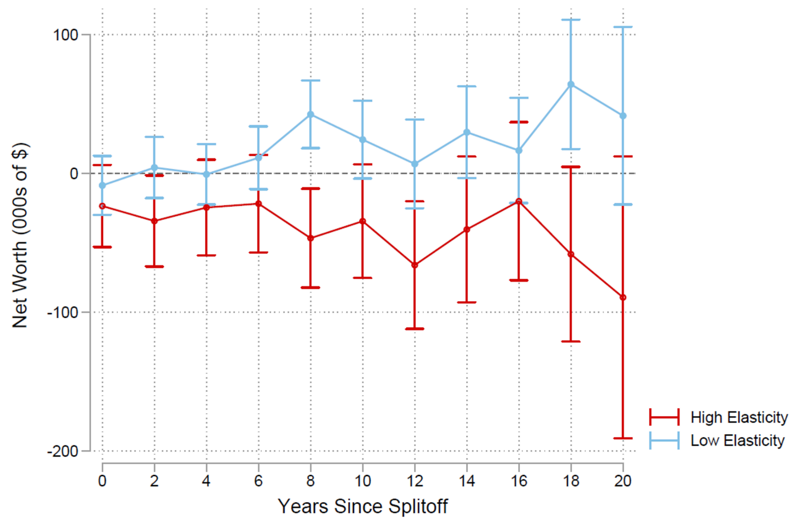


Figure 1.9: Association of Better Parental Labor Markets with Child's Net Worth by House Supply Elasticity (Homeowner Parents Only)

Years Homeowner	**Number of Households**	**Percent**
0	4809	43.48
1	13	0.12
2	148	1.34
3	35	0.32
4	127	1.15
5	130	1.18
6	199	1.8
7	150	1.36
8	135	1.22
9	228	2.06
10	5087	45.99
Total	11061	100

Table 1.3: Timing of Parental Homeownership Prior to Splitoff

appreciation compared to a parent who owned for all ten years.

Table 1.3 provides some descriptive statistics on the distribution of the length of parental homeownership. Given that homeownership is a long term outcome, most parents are either always renters (i.e., have 0 years as a homeowner) or are always homeowners. However, about 12% of the children in the sample have parents that became homeowners within the period of labor market growth we are considering.

Given this feature of the data, I run the regression in equation 1.4.2, but instead of parental homeownership being a binary variable, it is now a continuous variable

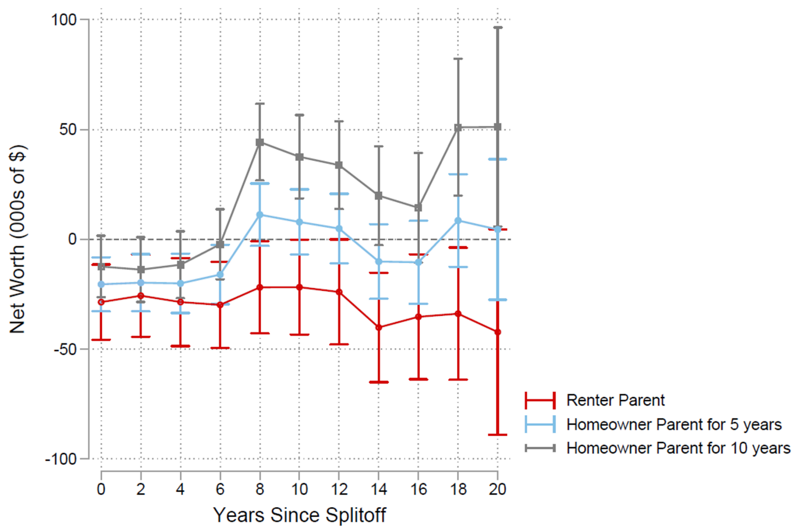


Figure 1.10: Association of Better Parental Labor Markets with Child's Net Worth by Length of Parental Tenancy

that accounts for the number of years the parent was a homeowner during the ten years before splitoff.

The results from this estimation are presented in Figure 1.10, and are consistent with the theory of parental home equity gains being important for their child's wealth accumulation. The figure shows that the longer a parent has owner a home, the bigger the increase in net worth of the child.

1.4.5 Outcomes: What do Households do with the Extra Wealth?

Consumption

It is useful to know what happens to the consumption of children over this time, since this is directly correlated with the welfare of the household. The PSID collects information on certain key categories of expenditure over the entire time period of this paper: food, health, education, childcare, transport, and housing.[12] I aggregate these expenditures to create a measure of overall consumption, and use local CPI measures as a deflator. Urban CPIs are available for the large Metro Areas like

[12]Other categories, such as trips or clothing are also collected, but only after 2005. For this reason, I do not include them in the calculations here.

Atlanta, Chicago, Detroit, Los Angeles, Miami, New York, San Francisco, etc., and include a measure of housing related growth. However, this coverage is not a problem since the PSID samples disproportionately from larger metro areas. It is important to use these deflators since the measure of consumption is highly local (including food, transport, etc.).[13]

The association of better parental labor markets with the child's consumption can be found in Figure 1.11. I find that there is a significant short term association of around $5,000 between consumption and better parental labor market growth, although this fades away towards about 18-20 years after splitoff. On the other hand, the children of renter parents show no significant association, and if anything, consumption is negatively affected towards the end.

This makes sense in light of the the association of parental labor markets with wealth that were presented in Figure 1.5. Recall that for the children of homeowners, better parental labor markets lead to high increases in wealth only during the later periods, i.e., 14-20 years after splitoff. For the children of renters, this is where the association becomes negative. Therefore, the positive, albeit short term, association between consumption and better parental labor markets can be explained using standard theories of consumption smoothing: the children of homeowners anticipate wealth transfers in the future, and therefore increase consumption in the lead up to the transfer. Once the wealth transfers are realized, their consumption level does not change. On the other hand, children of homeowner parents who faced worse labor markets growing up follow a more standard consumption pattern, and increase consumption as their incomes rise in adult life, leading to a "catch-up" in terms of consumption between the children of homeowners who faced better vs. worse labor

[13] The data can be found at: http://www.bls.gov/cpi/regional-resources.htm

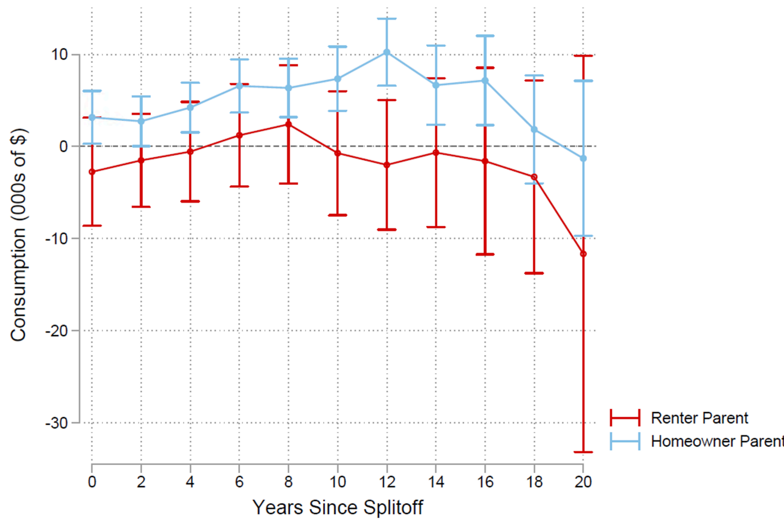


Figure 1.11: Association of Better Parental Labor Markets with Child's Consumption by Parental Tenancy

markets when growing up.

In this way, growing up to homeowner parents in a better labor market has an additional positive effect on the lives of households.

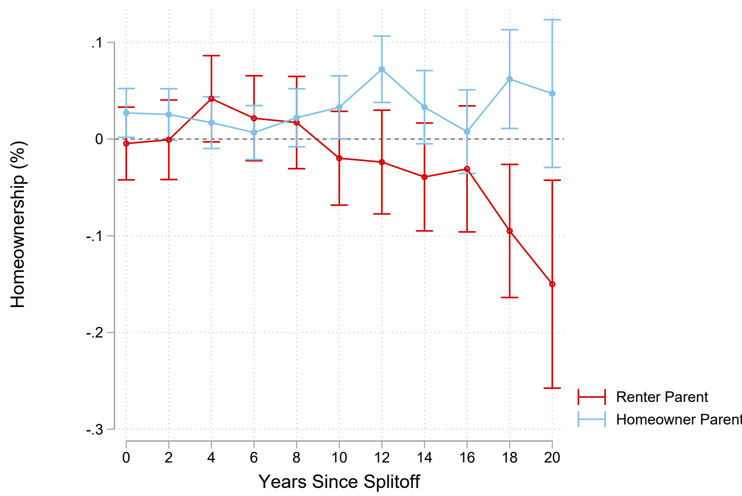
Homeownership

It is possible that children of parents who had better labor markets find it easier to enter into homeownership. Some context for this was already provided in the discussion on home equity in Figure 1.8 and Figure 1.7.

Figure 1.12 presents evidence that starting around 12 years of splitoff, a 1 s.d. better parental labor market is associated with a 5 percentage point increase in homeownership rate for children of homeowner parents. On the other hand, the children of renter parents are actually worse off in terms of ownership, and 18 years after split off are 10 percentage points *less* likely to be homeowners.

Once again, it is best to frame these results in the context of the example of San Francisco. One child split off when times were great, which means house prices were high. In this case, having parents who rent might make it impossible to enter homeownership, while wealthier, home-owning parents could help with downpayments. In this way, booming labor markets can be bad in terms of homeownership for the children of renter parents.

Figure 1.12: Association of Better Parental Labor Markets with Child's Homeownership



This figure presents the association of a 1 s.d. increase in parental labor market growth with the homeownership of a child, t years after splitting off. There is no association or significant trend in this picture, which shows that better parental labor markets likely do not affect the labor market outcomes of the child. So, we need to look elsewhere for the intermediating outcome responsible for the wealth differences found in Figure 1.5.

The results on home equity and homeownership make it seem particularly plausible that parents in better labor markets are more able to help with the purchase of the home. However, so far, there hasn't been any direct evidence of this happening. In the next section, I leverage the PSID's 2013 Family Rosters and Transfers Module to provide this evidence, because this module asks children whether they were helped with the purchase of a home since turning 18.

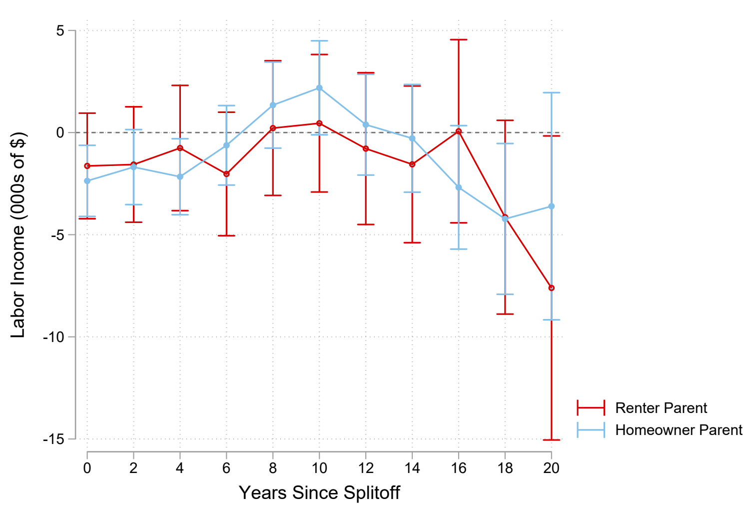
1.4.6 Intermediating Outcomes

Now, I turn towards investigating outcomes that might mediate the wealth accumulation of splitoff households. I consider income, homeownership, and gift receipt as possible channels. There are reasons to believe each of these is tied to both parental labor markets and child wealth accumulation. For instance, if San Francisco is growing at a rapid pace, and children tend to live near their parents, then the children of SF parents split off and can take advantage of SF markets to get a higher income. Second, parents could help children buy their home, which helps them accumulate wealth in other ways (instead of saving up and spending on a home). Finally, parents can make gifts or leave an inheritance for their child, which directly influences her wealth.

Income

Figure 1.13 shows that 1 s.d. better parental labor markets have no significant association with the labor income of the child. This is somewhat surprising given the literature on the effect of parental wealth on a child's education. However, recall that all regressions control for parental area fixed effects, which means that we are comparing a child who splitoff from Detroit parents in 1999 (when times were good) vs. in 2009 (in the wake of the Great Recession).

Figure 1.13: Association of Better Parental Labor Markets with Child's Labor Income



This figure presents the association of a 1 s.d. increase in parental labor market growth with the labor income of a child, t years after splitting off. There is no association or significant trend in this picture, which shows that better parental labor markets likely do not affect the labor market outcomes of the child. So, we need to look elsewhere for the intermediating outcome responsible for the wealth differences found in Figure 1.5.

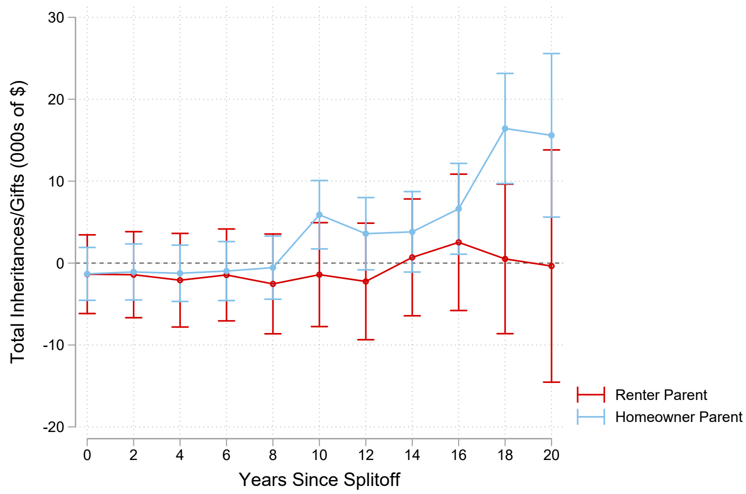
However, note that the PSID defines the split off as having occurred *after* the child has completed education. Secondly, the labor market growth of the parent that I calculate occurs in the ten years prior to splitoff. So, if a child completes a Bachelor's degree and splits off at age 23, and the labor demand growth I consider is between ages 13 and 23 for the child. This has no impact on the education of the child (as seen in Figure A.21) and so it makes sense that it wouldn't impact income, either.

Inheritance

Another way parents could affect a child's wealth is through direct intervivos gifts or inheritances and bequests. Figure 1.14 presents the association of a 1 s.d. better parental labor markets on gift receipt or inheritances. These results show that children inherit almost $15,000 more for a 1 s.d. better parental labor market. While this data is very noisy, and inheritances are often underreported in the PSID, there is a significant positive effect of parental labor markets on inheritances, especially for the children of homeowner parents. It should be noted, however, that their response isn't statistically different in many periods, although this is possibly due to the small sample sizes, and also because not many children receive a positive inheritance in any period.

Finally, there is a big jump in inheritances around the Year 18-20 mark. This makes sense because the major gifts reported in this data are inheritances, which would usually be left at the death of a parent. Notice that children are followed by the PSID from when they are, on average, about 22 to 25 years old. This would mean their parents are approximately 50 years old at the start of the sample, and around 70 at the end of the sample period. Given average life expectancy in the U.S., they are likely still alive, and only just starting to leave inheritances.

Figure 1.14: Association of Better Parental Labor Markets with Child's Gift Receipt



This figure presents the association of a 1 s.d. increase in parental labor market growth with the labor income of a child, t years after splitting off. There is no association or significant trend in this picture, which shows that better parental labor markets likely do not affect the labor market outcomes of the child. So, we need to look elsewhere for the intermediating outcome responsible for the wealth differences found in Figure 1.5.

In this sense, these results dramatically underreport the role of inheritances in generating differences in wealth for the children of these households.

1.4.7 Evidence on Transfers and Help with Ownership

The PSID provides some more details about financial help received from parents in the 2013 Family Rosters and Transfers supplement. In this section, I use data on whether a households received financial help to buy a home (i.e., downpayment assistance) or other monetary help (except college or a downpayment) which could include gifts. I examine the association of these variables with the labor demand growth in the area of the parent before the child split off.

Recall that this information is only collected in 2013, and specifically asks whether help was received since the respondent turned 18. Therefore, I have a limited sample in this regression by definition, since only households who split-off before 2013 are in this sample. Specifically I run the following regression:

$$(1.10)\quad Y_{ij} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \beta_{2,t-T}\text{Own}^{\text{par}} + \beta_3(\Delta\theta^{\text{par}}_{j,T}\ \mathbf{x}\ \text{Own}^{\text{par}}) + \mu_{t-T} + \beta_4 X_{ij} + \beta_5 X^{par}_T + \epsilon_{ij}$$

where Y_{ij} is an indicator for whether a household received financial help from her parents for a downpayment on a house, or any other monetary help. I also control for split-off cohort fixed effects and area of parental residence fixed effects.

The results from this regression are presented in Table 1.4.7. Better parental labor markets only have an association with downpayment help or other financial help if the parent was a homeowner. This is seen in the third row of each column in the table, which report a positive interaction effect between the labor demand growth and parental homeownership. Specifically, homeowner parents are 3.8 p.p. more likely to help their child pay a downpayment on a house, while they are 5.8 p.p.more likely to provide other forms of financial help. Renter parents, on the other hand, show no increase in their propensity to help their kids given better labor markets.

This complements the earlier findings about home equity and homeownership. Specifically, I found that the children of homeowner parents were much more likely to be homeowners if they grew up in better labor markets. These results suggest that this could be because the parent is better able to help pay the downpayment on a home. Of course, conditional on already having bought a home, there are no differences in the home equity of the child of renter or homeowner parents.

These results are important because they provide direct evidence on how parents help their children accumulate wealth: they make it easier to buy a home by providing assistance with downpayments (Brandsaas [2021] provides evidence of this as well).

	Parental Help Since Age 18	
	Downpayment	**Other Financial**
Labor Demand Growth	-0.004	-0.008
	(0.003)	(0.031)
Homeowner Parent	0.003	0.032
	(0.019)	(0.037)
Labor Demand Growth	0.038**	0.058^
x Homeowner Parent	(0.016)	(0.035)
Demographic Controls	Yes	Yes
Years Since Splitoff F.E.	Yes	Yes
Parental Area F.E.	Yes	Yes
N	1662	1625
R-squared	0.148	0.116

Crucially, they are better able to do this if the parents were homeowners in better labor markets.

1.4.8 Summary

Overall, these findings point to some key factors that I summarize below. Twenty years after splitting off from their parents to form their own households:

1. One standard deviation (1 s.d.) better labor markets for parents are associated with an increase in their child's net worth by almost $45,000. This increase in wealth is reflected mostly in the non-housing wealth of the child, which increases by about $35,000. There is a positive effect on home equity as well of around $10,000, but all of this is driven by entry into homeownership. Conditional on the child owning a home, there is no effect on home equity.

2. 1 s.d. better labor markets for parents have no influence on their children's labor income. However, better parental labor markets are associated with an increase in the amount of inheritances or gifts received by children by almost $15,000. They are also associated with greater rates of homeownership by about 5 percentage points (p.p.). Finally, they are associated with a temporary increase in consumption of around $5,000 per year, which is consistent with anticipating

a wealth transfer in the future. All these positive outcomes only occur for the children of homeowner parents. Children of renter parents are worse off in every outcome.

3. 1 s.d. better labore markets for parents increase the probability of the parent helping pay the downpayment on a home by 4 p.p. and offering other financial help by 5 p.p.. This is also true only for homeowner parents.

Overall, there is strong evidence that strong parental local labor markets are strongly associated with a higher net worth for their children, but only if the parents were homeowners themselves. Appendix A.4 contains results from a variety of other measures of wealth including assets (Figure A.4), debt (Figure A.5), home values (Figure A.6), and college debt (Figure A.7). All these measures also show the same patterns as found in the results discussed here.

Taken together, these results imply that the local labor market growth of one's parent is an important determinant of the wealth of the child. Local growth has positive associations with child wealth if the parent was a homeowner, but no statistically significant association if the parent was a renter (if anything, the association is negative). Further, I also find that direct transfers in terms of inheritances, gifts, or help with downpayment for a home are key intermediating outcomes that could explain the greater wealth of the children of homeowner parents. These point towards parental considerations of gift giving as being an important driver of child wealth, and a crucial link for the persistence of wealth across generations.

As different areas grow at different rates across the United States, this has implications for wealth inequality. The children of homeowner parents who grew up in better areas do remarkably well in adult life compared to those who grew up in areas with relatively worse labor markets, or those whose parents were renters in growing labor markets. However, these implications are hard to identify the effects of local parental labor markets on wealth outcomes, because there is no "natural experiment" as such that I can leverage. Instead, I rely on strong correlations and regressions that control for a host of factors, including parental area fixed effects.

The other concern with finding such natural experiments is that there are many moving parts in the data. For instance, one would need to disentangle the role of homeownership, the reason different areas grow differently, whether there is something inherently different about growth in one areas versus another, what accounts for intergenerational transfers, etc. Each of these channels would require a different natural experiment. This is in addition to channels such as incentives to save, life cycle patterns of consumption, retirement, etc. which are important, but are beyond the scope of this paper.

Given the challenges involved with looking at the aggregate consequences of these trends for wealth inequality, I build a parsimonious model of homeownership and local markets as a first pass to quantify some of these channels. Specifically, the model gives me a framework to look at the effects of local labor and housing markets, homeownership, intergenerational transfers, and the fact that households can be mobile across space in a relatively straightforward way.

Using this, we can answer how important these channels have been in increasing wealth inequality between 1999 and 2019 in the United States. I descibe this model in the next section.

1.5 Local Markets and Wealth Inequality in a Parsimonious Model

I begin by studying local labor and housing markets within a stylized, general equilibrium framework. The model is a first pass at quantifying some of the channels that produced the empirical findings in the previous section. These channels include local labor and housing markets, homeownership, geographic mobility, and, in particular, intergenerational transfers.

The model incorporates multiple regions, each with its own labor and housing market that must clear separately. Households in the model live only for one period, and are assigned a productivity type which is inherited across generations. These productivity types can be one of ten levels and correspond to deciles of the wage distribution. Further, there is no income mobility in the model, i.e., a household cannot change its productivity type, although the wages of each productivity type can differ by location.

At the end of the period, the household leaves bequests to kids that can include a home (if they own one). These bequests are modeled as "warm glow" preferences (following De Nardi [2004] and Straub [2019], and are not allowed to be negative. This is a key mechanism in the model that is inspired by the findings in the data (the difference is that since households only live for one period, bequests represent lifetime gift giving, and subsume inter-vivos transfers, help with downpayment, and inheritances), and drives many of the results that will be discussed later. In particular, warm glow preferences mean that bequests are a luxury good for households, i.e., an increase in income leads to a disproportionately large increase in bequests.[14] As different areas grow differently, this introduces an incentives for households in the fastest growing areas to save disproportionately more, and for homeowners to consume disproportionately more housing.

I calibrate the model to an initial (steady state) equilibrium in T_0 by matching local house prices, local employment by area, deciles of the local wage distribution, and

[14]This is what differentiates the model from the one in Greaney [2020], along with the fact that the model here is "full" general equilibrium, since interest rates are endogenous as well.

national homeownership rates by wage decile. I then calculate the increases in local productivity by wage decile between T_0 and T_1, and solve for the final equilibrium in T_1 using these new productivities.[15] Note that the parameters calibrated in the initial equilibrium do not change in the final equilibrium, although the moments they targeted (local house prices, local populations, etc.) respond endogenously to the changes in local productivities. None of the other calibrated fundamentals change between T_0 and T_1. This allows me to compare wealth distributions in these two equilibria, study the differences, and quantify how shutting off the various channels mentioned above can lead to a different wealth distribution in the final equilibrium.

1.5.1 Environment

In this section, I describe the demographics, timing, and market structure fundamental to the model. There are 100 areas in the economy.

Demographics

The total population of the country is normalized to be 100. Households live for one period, during which they choose location, homeownership, how much to consume of a consumption good, how much housing to buy or rent, and the amount of bequests they wish to leave their kids. At the end of the period, the household has a child and dies.

Each household is born with a productivity "type" $z \in \{1, 2, ..., 10\}$ (corresponding to income deciles) which is inherited from her parent, and there is no income mobility across deciles. I also make the assumption that the population in each income decile is 10.

Note that given local labor markets, each productivity type is allowed to have a

[15]The initial equilibrium corresponds to the economy in 1999, and the productivity increases occur between 1999 and 2019.

different wage in each area.

Timing

A household of a particular productivity type z is born, and it first chooses location given some preferences that it draws from an i.i.d. Extreme Value Type-I distribution. Once it has chosen a particular location, it draws homeownership preferences from a different i.i.d. Extreme Value Type-I distribution, and given these, chooses whether to be a homeowner or a renter household. After this choice is made, it solves the household's problem, i.e., it chooses the amount of the consumption good and housing it wants to consume, as well as the amount of bequests to leave to its kid.

Given the timing described here, the household problem is solved by backward induction: given that a households already chose its location and homeownership, it solves the household problem. Given that it knows it's location, it chooses ownership. And finally, before choosing ownership or solving the household problem, it chooses location.

Market Structure

Labor markets are segmented by productivity, so that each productivity type are not mobile across types. Each area has its own labor and housing markets, which set local wages for each type of worker and the local house price in equilibrium.

Interest rates are set nationally, and capital is freely mobile across areas. Households across the country rent capital out to firms at a gross interest rate of $R > 1$. In the background, there is also an assumption that the consumption good, produced by all local firms, is freely traded across areas. I set the price of this consumption good to be numeraire.

1.5.2 Households

Households in each area can choose to be renters or homeowners. They supply labor inelastically. Their wages depend on their productivity type, $z \in \{1, 2, ..., 10\}$. The current generation makes a decision about how much to consume of a consumption good, how much housing to buy or rent, and how much to save in the risk free asset, which pays a gross interest rate $R > 1$. At the beginning of their lives, they also draw preferences for areas and homeownership from a Type-I extreme value distribution. At the end of the period, they have a kid, bequeath their savings, and die.

For the purposes of this exercise, I also make the simplifying assumption that households cannot borrow, i.e., they cannot leave debt to their kids. Recall that households solve this problem given that they have already chosen their location and homeownership, and so each problem is specific to a local area.

Renters

Renter households, denoted by $\mathcal{O} = 0$, do not buy housing, but rent it at a rental rate q. In each period $t = 0, 1, 2, ...$, a renter of productivity type z in area j solves:

$$U_t(a, z, j, \mathcal{O} = 0) = \max_{c_t, h_t, a_{t+1}} \frac{(c_t^{\alpha} h_t^{1-\alpha})^{1-\sigma}}{1-\sigma} + \beta \frac{(a_{t+1})^{1-\gamma}}{1-\gamma} + A_j + \lambda_{j,z}$$

$$\text{s.t.} \quad \frac{a_{t+1}}{R} + c_t + q_t h_t = w_z + a_t$$

where the c is the level of consumption, h is the amount of housing rented, a_{t+1} are the savings, and A_j is a measure of amenities that the household enjoys in Area j.

Notice that the flow utility is governed by the parameter σ, while the “warm-glow” bequest function is governed by the parameter γ. Crucially, I assume that $\gamma < \sigma$, like in Straub [2019]. This makes the bequests a luxury good[16], which means that as wages increase, households want to increase bequests disproportionately more. Effectively, it means that richer households save more, and consequently their kids benefit more from an increase in local labor demand.

Note also that bequests are modeled here as a lifetime transfer between generations. The PSID data does capture gifts and inheritances in the early to middle stages of a child's life cycle, but is not able to capture bequests in the later stages of the life cycle (when the child is over 50 years of age), which is when bequests are most commonly received. In this way, the model does a better job of capturing parental transfers. However, it misses out on the life-cycle element in the data: households in the model make a transfer between generations only once, which is at the end of their lives. Therefore, bequests in the model fold in everything that we observe in the data (help with downpayment, gifts, inheritances, etc.).

Homeowners

Homeowner households ($\mathcal{O} = 1$) in an area j and productivity type z solve the following problem:

$$U_t(a, z, j, \mathcal{O} = 1) = \max_{c_t, h_t, a_{t+1}} \frac{(c_t^{\alpha} h_t^{1-\alpha})^{1-\sigma}}{1-\sigma} + \beta \frac{(a_{t+1} + p_{h,t} h_t)^{1-\gamma}}{1-\gamma} + A_j + \lambda_{j,z} + \kappa_z + \zeta_z$$

$$\text{s.t.} \quad \frac{a_{t+1}}{R} + p_h h_t + c_t = w_z + a_t + (1 - \delta^h) p_h h_{t-1}$$

where p_h is the price of housing, and δ^H is the depreciation rate of housing stock, and κ_z is the utility bump that households get from being homeowners. This can also

[16] This follows work by De Nardi [2004] and Lockwood [2018].

be negative. The purpose of this term is to capture the value of being a homeowner, and practically, also to match the homeownership rates by income group.

The most crucial difference between homeowners and renters is that owners leave their house to their kids, i.e., $p_h h$ is a part of the bequest function. Combined with the fact that $\gamma < \sigma$, this implies that as income increases, homeowner households also want to buy disproportionately more housing since they get an additional utility "bump" from leaving their house to their kids.

1.5.3 Homeownership and Location Choice

At the beginning of the period, households of each productivity type z draws tenure preferences $\boldsymbol{\zeta_z} = \{\zeta_0, \zeta_1\}$ and location preferences $\boldsymbol{\lambda_z} = \{\lambda_1, ..., \lambda_J\}$ from an i.i.d. Extreme Value Type-I distribution with mean zero and scale parameter ξ_H and ξ_M respectively.

The scale parameters controls the relative importance of systematic preferences for homeownership or location, i.e., κ_z and A_j, and the flow utility households get every period, the pecuniary costs and benefits of being a homeowner or renter in a particular location. Note that the homeownership bump does not depend on area, and the amenities enjoyed by households in an area do not depend on productivity type.

These preferences allow me to solve for the proportion of renters and homeowners in each area at every productivity level, and enter utility additively.

1.5.4 Population Shares

I assume that the total population of the country is 100, and this is evenly distributed among the ten productivity types. Since they draw both tenure and location preferences together, I first calculate the tenure shares in each area, *assuming house-*

holds have already made the location choice. Tenure preferences being of Extreme Value Type I let's me back out the shares in each area j at productivity z:

$$\mu^H(d \mid a, z, j) = \frac{\exp(U(a,z,j,d))^{\xi^H}}{\sum_{d'=0}^{1} \exp(U_{a,z,j,d'})^{\xi^H}}$$

where $d = 1$ if the household owns, and $d = 0$ otherwise.

To get population shares by location, I first integrate out tenure preferences from utility:

$$U^H(a, z, j) = \xi^H \log \sum_{d=0}^{1} \exp(U(a, z, j, d))$$

Given this, population shares in each area j and tenure d are given by:

$$\mu^L(j, d \mid a, z) = \left[\frac{\exp(U^H(a, z, j))^{\xi^M}}{\sum_{j'=1}^{J} \exp(U^H(a, z, j'))^{\xi^M}} \right] \mu^H(d \mid a, z, j)$$

1.5.5 Labor Markets

Each region j has firms which use labor of type z and produces using a constant returns to scale technology. The rent capital from households on a national market, which implies that while wages are local, interest rates are national. Capital is also freely mobile across areas.

$$Y_{z,j} = \theta_{z,j}[\mu K^\rho + (1-\mu)L^\rho]^{1/\rho} \implies$$

This implies that labor and capital are given by:

$$K_{z,j} = \frac{Y_{z,j}}{\theta_{z,j}} \left(\frac{\mu \theta_{z,j} c(r_j, w_{z,j})}{r} \right)^\nu$$

$$L_{z,j} = \frac{Y_{z,j}}{\theta_{z,j}} \left(\frac{(1-\mu)\theta_{z,j} c(r, w_{z,j})}{w_j} \right)^{\nu}$$

where $\nu = \frac{1}{1-\rho}$ and $c(r_j, w_{z,j})$ is the unit cost function:

$$c(r_j, w_{z,j}) = \frac{1}{\theta_{z,j}} [\mu^{\nu} r_j^{1-\nu} + (1-\mu)^{\nu} w_{z,j}^{1-\nu}]^{\frac{1}{1-\nu}}$$

I assume that any profits accrue to absentee investors.

1.5.6 Housing Markets

Housing is built by absentee investors who sell it to owners and rent it out to renters. I assume that they supply housing using a constant elasticity supply function:

$$H_j^S = D_j p_{hj}^{\eta_j}$$

where η_j is the elasticity of housing supply and D_j is a supply shifter that I use to calibrate house prices. As in the labor market, all profits from building accrue to these absentee investors.

Additionally, there is a no arbitrage condition between owning and renting which pins down the ratio of the price of housing to its rental rate. Specifically, one should be indifferent between renting out a unit of housing and getting back the rental rate q, or purchasing a house at an opportunity cost of $(r + \delta^H)p_h$. This means:

$$q = (r + \delta^H)p_h$$

1.5.7 Equilibrium

An equilibrium is a set of prices $\{q_j, p_{hj}, w_j\}$, allocations $\{c_j, h_j, a_j\}$ for renter and homeowner households of each productivity type z, and allocations $\{K_j, L_j\}$ for firms, in each area $j \in J$ such that:

1. Households maximize utility by solving the problem in Section 1.5.2.

2. Firms maximize profits by solving the equations in Section 1.5.5

3. Labor, housing, and capital markets clear:

$$L_z = 10 \quad \forall \quad z \in \{1, 2, ..., 10\}$$

$$L^{S\star}_{j,z} = 10 \sum_{d=0}^{1} \mu^L(j, d \mid a, z) = L^{D\star}_{j,z}$$

$$H^{S\star}_j = H^{D\star}_j = \sum_{z=1}^{10} \sum_{d=0}^{1} h^\star(a, j, z, d) L_{j,z,d}$$

$$K^{S\star}_j = \sum_{z=1}^{10} \sum_{d=0}^{1} a^\star(j, z, d) L_{j,z,d}$$

1.5.8 Calibration

The model is calibrated to the 100 most populous CBSAs in the U.S. in $T_0 = 1999$. For context, the largest CBSA in this setting is New York-Newark-Jersey City, NY-NJ-PA, and the smallest is Vajello-Fairfield, CA.

Labor Markets and Productivity Following Karabarbounis and Neiman [2014], I set the labor share to be 0.66 and the capital share to be 0.33.

I use the County Business Patterns (CBP) data to calculate wages and employment at each decile (starting from the 1st percentile to the 90th percentile) in each CBSA in 1999. Using these and equilibrium interest rates, I back out the productivity levels for the ten deciles of the wage distributions.

Households Households in each area are one of 10 productivity types, which is predetermined. Since households supply labor inelastically, wages are set by firms, and depend on the household's productivity type.

Homeownership Rates The parameter κ_z is calibrated to match homeownership rate by decile calculated in the PSID in 1999. The preference shocks for homeownership are assumed to be drawn from an i.i.d. Extreme Value Type I distribution with mean zero and scale parameter $\xi_H = 1$. Figure 1.15 shows the calibration for homeownership rates across wage deciles. The homeownership rate increases almost linearly through the deciles.

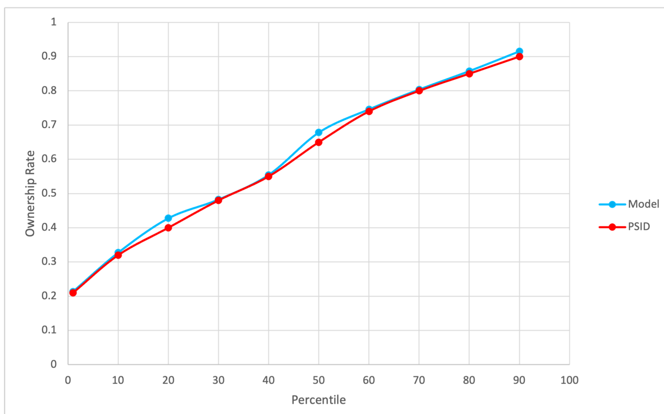


Figure 1.15: Calibration of Homeownership in Initial Equilibrium

Local Population The parameter A_j is calibrated to match total employment in an area in the CBP data. Specifically, I select the 100 largest area by size in the CBP, and calculate the share of employment in each area. The preference shocks for location are assumed to be drawn from an i.i.d. Extreme Value Type I distribution with mean zero and scale parameter ξ_M. The scale paramater is calibrated to match the migration elasticity estimated in Hornbeck and Moretti [2018], which is 2.37. Figure 1.16 shows the matching for local employment.

Housing Markets I use house supply elasticities from Saiz [2010] for the pa-

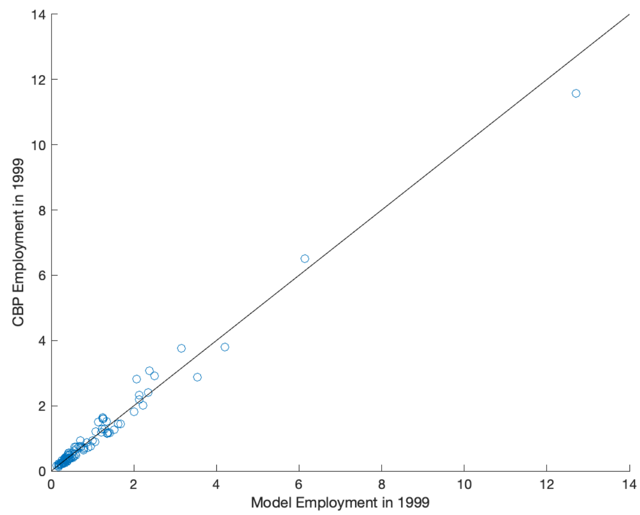


Figure 1.16: Calibration of Employment in Initial Equilibrium

rameter η_j, and the model is calibrated so that house prices in the model exactly match the FHFA house price index by area in 1999. In order to do this, I need one parameter that is free to move around, and this is the supply shifter D_j. Figure 1.17 shows the the exact matching of the FHFA price index in the initial equilibrium.

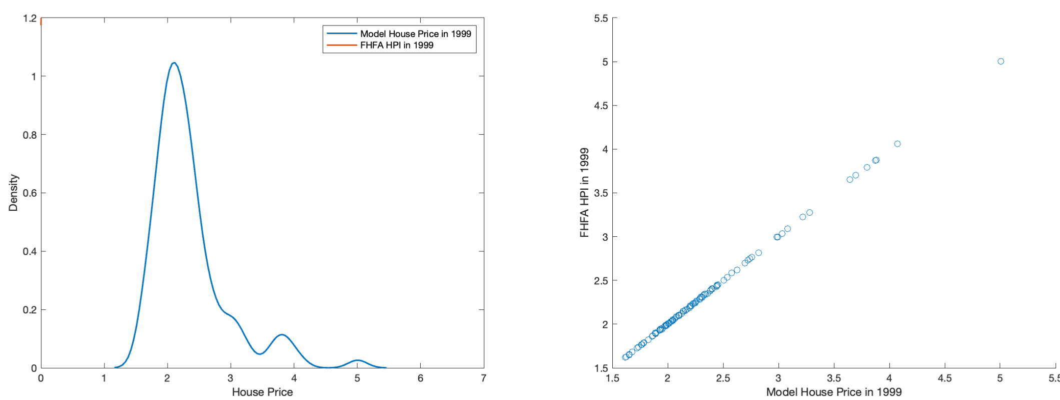


Figure 1.17: Calibration of House Prices in Initial Equilibrium

Summary Table 1.4 provides a summary of the parameters I use in the calibration. Appendix A.9 describes the data sources I use in the model in greater detail.

Parameter	Description	Value
Households		
α	Consumption share	2/3
β	"Altruism" parameter	0.75
σ	Curvature of own utility	2.5
γ	Curvature of bequests	1.05
Firms		
μ	Capital share	0.25
ν	Labor share	0.65
θ_i	Productivity	CBP
Housing		
η	Elasticity of housing supply	Saiz [2010]
D	Supply shifter	Calibrated
Preferences		
κ_z	Homeownership Utility	PSID
ξ_z	Idiosyncratic ownership preferences	PSID
A_j	Local Amenities	CBP
λ_j	Idiosyncratic location preferences	Hornbeck and Moretti [2018]

Table 1.4: Summary of Parameters

1.5.9 Simulation

Once the calibration is completed, I go back to the CBP data in $T_1 = 2019$. Using this, I calculate the implied distribution of productivites in each CBSA using the same method as before (i.e., to match wage deciles), and solve the calibrated model using these new productivities. All other calibrated parameters in the model remain unchanged. The exercise here is to compare initial and final equilibria to examine the role of local labor markets in explaining wealth inequality.

To analyze the importance of the role of local markets, I perform four quantification exercises in the model. First, I examine the role of the dispersion in local labor market growth. In other words, what if every local market in the country grew at the same rate? To do this exercise, I calculate the average growth in productivities between $T_0 = 1999$ and $T_1 = 2019$ across all local markets, and assign this to each local market.

Second, I study the role of homeownership within the model by shutting off this channel altogether – i.e., what if no household was permitted to buy their home? This is an important benchmark because most models of local labor markets and real wage inequality (Roback [1982], Moretti [2013]) make this assumption in their models.

Third, I look at the role of housing markets in mediating wealth inequality via local labor markets. Specifically, house prices react to changes in local labor demand, but this reaction depends on the elasticity of housing supply in the area. I quantify how important the reaction of house prices is by setting the elasticity to be very high in all markets.

Fourth, the literature has often postulated migration and mobility as being an important margin of adjustment to local labor market shocks (Bound and Holzer [2000], Bartik [1991], Blanchard and Katz [1992]). In this exercise, I shut off the migration channel by making it impossible for households to move after the initial equilibrium is calibrated.

1.5.10 Results from Main Model

House Prices

Figure 1.18 shows the house prices distribution that results from the model in the final equilbrium. As one can see, the actual distribution of house prices is more spread out than the model-generated one. However, the model only includes movements in house prices that are the result of a change in labor demand, and so perhaps it should be expected that the model wouldn't capture all the dispersion of in the house prices distribution. The coefficient of variation on house prices, for instance, increases in the model from 0.25 in 1999 to 0.30 in 2017. In the data, the increase is from 0.25 to 0.45.

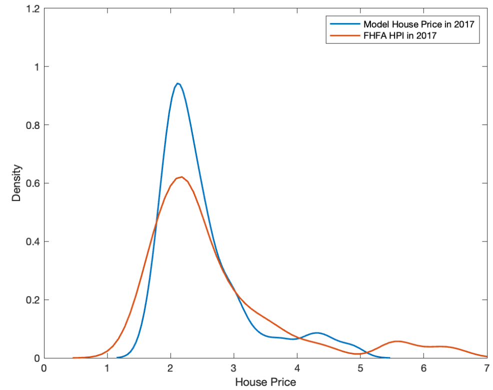


Figure 1.18: Comparing Model-Generated House Price Distribution to FHFA HPI in 2017

Figure 1.19 compares the two model-generated distributions of house prices in 1999 and 2017. It should be noted that the 1999 distribution is exactly calibrated to match the data (as was seen in Figure 1.17).

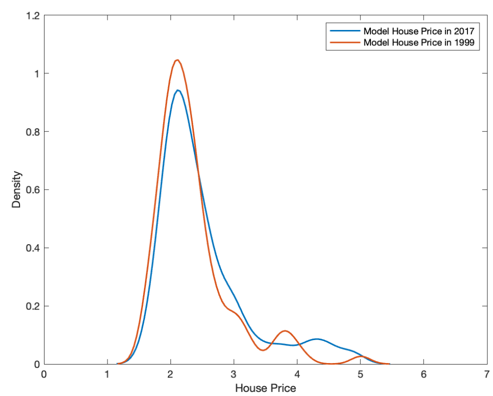


Figure 1.19: Comparing Model-Generated House Price Distribution in 1999 and 2017

Labor Markets and Homeownership

It is not clear ex-ante what happens to homeownership rates when labor markets are doing well. On one hand, households are richer, and so they might want to buy a home and get the benefits of homeownership. On the other hand, the price of housing increases, which makes it less attractive for households to buy.

In the model, I find a small negative relationship between labor market growth and homeownership changes, i.e., stronger labor market growth is associated with a mild decrease in the homeownership rate, which roughly matches the data – the U.S. has seen homeownership rates decline from 63% in 1999 to about 60% in 2019.

The importance of this change for wealth inequality can be seen in 1.3, where a change in homeownership rates is the second more important component of the overall change in mean wealth between 1999 and 2019.

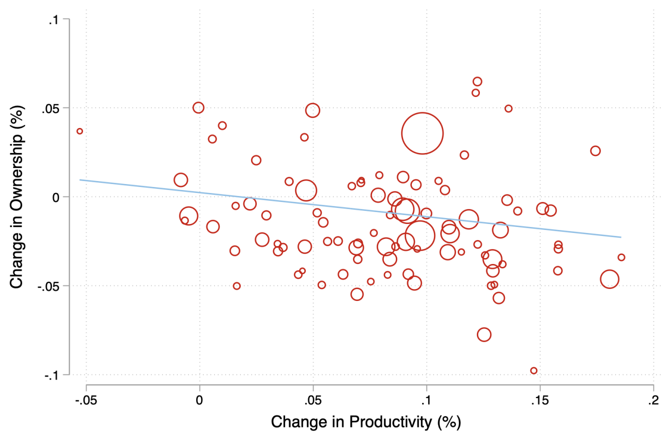


Figure 1.20: Ownership and Homeownership in the Model

Interest Rates

Interest rates are set in equilibrium. In the initial equilibrium, I calibrate the discounting rate β to set the interest rate at 3%. This increases to 3.48% in the final equilibrium. Ex ante, it is not clear how interest rates would react to an increase in local labor productivities. This is because as local productivities increase, so does the demand for capital, which raises interest rates. At the same time, there is an increase in the incentives to save, which means households are willing to supply more capital in the economy, lowering interest rates.

However, homeowning households, who are wealthier, have two methods to save:

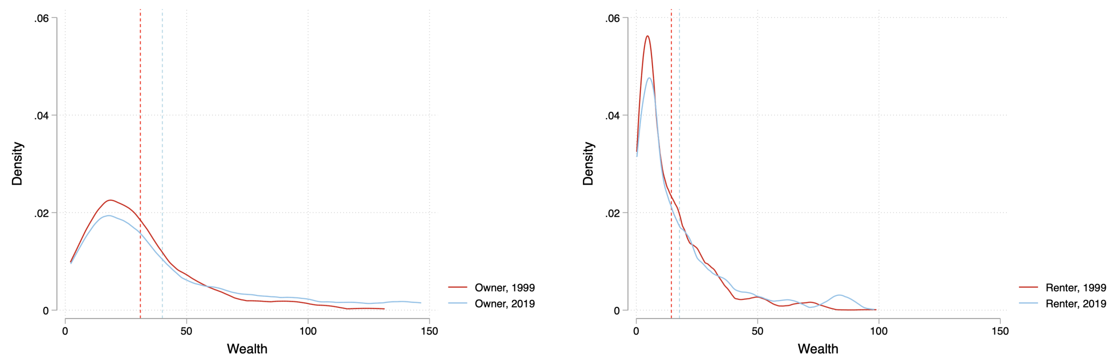


Figure 1.21: Wealth Distributions of Owners and Renters

they can either increase their holdings of the risk free asset, or they can consume more housing. When making these considerations, the household trades off getting an interest payment on the risk free asset versus the utility value of consuming more housing as well as the utility value of leaving the home value to their kids. In equilibrium, this means that all else equal, they do not increase their holdings of the risk free asset as much as renters, because they can leave their house to their kids as well. In turn, this leads to the increase in supply of capital not being large enough to counter the increase in demand, which leads to an increase in interest rates in the final equilibrium.

Wealth Inequality in the Model

Figure 1.21 plots the initial and final distributions of wealth in the model for both owners and renters. Note that for owners, their wealth includes both housing and non-housing wealth – housing wealth is just the value of their home, i.e., $p_h h$, and non-housing wealth is their investment in the risk free asset, a. For renters, their wealth is non-housing wealth by definition.

One can see that the wealth distribution of renters is much narrower than that of owners, and this is borne out by the data as well. I calculate various statistics of inequality (specifically, the Gini coefficient and the 90/10 ratio) in the model and in the PSID data. In the data, I consider the bottom 90% of households that have positive wealth holdings to calculate the statistics in order to better match them to the model, where households are not allowed to leave negative bequests to their kids.

Gini coefficients are presented in Table 1.5. In the 1999 PSID data, the Gini on the wealth of renters is around 0.74, while that of homeowners is around 0.44. These increased to 0.50 and 0.78 respectively in 2019. Overall, the wealth Gini increased from 0.56 to 0.62 in this period. These patterns are roughly borne out by the model as well. The wealth Gini for owners in the model is 0.40 in 1999, and increases to 0.45 in 2019, an increase of 0.05 units. The corresponding numbers for renters are 0.51 in 1999 and 0.55 in 2019. Overall, the model produces an increase in the wealth Gini of 0.05 points from 0.46 to 0.51. This increase is roughly $0.05/0.07 = 71\%$ of the increase observed in the data.

It is also worth noting that the model does a much better job of matching the gini coefficient of the wealth of homeowners (0.4 in the model compared to 0.44 in the PSID data) than non-housing wealth (0.51 compared to 0.74), although it fares better in capturing increases. One reason for the level differences could be that the propensity to beqeath assets, or non-housing wealth, is different from housing wealth, although the model treats them in the same way. It is likely, for instance, that non-housing wealth is even more of a luxury good compared to housing wealth when it comes to bequests (very wealthy families leave behind estates that contain more than just a house). In this case, the model will predict similar gini coefficients for these two forms of wealth, when in reality they could behave in different ways.

Perhaps a more intuitive way to understand the level of inequality is the 90/50 ratio. This is simply the ratio of the 90th percentile of wealth to the 50th percentile.

	1999		2019		Increase	
	Model	**Data**	**Model**	**Data**	**Model**	**Data**
Owners	0.40	0.44	0.45	0.50	0.05	0.06
Renters	0.51	0.74	0.55	0.78	0.04	0.04
All	0.46	0.56	0.51	0.62	0.05	0.06

Table 1.5: Gini Coefficients in Model and PSID Data

	1999		2019		Increase	
	Model	**Data**	**Model**	**Data**	**Model**	**Data**
Owners	2.35	2.86	3.57	3.95	1.23	1.08
Renters	3.69	10.47	4.25	11.25	0.57	0.78
All	2.79	4.05	3.84	6.02	1.06	1.97

Table 1.6: 90/50 Ratio in Model and PSID Data

These can be found in Table 1.6. Once more, I am able to match the ratios of owners much better than renters, and the overall patterns remain the same as the Gini coefficient.

In both tables, it is worth noting the fact that inequality among owners has risen more than that for renters, and this is reflected in the model calculations as well. This is not a finding that has received any attention in the literature to the best of my knowledge.

The model also is able to capture the increase in the Gini coefficient well in the model vs. the data.

1.5.11 Model Regressions

In general, the labor market dynamics between 1999 and 2017 lead to a greater increase in wealth for homeowners than for renters. To see this, I estimate the following regression:

$$\Delta W_i = \beta_0 + \beta_1 \Delta\theta_i + \beta_2 \text{Own}_i + \beta_3 (\Delta\theta_i \textbf{ x } \text{Own}_i) + \epsilon_i$$

where ΔW is the percent change in wealth in the model between the initial and final equilibrium for each type i household, and $\Delta\theta_i$ is the change in productivity. I can also estimate the same regression in the PSID data using cross sections of households in 1999 and 2019.

	Model	**Data**
$\Delta\theta$	1.725	-0.652
	(0.167)	(1.086)
Owner	-0.085	-1.428
	(0.015)	(0.279)
$\Delta\theta$ **x Owner**	0.426	2.475
	(0.196)	(1.113)

Table 1.7: Effect of a Change in Labor Demand on Wealth by Tenancy in Model

Table 1.7 presents the results from this estimation. The results show that owners are much more responsive to the productivity increase in terms of their wealth compared to renters. This result in the model can also be seen in the data. The major difference between the two is that in the model, there is a positive impact of the increase in productivity on renters as well as owners – however, this is not true in the data, where renters do *not* benefit from growing labor markets.

It is worth discussing why these results might occur in the model. There are two main reasons. First, consider the local labor markets channel. Here, as productivity increases, so does wage. This increases housing demand and savings, which implies housing and non-housing wealth increase. Since these productivity increases are not uniform across areas, there is an increase in inequality that happens through this channel.

Second, consider the bequest motive. Bequests are a luxury good in this model, and consist of both housing and non-housing wealth. For the reasons discussed above, households increase savings and home values. However, because they are to leave this wealth to their kids, they increase savings and housing wealth disproportionately more. Essentially, this second channel acts as an exacerbator of the first channel.

In this way, local labor and housing markets interact to affect wealth inequality.

1.5.12 Quantifying Mechanisms That Lead to Wealth Inequality

Using this model, I now begin running simulations with some channels switched "off" in order to investigate their relative importance in generating wealth inequality. In particular, this paper concerns the role of divergent local labor market growth and homeownership, and so these will form the core of the quantification exercises. I also conduct additional exercises: first, I switch off the link between housing and labor markets by making all housing markets perfectly elastic (so that increases in housing demand do not lead to increases in house prices); second, I shut off labor mobility across areas, so that all households are forced to stay in the same area regardless of the growth or contraction in labor markets.

Each of these exercises is described in greater detail below.

What if all labor markets grew equally?

The San Francisco and Detroit metro areas have grown at dramatically different rates between 1999 and 2019. While Detroit has seen declines in wages, San Francisco has seen increases. These trends are mirrored by the movements in house prices across these areas as well. As different areas grow different, it is likely that the wealth holdings of households in these areas diverge away from each other. However, even uniform growth is likely to produce an increase in inequality, especially because homeowners and renters have different incentives to leave bequests. How much of the increase we observe, then, is due to the fact that San Francisco and Detroit have grown at different rates?

To answer this question, I calculate the average growth in productivities across all areas between 1999 and 2019, and assign this to be the growth of each area. Essentially, Detroit and San Francisco now grow at the same rate between 1999 and 2019. I simulate this new model using the same methodology as before.

	Main Model	**Uniform Labor Growth**
All	0.05	0.03
Owners	0.05	0.03
Renters	0.04	0.02

Table 1.8: Increase in Gini Coefficients in Model Without Dispersion in Local Labor Growth

	Main Model	**Uniform Labor Growth**
All	1.06	0.64
Owners	1.23	0.68
Renters	0.57	0.37

Table 1.9: Increase in 90/50 Ratio in Model Without Dispersion in Local Labor Growth

The resulting increases in Gini coefficients and 90/50 ratios from this exercise are presented in Table 1.8 and Table 1.9 respectively. The Gini coefficient increases from 0.46 to 0.49, an increase of 0.03 units, while the 90/50 ratio increases from 2.81 to 3.44, an increase of 0.64 units. Both these numbers are approximately 60% of the increase I see in the main model, which implies that 40% of the increase in the model is explained by the dispersion in local labor market growth. In other words, the fact that metro areas like Detroit and San Francisco grow at different rates and not the same rate is responsible for 40% of the increase in wealth inequality among the bottom 90% of households in the United States.

This dramatic increase occurs because of the key mechanism in the model: local increases in income translate into disproportionate increases in bequests. These local increases, in the main model, are not uniform. In other words, in the highest growing areas, households want to leave disproportionately more bequests, while in slower growing areas, the increase in bequests is more modest. This exacerbates the effects uneven regional growth on wealth inequality.

This particular counterfactual sets growth in all areas to be the same. This implies that the relative increase in bequests across areas is also similar, and therefore, the resulting increase in wealth inequality isn't as high.

What if there was no homeownership?

A major theme in the empirical results is that parental homeownership was a vital determinant of the wealth accumulation of children. In Section 1.3, it was clear that the wealth of homeowners was the one responsible for most of the change in mean wealth between 1999 and 2019. However, papers in the literature on local markets (Moretti [2013], Rosen [1979], Roback [1982]) usually do not model homeowners and renters separately. Of course, these papers are not concerned with wealth, which makes it perhaps an understandable omission.

What happens if I make this assumption in the model presented in this paper? To see this, I shut off the homeownership channel altogether. This means that there are only renters in the model. The change in Gini coefficients resulting from this exercise are presented in Table 1.10.

	Main Model	**No Ownership**
All	0.05	0.02
Owners	0.05	
Renters	0.04	0.02

Table 1.10: Increase in Gini Coefficients in Model Without Homeownership

The results indicate that without homeownership, the wealth Gini would increase by 0.02 points, or about 40% as much as in the main model. This implies that roughly 60% of the increase in wealth inequality (as measures by the gini coefficient) was due

	Main Model	No Ownership
All	1.06	0.2
Owners	1.23	
Renters	0.57	0.2

Table 1.11: Increase in 90/50 Ratio in Model Without Homeownership

to homeownership. Moreoever, this percentage increases to 80% if we consider the increase in the 90/50 ratio (Table 1.11), which increases only by 0.2 in the model without homeownership, compared to increasing by 1.06 in the main model.

These results underscore the importance of homeowners when studying wealth inequality.

What if all housing markets were perfectly elastic?

Instead of shutting off the homeownership channel altogether, the model also allows for subtler experiments. One of these is to shut off the effect of local labor markets on house prices. Since the wealth of homeowners and renters is especially affected through a change in rents and house prices, it is important to quantify the extent to which the pass through of labor market into house prices matters for wealth. This is similar to the exercise conducted in Greaney [2020], who finds that house supply elasticities have only a minor role to play in exacerbating wealth inequality. I use Greaney [2020] as a benchmark to compare my estimates against because the model presented in the paper considers housing markets and house price movements in a dynamic framework (specifically, Greaney [2020]'s model considers house price volatility as well).

I follow Greaney [2020] in this exercise and set house price elasticities across the United States to be very high (I arbitrarily pick a supply elasticity of 50, which ensures no movement in house prices). The resulting increases in wealth inequality are presented in Table 1.12 (changes in Gini coefficients) and Table 1.13 (90/50 ratios).

The results indicate that infinitely elastic housing supply is only marginally responsible for the rise in wealth inequality. The resulting increase in the wealth gini for all households is 0.047, compared to 0.05 in the main model. This implies that even with all house supply elasticities being infinite, wealth inequality would rise by 92% as much. These patterns are also borne out by the 90/50 ratio.

Why is this the case? This happens because in the long run, households adjust using alternate margins. In growing areas, as wages increase, households demand more housing. However, under the assumption of perfectly elastic housing markets, housing supply adjusts freely to keep the house prices and rents constant. Since there is no increase in house prices, households consume even more housing than they did in the main model, resulting in an increase in housing wealth. Essentially, there are two components of housing wealth: the amount of housing stock, and the price of housing. In the main model, the amount of housing stock goes up, but so does the price of housing, which in turn limits the increase in housing stock. In the alternate world where house prices are unaffected by labor markets, the increase in housing stock in unchecked by house prices – this is why the Gini coefficient for homeowners goes up even more in this scenario compared to the main model (as seen in Row 2 of Table 1.12).

	Main Model	**Perfect Elasticity**
All	0.05	0.047
Owners	0.05	0.055
Renters	0.04	0.03

Table 1.12: Increase in Gini Coefficients in Model With Perfectly Elastic Housing Markets

	Main Model	**Perfect Elasticity**
All	1.06	0.91
Owners	1.23	0.74
Renters	0.57	0.79

Table 1.13: Increase in 90/50 Ratio in Model With Perfectly Elastic Housing Markets

What if there was no labor mobility?

Finally, labor mobility is often postulated as an important margin of adjustment to local labor market shocks (Bartik [1991], Blanchard and Katz [1992], Bound and Holzer [2000]). For instance, if Detroit isn't doing great, households might want to respond by moving somewhere else. On the other hand, it San Francisco is growing, it is likely to attract people. What happens if people were not allowed to move?

I look at this question by quantifying the extent to which labor mobility affects wealth inequality. It is worth noting that here, a lack of mobility is expected to *increase* wealth inequality – essentially, the question this exercise answers is: how much more would wealth inequality increase by if nobody in the United States could relocate to a different area? The results of this exercise are presented in Table 1.14 (Gini coefficients) and Table 1.15 (90/50 ratios).

	Main Model	**No Mobility**
All	0.05	0.06
Owners	0.05	0.06
Renters	0.04	0.05

Table 1.14: Increase in Gini Coefficients in Model Without Geographic Mobility

Gini $\uparrow$ 13% $\rightarrow$ overshoots growth by 13% $\rightarrow$ 13% $\downarrow$ in Gini due to mobility

The results indicate that in the absence of geographic mobility, wealth inequality would rise even more than it did between 1999 and 2019. Specifically, the gini coefficient would increase by 0.06 relative to 0.05 in the main model, and the 90/50

	Main Model	No Mobility
All	1.06	1.20
Owners	1.23	1.37
Renters	0.57	0.76

Table 1.15: Increase in 90/50 Ratio in Model Without Geographic Mobility

ratio increases by 1.20 compared to 1.06 in the main model. This indicates that labor mobility across the United States meant that wealth inequality increased by 18% *less* than what it would have if households were not mobile. This underscores the importance of labor mobility in dealing with labor market changes.

It also adds to the literature on geographic mobility and shows its relevance to wealth inequality in addition to income inequality (as explored in Chetty et al. [2014], for example): more mobility would not just imply lesser income inequality, but also lesser wealth inequality.

1.6 Conclusion

In this paper, I ask how local labor and housing market shape wealth inequality in the United States by affecting the wealth accumulation of the next generation. Specifically, I study how parental labor markets affect their child's wealth after the child splits off and forms her own household. To answer these questions, I leverage the Panel Study of Income Dynamics (PSID), a household level survey dataset that allows me to link households across generations, and augment it with information about local markets based on the location of the parent's household. I find that twenty years after splitting off, the children of parents who lived in one standard deviation better labor markets have a higher net worth by about $45,000, but only if the parents were homeowners. If anything, the children of renters are worse off. Further, the increase in wealth is unevenly split between the housing and non-housing parts of the child's wealth portfolio: housing wealth increases by about $10,000, while non-housing wealth increases by about $35,000. I find that most of the increase in housing wealth is driven by entry into homeownership rather than the purchase of a more expensive home.

I also find that the children of homeowner parents who grow up in better labor markets are more likely to be homeowners themselves by about 5 percentage points, and are 4 percentage points more likely to receive help from their parents to make a downpayment on a home. However, they do not earn higher labor income. Further, inheritances and gifts made to children play an important role in the transfer of wealth between generations – gift receipt increases by about $15,000 for a 1 s.d. better parental labor market, twenty years after split off. Finally, there is a positive, temporary increase in consumption of the children in early adulthood, which is consistent with anticipatory effects of a future transfer. Again, these positive outcomes are only for the children of homeowner parents, and the children of renter parents, if anything, are negatively affected.

To explain the role of these mechanisms in generating wealth inequality in the U.S., I build a parsimonious, general equilibrium model with the hundred largest CBSAs in the country, each having its own labor and housing market, with households being allowed to be mobile across them and free to choose their housing tenure (i.e., ownership) given some preference shocks. Households also leave bequests to their kids at the end of their lives which includes their home if they are homeowners. These bequests are modeled as being luxury goods following the literature [De Nardi, 2004]. This is a key mechanism in the model, because it means that an increase in wages translates to a disproportionate increase in bequests. As different areas grow at different rates, the highest growth areas see the largest increase in bequests, since the households in those areas have the greatest incentive to save more and consume more housing if they are homeowners.

Using this model, I find that dispersion in labor market growth across areas can explain approximately 40% of the increase in wealth inequality among the bottom 90% of the households in the United States between 1999 and 2019. Further, the fact that households can own plays an important role in models of spatial equilibrium – homeownership is responsible for 60% of the rise in wealth inequality during this period. I also confirm Greaney [2020]'s result that house supply elasticities have played only a minor role in generating this inequality and are responsible for about 8% of the increase in inequality, mostly because in the absence of house price effects, people just consume a higher quantity of housing, and the effect on total housing wealth evens out. Finally, absence of labor mobility would imply that that wealth inequality would increase by 13% more than it did in this period.

Taken together, these findings indicate that the wealth effects of labor markets are large and persistent across generations. The housing wealth of the parents is a key driver of this effect, although for the children, the effect shows up in the non-housing part of their wealth portfolio. There is some debate in the literature about whether housing wealth is real wealth, and there is evidence for both sides of the argument, with Guren et al. [2021] finding small propensities to consume out of housing wealth and Mian et al. [2013] and Aladangady [2017] finding larger ones, while Lovenheim and Reynolds [2013] finds effects of housing wealth that show up on children's education.

This paper shows that even if one believes that higher housing wealth, being illiquid, does not lead to substantially higher welfare, it seems that local labor market growth affects the *non-housing* wealth of their children, which is certainly relevant for welfare. It is important to study further the life-cycle behavior of households as they pass on benefits to the next generation, and the mechanisms involved.

CHAPTER II

The Effect of Local Labor and Housing Markets on Household Wealth in the United States

2.1 Introduction

The recent increase in wealth inequality within the United States (documented by Saez and Zucman [2016], among others) has led to debates about its extent and causes both within economics and public policy. When considered together with the rise in income inequality in the last few decades [Bloome, 2015], wealth inequality could have serious implications for access to opportunities. Most of the focus on wealth inequality has been on the top 1%, whose wealth comprises mostly of business and stock holdings. On the other hand, the wealth of the bottom 90% is help primarily in housing.[1] In this way, home ownership is an important aspect of the wealth holdings of a household, and deserves focus on how it contributes to U.S. wealth inequality.

This focus is especially salient because housing wealth is particularly sensitive to movements in house prices. If an area is doing well in terms of its labor market, households in the area earn more, and also demand more housing. This puts upward pressure on house prices, which in turn benefits homeowners. In this way, homeowners get not only the income benefits of being in a strong labor market, but also benefit in terms of their housing wealth. While they can also save the extra income,

[1]This measure excludes Social Security wealth.

the second, home equity channel of wealth accumulation occurs due to the general equilibrium effects of labor markets on housing markets.

In this paper, I quantify the extent to which growth in local labor markets has led to some households acquiring more wealth than others by using a household-level panel of household wealth from the Panel Study of Income Dynamics (PSID). Using a difference-in-difference framework, I find that homeowner households who lived in a one standard deviation better labor market between 1999 and 2019 accumulated \$43,000 more in net worth.[2] Most of these gains are due to housing wealth (about \$25,000) compared to non-housing forms of wealth like stock market investments or savings (\$11,000). I also find gains in the consumption patterns of these households, which implies that the gains in wealth have real effects on household welfare. On the other hand renters in these labor markets were not able to accumulate any additional net worth, and did not increase their consumption levels. Further, the effects are even stronger in markets with a lower elasticity of housing supply (such as the San Francisco metro area) compared to ones with a higher elasticity of housing supply, implying that the nature of local housing markets can exacerbate the effects of local labor market growth.

Further, labor market growth between 1999 and 2019 was concentrated in areas with a low elasticity of housing supply like the San Francisco metro area. Consequently, in this time period, there were major increases in home equity of households, particularly at the peak of the housing boom. These increases did not completely go away in the wake of the Great Recession. In fact, house prices increased steadily through the 2010s, which resulted in major gains in housing wealth for households living in good labor market areas.

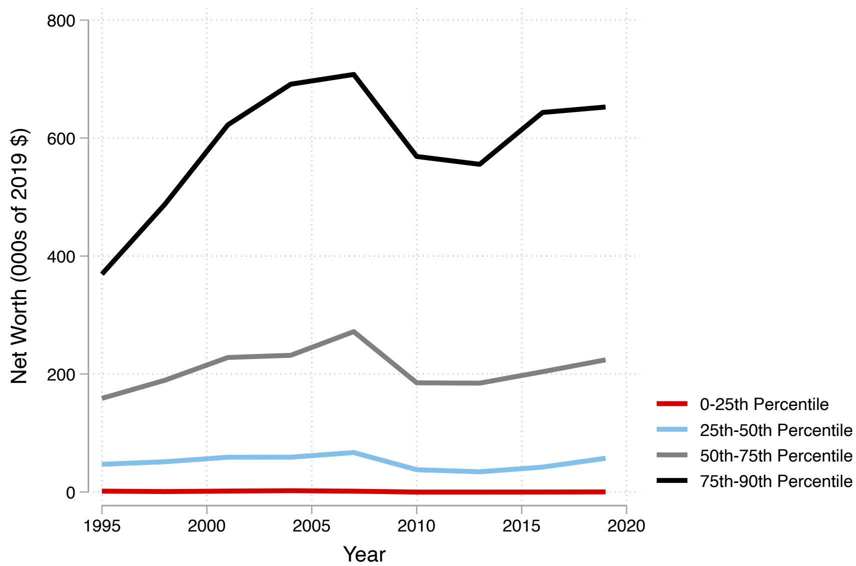
[2] the mean wealth of these households in 1999 was around \$260,000, meaning that the size of the effect is about 15% from the average

The pattern of labor demand growth and its tight correlation with wealth accumulation isn't something that was always true. The paper shows that the pattern of labor market growth was different between 1980 and 1999. In particular, there was no correlation between labor market growth and house supply elasticities. Consequently, I find that while households living in better labor markets did accumulate more wealth, but not by as much – homeowners accumulated about \$17,000 more net worth, but most of this was through *non-housing* forms of housing (\$12,000) compared to home equity (\$5,000).

It is worth noting that while a majority of the literature has focused on the rise in the wealth shares of the top 1% [Saez and Zucman, 2016], there is also evidence of growing wealth inequality among the bottom 90% of households. Figure 2.1 gives a sense of this divergence in the last few decades. It plots the median net worth of households as measured by the Survey of Consumer Finances (SCF) for households in four percentile groups: the bottom 25%, the 25th-50th percentiles, the 50th-75th percentiles, and the 75th-90th percentiles. The caveat is that these measures do not include Social Security of pension wealth, although they do include wealth in IRA accounts. It shows that the total wealth holdings of these groups are diverging away from each other. The divergence is particularly salient for two highest groups, although even the 25th-50th percentile group has been pulling away from the bottom 25%.

Meanwhile, local markets across the U.S. have been diverging away from each other: between 1999 and 2019, the Detroit metro area has seen real wages decline by 2%, while real house prices have decreased by 12.5%; on the other hand, the San Francisco metro area has seen real wages increase by 50%, and real house prices increase by 99%. These trends, in turn, affect the wealth holdings of households

Figure 2.1: Median Net Worth in the United States by Percentile Groups



This figure plots the evolution of median net worth between 1995 and 2019. The numbers are calculated from the Survey of Consumer Finances (SCF). Median net worth is plotted according to four percentile groups: 0-25th percentile, 25th-50th percentile, 50th-75th percentile, and 75th-90th percentile. The trend suggests that the wealth of the top two percentile groups has been diverging away from the bottom two in this period.

experiencing them. For homeowners in these areas, they affect their housing wealth as well. In this way, areas with persistently positive labor demand shocks keep growing, and the wealth of homeowners in these areas keeps increasing. Such a persistent increase in wealth also has consequences for the children of these households, and this is explored in Rao [2023]. How important is the spatial distribution of increasing labor demand and house supply restrictions in determing the extent of wealth inequality in the US? How much of the increase in wealth inequality comes from an increase in housing wealth as opposed to an increase in the amount of savings?

In order to investigate these questions in greater detail, I use data from a variety of sources to provide some baseline empirical facts about local labor and housing markets. I define local areas as Core Based Statistical Areas (CBSAs) because CBSAs are areas which capture large urban centers, meaning that households can live and work in the same CBSA. I start by showing that in fact, house prices increase disproportionately more in CBSAs with greater labor demand shocks, especially between 1999 and 2019. For a market with a 1 s.d. better labor market in this period, house prices grow by 1.6 percentage points more. This effect is exacerbated in markets with a lower supply elasticity: within these markets, like San Francisco, a 1 s.d. better labor market leads to a 10 percentage point increase in house price growth rates. Finally, between 1999 and 2019, local labor market growth was negatively correlated with house supply elasticity, i.e., areas in which it was difficult to build housing were exactly the areas that grew in terms of their labor markets. This meant that in this period, the increase in house prices was particularly salient and could have driven household portfolio more than before. In fact, I also find evidence that this negative correlation between labor market growth and house supply elasticities did not exist between 1980 and 1999. Consequently, the link between labor market growth and house prices was also weaker in this period.

These movements in house prices have real effects on the wealth and welfare of households. Using the PSID, I assign each household the labor market growth between 1999 and 2019 based on their area of residence in 1999, and study the evolution of a household's wealth between 1999 and 2019 based on the strength of their local labor market. This can be thought of as an "event study" type framework, but this framing is not precise. The "event" is labor market growth between 1999 and 2019, and the associations I find are between this growth and the evolution of wealth as measured in each interview wave of the PSID.[3]

Since local labor markets have knock on effects on local housing markets, their effects might be heterogeneous with respect to homeownership. One might suspect

[3] The advantage is that I follow the same families over time and track their household level wealth. In a repeated cross-section, cities would evolve in their composition as households migrate, meaning that we would not be able to delineate the effects of a particular labor market on wealth accumulation versus population composition.

that incumbent homeowners benefit further from rising house prices as their home equity rises, but renters suffer as rents increase. Further, transitioning into homeownership also becomes more challenging.

I find that between 1999 and 2019, homeowner households in 1 s.d. better labor markets were associated with a higher net worth of almost $43,000. Most of this association was due to an increase in their home equity of almost $25,000, and an increase in their non-housing wealth of about $11,000. On the other hand, renter households in 1 s.d. better labor markets hardly see any rise in their wealth. This large increase in home equity is perhaps what one would expect given the large increase in house prices that occurs in this period in response to growth in local labor markets.

This increase in wealth, even if mostly from home equity, has real effects on the welfare of households. Homeowner households are able to consume an average of $4,500 per year more than those in poorer labor markets. Meanwhile, renter households in better labor markets also see an increase in their consumption, but only of around $2,000 per year. It is also worth noting that homeowners see an increase in income of around $6,000 per year, while renters see an increase of around $2,000, almost all of which is spent on additional consumption.

Finally, I also find some suggestive evidence that between 1980 and 1999, the wealth accumulation of households in better labor markets was not as salient as in the later period. This is in line with the results on house prices, which were also not as responsive to labor markets in this period. The PSID collected data on the wealth of households in 1984, 1989, 1994, and regularly from 1999 onwards, which makes this analysis possible. Using these data, I find that homeowner households are able to accumulate more net worth of around $17,000 by 1999, although most of this is due to non-housing forms of wealth ($12,000) rather than home equity ($5,000).

Related Literature This research is broadly related to two strands in the economics literature.

First, it relates to the analysis of local labor and housing markets. The mechanism of labor market shocks leading to house price declines has been studied extensively in the literature in the context of spatial equilibrium. Rosen [1979] and Roback [1982] analyze the optimal choice of location when areas differ by amenities. Spatial equilibrium models have been the foundation of many subsequent papers that also look at differences in wages and amenities across areas to study inequality in real wages (Topel [1986], Moretti [2013], Diamond [2016], Notowidigdo [2011], Zabek [2017]). Meanwhile, other studies have shown the complex interplay between labor markets and housing availability. Glaeser and Gyourko [2005] note that housing supply constraints, resulting from both geographical limitations and regulatory restrictions, can result in higher house prices in high-demand areas. This finding is particularly relevant to our study, where such constraints exacerbate the effects of local labor markets in favor of homeowners vs. renters.

I add to this literature by explicitly considering the role of homeownership within local markets. My findings indicate that the fact that some of the people living in an area own their residence is quantitatively relevant in determining how they react to labor market shocks and their wealth holdings over time.

Second, this paper relates to the literature on the documentation, determinants, and causes of wealth inequality. Important papers in this literature include Saez and Zucman [2016] (the importance of taxation in determining the wealth shares of the top 1%), and Moll et al. [2021] (automation and wealth inequality). Other studies, such as Fisher et al. [2022] and Killewald et al. [2017], document the increase in wealth inequality in the United States. Case et al. [2012] argue that fluctuations in house prices significantly affect the economic behavior of households, impacting consumption and savings and, by extension, overall wealth.

The closest analysis to this paper is Greaney [2020], who also looks at the role of local labor and housing markets in determining wealth inequality in the long run. However, there are three key differences between the two papers. First, and most importantly, this paper relies on direct measurements of household wealth to provide evidence that the wealth of households is impacted by local labor markets in the long run. Second, it shows the importance of splitting the time period between 1980 and 2019 into two parts: while the first twenty years in this period has a more even distribution of labor demand growth, the second twenty years saw growth in areas with a low elasticity of housing supply, particularly during the Housing Boom. Therefore, the dynamics of wealth inequality look different at different points in between 1980 and 2019. Third, this study is largely empirical, while Greaney [2020] focuses on a modeling-based approach to generate counterfactuals.

Despite this considerable body of research, few studies have explored the effect of local labor market conditions on household wealth via the housing market in the long run. This paper contributes to this literature by shedding light on the significant impact of local labor market conditions on household wealth, mediated by local housing markets. Our findings reinforce the interconnectedness of these markets and underscore the need to consider them collectively when crafting economic policies.

The paper proceeds as follows. Section 2.2 presents some descriptive work on U.S. wealth holdings and wealth inequality, including how it has changed over time. Section 2.3 describes the data that is used in this paper. Section 2.4 describes empirical

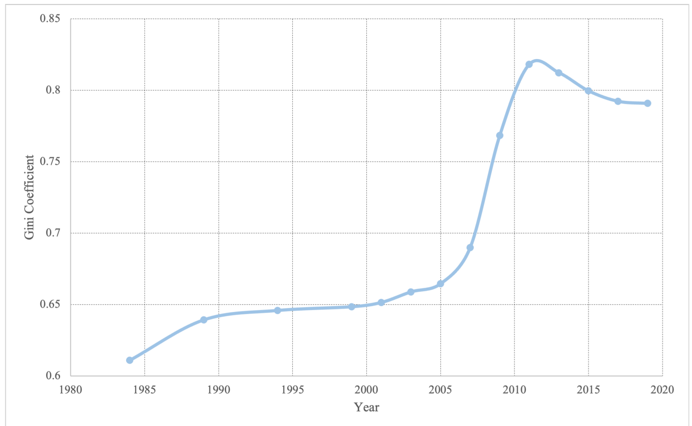


Figure 2.2: Gini Coefficient of Bottom 90% of Households in the United States over Time

results about local house prices and the distribution of labor market growth across the U.S, and Section 2.5 links these to the wealth and welfare of households. Section 2.6 discusses the results and provides implications for long run wealth inequality in the U.S., and Section 2.7 concludes.

2.2 Wealth Inequality among the Bottom 90%

Wealth inequality in the United States certainly increased due to a rise in top wealth shares (Saez and Zucman [2016]), but it also increased at other points in the wealth distribution. In particular, the wealth of the bottom 90% of households also shows an increase in the gini coefficient of wealth. For instance, Figure 2.2 plots the evolution of the wealth gini for the bottom 90% of households within the Panel Study of Income Dynamics.[4] One can see that between 1984 and 1999, the wealth gini increased from 0.61 to 0.65 – an increase of about 0.04 units, or 6.5%. However, between 1999 and 2019, the wealth gini shot up to almost 0.8, an increase of 0.15 units. It is also apparent that most of the increase in wealth happened in the lead up to the Great Recession, but has persisted in the ten years since then.

[4]This measure includes negative values, but similar numbers can be calculated for non-negative wealth holdings only.

2.2.1 Decomposing Wealth Changes between 1999 and 2019

The mean level of wealth in the United States among the bottom 90% of households increased between 1999 and 2019. Using the Panel Study of Income Dynamics (PSID), I find that among this group, the average net worth (including home equity) was \$142,299[5] in 1999. This went up to \$168,022 by 2019, a real increase of almost \$26,000.

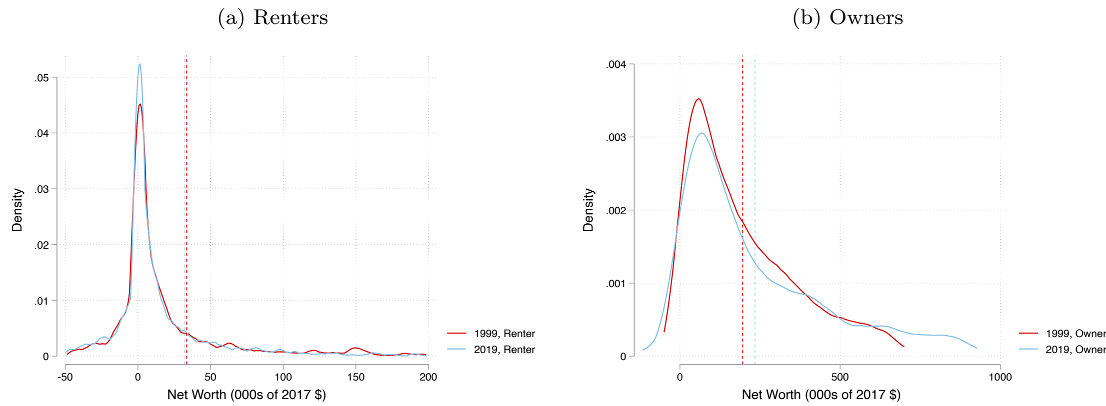
Figure 2.3 presents the wealth distribution of the bottom 90% of households in 1999 and 2019. The left panel shows the distribution of renters, and the right panel shows the distribution of homeowners. The wealth of owners, as expected, is much higher than the wealth of renters. This could be due to factors such as the age and income profiles of homeowners being substantially different than that of renters. However, while the wealth of renters has barely increased, and if anything slightly decreased between 1999 and 2019, the wealth of homeowners has gone up considerably. Again, this could be due to many factors, and I do not take a stand on this.

Given the importance of housing wealth in the wealth portfolio of these households, it is useful to decompose the change in mean wealth as coming from homeowners or renters. However, the homeownership rate has also changed in this time span, which makes it harder to see how much of the increase in mean wealth overall is due to each group. Therefore, I decompose the change in mean wealth between 1999 and 2019 as coming from three components: the change in the wealth of homeowners and renters respectively, keeping ownership rates constant, and the change in the ownership rate, keeping the wealth difference between owners and renters constant.

Specifically, we can write the change in mean wealth between 1999 and 2019, $\Delta\bar{W} = \bar{W_{2019}} - \bar{W_{1999}}$ as:

[5] All prices are in real 2019 dollars.

Figure 2.3: Distribution of Wealth of Renters and Homeowners in 1999 and 2019



This figure presents the wealth distribution of the bottom 90% of households in 1999 and 2019. The left panel shows the distribution of renters, and the right panel shows the distribution of homeowners. The wealth of owners, as expected, is much higher than the wealth of renters. However, while the wealth of renters has barely moved, and if anything slightly decreased between 1999 and 2019, the wealth of homeowners has gone up considerably.

$$\begin{aligned}\bar{W}_0 &= \frac{1}{N}\sum_{i=0}^{N} W_{i,0}\\ &= \frac{N_{R,0}}{N}\frac{1}{N_{R,0}}\sum_{i=1}^{N_{R,0}} W_{i,R,0} + \frac{N_{O,0}}{N}\frac{1}{N_{O,0}}\sum_{i=1}^{N_{O,0}} W_{i,O,0}\end{aligned}$$

We can further define $Q_{R,1} = N_{R,1}/N$ as the proportion of renters in period 1, $Q_{O,1} = N_{O,1}/N$ as the proportion of owners, and ΔQ_O as the change in the fraction of owners over time. Assuming N is constant over time,

$$N_{R,0} + N_{O,0} = N = N_{R,1} + N_{O,1} \implies \Delta Q_R = -\Delta Q_O$$

We can now rewrite the difference in mean wealth between period 1 and period 2:

$$\Delta\bar{W} = \bar{W}_1 - \bar{W}_0 \tag{2.1}$$

$$= \left(Q_{R,1}\frac{1}{N_{R,1}}\sum_{i=1}^{N_{R,1}} W_{i,R,1} + Q_{O,1}\frac{1}{N_{O,1}}\sum_{i=1}^{N_{O,1}} W_{i,O,1}\right) - \left(Q_{R,0}\frac{1}{N_{R,0}}\sum_{i=1}^{N_{R,0}} W_{i,R,0} + Q_{O,0}\frac{1}{N_{O,0}}\sum_{i=1}^{N_{O,0}} W_{i,O,0}\right) \tag{2.2}$$

$$= Q_{R,0}\Delta\bar{W_R} + Q_{O,0}\Delta\bar{W_O} + \Delta Q_O(\bar{W_{O,1}} - \bar{W_{R,1}}) \tag{2.3}$$

where ΔW_R is the change in the average wealth of renters between periods 0 and 1, and ΔW_O is the same statistic for the wealth of owners. Notice that in the last equation, these changes are weighted by the proportion of renters and owners in the first period. In other words, it's the contribution of the mean changes in rental and owner wealth keeping constant the proportion of renters and owners. The final term of Equation (2.3) is the change in the proportion of owners multiplied by the difference between the mean wealth of owners and renters in the final period.

To aid interpretation, we can divide both sides of the last equation (Equation (2.3)) by the left hand side to get:

$$1 = \frac{Q_{O,0}\Delta\bar{W_O}}{\Delta\bar{W}} + \frac{Q_{R,0}\Delta\bar{W_R}}{\Delta\bar{W}} + \Delta Q_{O,0}\frac{(\bar{W_{R,1}} - \bar{W_{O,1}})}{\Delta\bar{W}} \tag{2.4}$$

The first term on the right hand side captures the mean change in the wealth of owners over time, keeping constant the ownership rate. The second term captures a similar change in the mean wealth of renters, keeping constant the ownership rate. The third term is the change in the ownership rate, keeping constant the difference in the mean wealth of owners and renters. Table 2.1 provides the moments of the wealth distribution needed for the calculation using household level PSID data in 1999 and 2019.

Table 2.1: Mean Wealth for Bottom 90% Households in PSID (in 000s of 2019 dollars)

	1999	2019
Owners	\$192,648	\$246,161
Renters	\$43,618	\$42,606
All	\$142,299	\$168,022
Ownership	0.662	0.616

Plugging in the numbers, I find that:

(2.5)

$$1 = \underbrace{(1.377)}_{\text{Due to change in wealth of owners}} + \underbrace{(-0.0133)}_{\text{Due to change in wealth of renters}} + \underbrace{(-0.364)}_{\text{Due to change in ownership rate}}$$

The calculations reveal that almost the entirety of the change in means between 1999 and 2019 has come from the wealth of homeowners and the fact that homeownership rates have declined. The wealth of renters, on the other hand, is barely responsible for the change in means.

This indicates that homeowners and renters had dramatically different dynamics of wealth over this time period, and while one group increased their wealth, the other group stagnated. Ownership rates decreased, which means that more people are excluded from future gains in housing wealth.

We can do a similar decomposition for the earlier period, i.e., between 1984 and 1999. Table 2.2 provides the summary statistics used in the calculations.

Table 2.2: Mean Wealth for Bottom 90% Households in PSID (in 000s of 2019 dollars)

	1984	1999
Owners	\$147,039	\$192,648
Renters	\$31,044	\$43,618
All	\$100,707	\$142,299
Ownership	0.62	0.662

Unsurprisingly, the numbers paint a different story in this time period:

(2.6)

$$1 = \underbrace{(0.671)}_{\text{Due to change in wealth of owners}} + \underbrace{(0.120)}_{\text{Due to change in wealth of renters}} + \underbrace{(0.209)}_{\text{Due to change in ownership rate}}$$

The numbers show that while the change in average wealth was still driven by the wealth of homeowners, the wealth of renters also increased in this time period. Moreover, the homeownership rate went up by 4 percentage points.

Given these different dynamics, it is evident that homeownership and housing wealth changes were more important to explain the dynamic of wealth inequality between 1999 and 2019 compared to the earlier time period. Further, the distribution of the growth was more equitable between 1984 and 1999: access to homeownership was higher, and renters gained in terms of their wealth holdings as well, even though homeowners still gained the most.

In the next sections, I explore the relationship between local labor markets and house prices, and then move on to investigating the links between local labor markets and household wealth, which provide further context to these decompositions.

2.3 Data and Measurement

I use two main data sources for the empirical analysis presented in this paper. The first is the County Business Patterns (CBP) dataset, which I use to construct measures of local labor market growth in areas. The second is the Panel Study of Income Dynamics, which is a panel of households followed over time and space, and linked across generations. Both these sources are describes in detail below.

2.3.1 County Business Patterns (CBP)

The County Business Patterns (CBP), released publicly by the United States Census Bureau is a dataset that reports industry level employment and annual payrolls in the United States at the county, Meteropolitan Statistical Area (MSA), and state levels. For the various analyses in this paper, I use the county level data and aggregate these up to the level of Core Based Statistical Areas (CBSAs), which are collection of counties meant to capture larger areas in which people live and work. I define local areas as Core Based Statistical Areas (CBSAs) because they capture urban centers where households live and work. They consist of groups of counties. I do this by using a county-to-CBSA crosswalk, with county specific weights used to capture the relative importance of each county to the CBSA in terms of population. CBSAs are similar to Metropolitan Statistical Areas, but also include smaller urban areas (defined as Micropolitan Statistical Areas) which lets me capture more households in the data. On the other hand, Commuting Zones, the other most commonly used definition of local markets, include rural areas as well as urban areas. Since my focus is on aggregate markets in *urban* areas, CZs are not appropriate in my context.

I use employment changes from the CBP over time to define the shift-share labor demand growth that forms the main measure of local labor markets. In particular, I collect employment by industry (I use the 3-digit 2012 NAICS industry classifications) in each area between 1984 and 2019. These statistics, as mentioned previously, are aggregated up to the CBSA level. I provide more details about calculating the measure of labor demand growth by area in Section 2.3.6.

2.3.2 Panel Study of Income Dynamics (PSID)

The Panel Study of Income Dynamics (PSID) is a household survey that began in 1968, and in 2019 collected data for about 9,000 households. It was a yearly survey until 1999, at which point it became biennial. It asks interviewees detailed questions about housing, wealth, employment, and mobility, and follows families over time and even across generations.

This is the primary source of data for this paper. The richness of the PSID makes it particularly amenable to answering questions about wealth and the labor market, since it contains details not only about (self-reported) home values and income, but also about the wealth portfolio of households. The PSID first asked about wealth in 1984, and then once every five years until 1999, after which every interview wave has collects this information. This makes the PSID particularly useful in exploring wealth dynamics, since we are able to follow the same households over time as they interact with the labor market, save, purchase housing stock, and so on.

It should be noted that information about wealth portfolios is available at the household level, and is asked to the "household head", or "reference person" (RP). So, the unit of analysis in this paper will be the household, and not individuals. The specific wealth variables I consider are:

1. Wealth with home equity: total net worth, calculated as the sum of all assets minus all debt.

2. Wealth without home equity: the sum of all other forms of wealth, including cash, bonds, sums in checking and savings accounts, etc. minus all outstanding debt.

3. Home equity: calculated as self reported home value minus all outstanding mortgages on the house.

Note that these measures of wealth include retirement wealth in IRA accounts. However, they do not include other sources of wealth such as pensions or Social Security, because these are not "owned" by the household yet. In principle, it is possible to calculate future Social Security wealth based on current income, but this is not reflective of life cycle income patterns, which is what determines Social

Security returns. This matters because a household might change its consumption and savings behavior in the present given future sources of wealth. In other words, all forms of wealth could potentially be fungible across the life cycle. However, given the difficulty in estimating retirement wealth more completely, I only use wealth in IRA accounts in my measures.

In addition to these, I use the vast array of household level characteristics that the PSID is known for, including measures of family income, employment, race, age profiles, number of children, marital status, etc.

2.3.3 FHFA House Price Index

The FHFA HPI is a broad measure of the movement of single-family house prices, and serves as an accurate indicator of house price trends at various geographic levels. The FHFA HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancings on the same properties, and is available 1975 onwards.

This uniformity in measurement is useful because the FHFA takes care to measure the price of the same housing unit if it were in, say, San Francisco, or Indianapolis. This is important because the value of a house can be written as $p_h h$, where p_h is the price of housing, and h is the amount or stock of housing. Since the FHFA index keeps h constant across regions, the differences in the index reflect differences in p_h across areas.

2.3.4 Saiz [2010] House Supply Elasticity

A key parameter of interest is the house supply elasticity, which determines the responsiveness of prices to population changes. Data for this comes from Saiz [2010], who uses local land availability measures to construct a measure of house supply

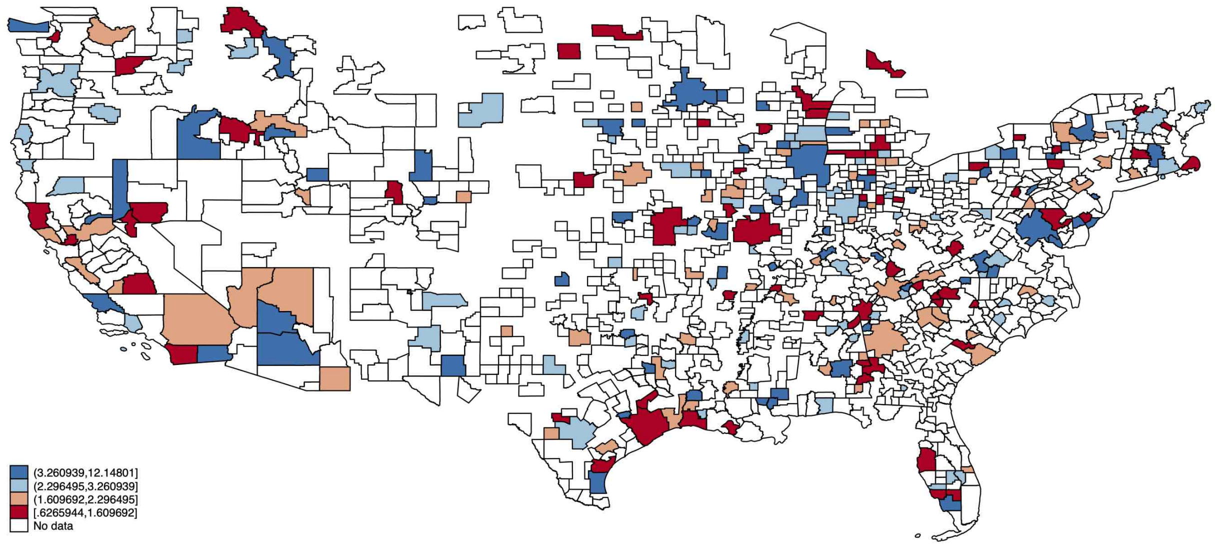


Figure 2.4: House Supply Elasticities Across the United States

elasticity that is plausibly exogenous to local labor market conditions. Essentially, these elasticities are a measure of how difficult it is to build new housing in an area – areas where the land is steep (San Francisco, for example), or areas near water bodies (Miami, for example), are naturally areas with a low elasticity of housing supply, while areas located on plains (like Indianapolis) have a higher elasticity of housing supply.

Figure 2.4 presents a map of house supply elasticities across the U.S., where red areas have a lower supply elasticity and blue areas have a higher one.

2.3.5 Final Dataset

Finally, these datasets are merged to create the final dataset I use for the empirical analyses in the paper. All variables that contain monetary measures (such as house prices, income, or wealth) are deflated to 2019 prices using the Consumer Price Index for Urban Consumers provided by the Bureau of Labor Statistics. [6] I further rely on the fact that the PSID also collects information about the location of households,

[6]The data can be accessed at http://www.bls.gov/cpi/data.htm.

although this isn't made publicly available (except at the state level). However, the restricted version of the dataset does contain this information.

I further merge the labor demand growth constructed using the CBP data and Saiz [2010] house supply elasticities to the PSID based on the location of households in 1999 for the main time period (1999-2019) and 1984 for the secondary time period (1980-1999), respectively. This is done because the PSID only collects information on wealth beginning in 1984.

Table 2.3 provides some summary statistics for the main sample of households used for regressions between 1999 and 2019. In total, we have information on 12,950 households over 11 interview waves (biennially from 1999 to 2019). However, there is some attrition in the sample, which why the total number of observations (household x time) is not 12,950 x 11, but rather 65,834. The sample statistics are weighted using longitudinal weights provided by the PSID, which makes the data nationally representative every year.

	Mean	**S.D**
Age	43.5	12.1
Homeowner	0.584	0.493
Black	0.163	0.370
Married	0.517	0.500
Years of Education	13.6	2.65
Unemployed	0.056	0.230
Family Income	90.1	129
Labor Income	55.6	96.2
Net Worth	307	1555
Net Worth (without Equity)	220	1480
Home Equity	87	190
Observations	65834	
Families	12950	
Time Periods	1999, 2001, ... , 2019	

Table 2.3: Descriptive Statistics for Main Panel of Families, 1999-2019

The idea is to measure the evolution of wealth as labor markets are growing in an area. What is the association of net worth with 1 s.d. better labor markets?

Further, what part of the wealth portfolio is responsible for the changes – housing, or other forms of wealth? Do these relationships change with the time period under consideration, or the nature of the housing markets (as captured by the house supply elasticity)? These questions are answered in the next sections.

2.3.6 Measuring Local Labor Market Growth

Before presenting the regressions I estimate, it is important to define the measure of parental labor market growth that I use. Motivated by the literature (for instance Notowidigdo [2011] and Zabek [2017]), I construct local employment shift share shocks in the spirit of Bartik [1991] to measure changes in local labor demand. The shift-share shock, as illustrated in Goldsmith-Pinkham et al. [2020], takes the changes in national industrial employment and projects them onto the CBSA-level employment shares. These capture local changes in labor demand because they capture national level trends in industries, which are then weighted by the share of that industry in the area. Finally, this term is aggregated over industries. Specifically, I use employment shares for 3-digit 2012 NAICS private industries, and then project them onto leave-one-out national industry growth rates for the relevant time period.

In the main regression specification, I calculate labor market growth between 1999 and 2019. This is done for several reasons. First, the PSID measures wealth consistently starting in 1999, and biennially from that interview wave onwards. The latest interview wave available is 2019. This means that we have a long enough period of labor demand growth for households to accumulate wealth. Second, the period from 1999 to 2019 is an economically significant one, encompassing the housing boom and bust, the Great Recession, and the recovery from it. As seen in Figure 2.2, there was a significant increase in the wealth gini in the first half of this period, and these did not recede in the recovery – in fact, the gini coefficient seems to have stabilized at a much higher level after the housing boom and bust and the Great Recession. However, I also present results for local markets using a decade-specific definition of the shift-share labor demand growth (as is common in the literature, e.g., Moretti [2013], Goldsmith-Pinkham et al. [2020], Zabek [2017]).The results from these regressions are discussed in Appendix B.1.

Further, Goldsmith-Pinkham et al. [2020] show that the exogeneity of the shift-share instrument comes from employment shares, and not from the national level growth rates. To partially alleviate this concern, I take employment shares in an area five years prior to the growth period. For instance, I take employment shares in an area from 1994 for the growth period between 1999 and 2019. Second, I also leave out real estate and construction industries from my calculations since many of the increases in fast growing labor markets might be due to tight housing markets, which muddles the relationship between the two.

Specifically, I define parent's labor market growth as $\Delta\theta_{j,1999}^{2019}$, for a household in CBSA j in 1999 as:

$$\Delta\theta_{j,1999}^{2019} = \underbrace{\sum_{k \in ind}}_{\text{summing over industries}} \underbrace{\left(\frac{L_{k,-j,2019} - L_{k,-j,1999}}{L_{k,-j,1999}}\right)}_{\text{national growth rate}} \underbrace{\frac{L_{k,j,1994}}{L_{j,1994}}}_{\text{share of industry in area}} \tag{2.7}$$

where k is industry, and L is employment. Further, I also "standardize" the shocks by demeaning them and dividing by the standard deviation – this aids interpretation, as now the shock can be measured in standard deviation units. in words, $\Delta\theta_{j,1999}^{2019}$ captures how labor markets grow due to local labor demand.

In practice, how are these Bartik measures spread across the United States? Figures 2.5 presents the spatial distribution of labor market growth between 1999 and 2019. Most areas experienced moderate growth in this period. This is mostly due to the Great Recession wiping out the gains before 2007, and the Recovery bringing them back a little.

Figure 2.5: Regional Heterogeneity in 1999-2019 Labor Demand Shock

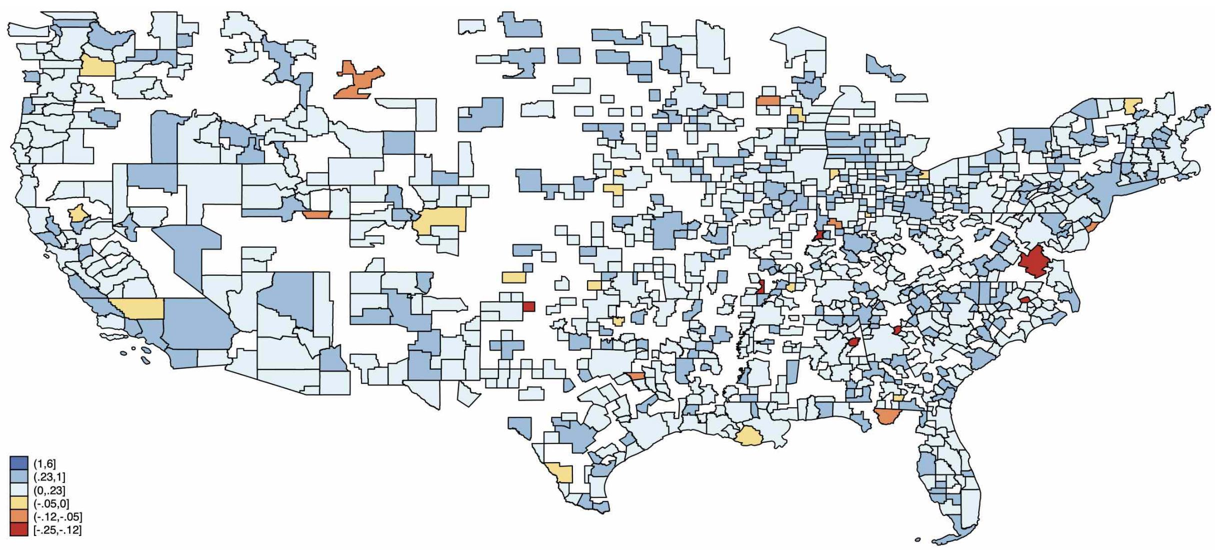


Figure 2.6 presents the same numbers in histogram form.

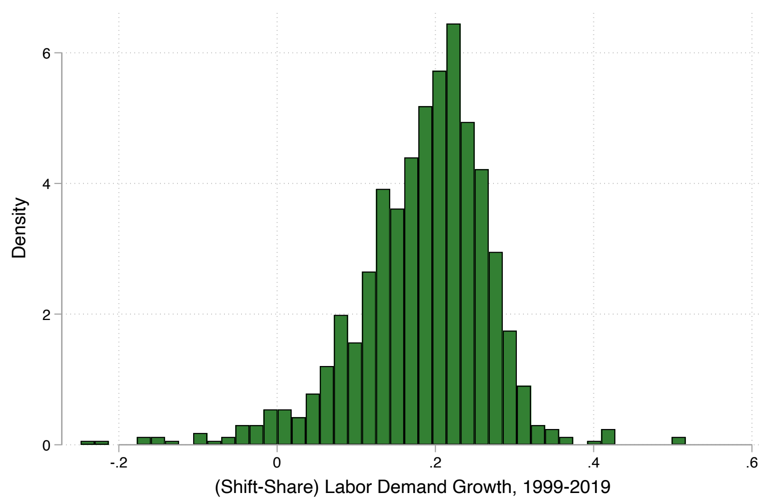


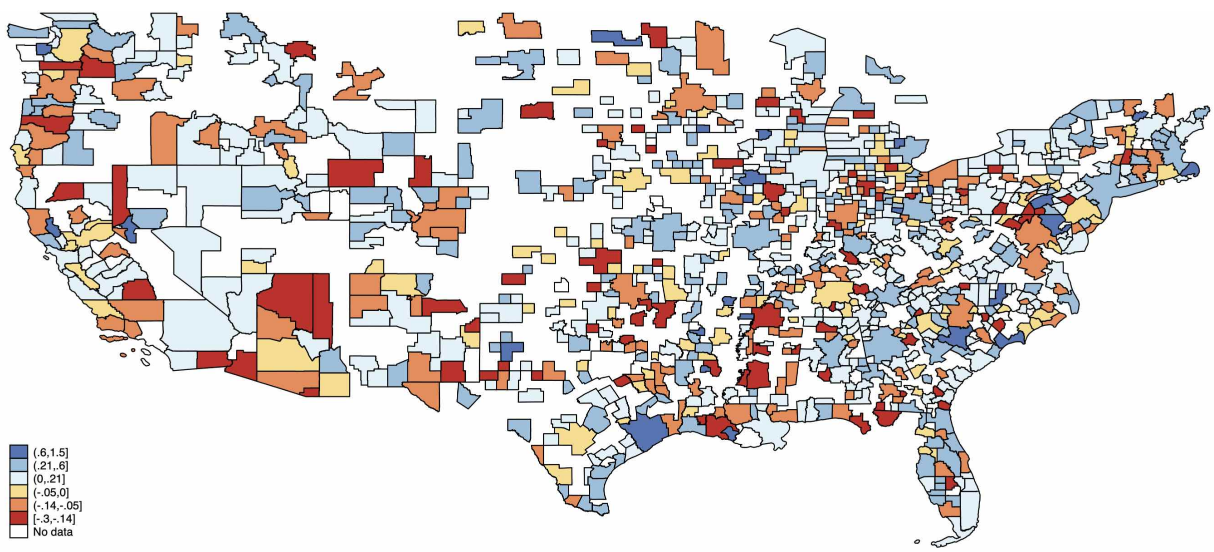
Figure 2.6: Distribution of Shift-Share Labor Demand Growth between 1999 and 2019

The main idea is to examine differences in regional house prices and household wealth 1999 onwards according to their CBSA's labor market growth between 1999 and 2019. In the next section, I formalize the notion of these regressions.

2.4 Empirics: Regional Labor Demand and Housing Markets

How have regional labor markets affected house prices? To answer this question, I regress the measure of labor demand growth between 1999 and 2019 on local house price growth. I use a non-housing CPI index to deflate the values of the house price index to 2019. Recall that the house price index is as measured by the FHFA. The regional heterogeneity in house price growth can be found in Figure 2.7. The map shows that there is substantial regional heterogeneity in house price growth, with areas in the rust belt and places like New Mexico not doing so well in this time period.

Figure 2.7: Regional Heterogeneity in 1999-2019 House Price Growth



I also include in this regression an interaction of the local labor market growth with the local house supply elasticity. Recall that this measures the extent to which new housing can be built in an area: a low supply elasticity implies that it is difficult to build more housing. This would imply that the effects of local labor market growth have a large pass through to house prices. The mechanism is that as labor demand increases, households get richer and more families move in. This raises housing demand and puts upward pressure on house prices. If housing supply was perfectly elastic (i.e., it was costless to build more housing), house prices would not move. On the other hand, in perfectly inelastic markets, house prices would increase by a larger margin. So, it is interesting to see how the supply elasticity interacts with the labor demand growth to explain house price growth.

Specifically, the regression is of the form:

(2.8)

$$\Delta HPI_{j,1999}^{2019} = \beta_0 + \beta_1 \Delta\theta_{j,1999}^{2019} + \beta_2 \text{Elasticity}_j + \beta_3 (\Delta\theta_{j,1999}^{2019} \text{ x Elasticity}_j) + \beta_2 \text{Pop}_j + \epsilon_j$$

where j is the CBSA in question, $\Delta HPI_{j,1999}^{2019}$ is the percentage growth in the FHFA House Price Index between 1999 and 2019, $Elasticity_j$ is the house supply elasticity, and Pop_j is a vector of area specific characteristics including population.

Ex-ante, we would expect β_1 to be positive, but β_2 and β_3 to be negative, since higher supply elasticities should be associated with a lower growth in house prices. β_3 being negative would imply that as housing becomes easier to build, the pass through of labor markets onto house prices becomes lower. In fact, this is exactly what I find in the regressions, whose results are presented in Table 2.4. Of course, it must be noted that these relationships have been studied before: some papers include Rosen [1979], Roback [1982], Bartik [1991], Moretti [2013], and Diamond [2016]. However, linking these outcomes to wealth has not been the subject of much prior research, mostly due to data availability (a notable exception is Greaney [2020], which is related to this paper).

The first specification (Column 1 of Table 2.4) shows that a 1 s.d. better labor market leads to a 1.6 percentage point increase in growth rates of house prices in this

	(1)	(2)	(3)
Labor Demand Growth	0.016**	0.089**	0.148**
	(0.003)	(0.014)	(0.032)
Elasticity		−0.049**	−0.043**
		(0.010)	(0.010)
Labor Demand Growth			−0.022*
x Elasticity			(0.011)
N	273	273	273
R^2	0.0338	0.2393	0.2476

Table 2.4: The Effect of Local Labor Markets on House Price Growth, 1999-2019

time period. The second specification controls for house supply elasticity, and finally the third one adds an interaction term between labor demand growth and elasticity. In other words, the third specification estimates Equation 2.4. We find that low elasticity areas are substantially more sensitive to an increase in labor demand in terms of the local house prices. These would be areas like San Francisco or Miami. On the other hand, since β_3 is negative (-0.022), it shows that areas like Indianapolis are not as sensitive to increases in labor demand.

We can also visualize how house prices have grown over time in this period. We can estimate regressions of the form:

$$HPI_{j,t} = \beta_0 + \beta_1 \Delta\theta_{j,1999}^{2019} + \mu_t + \sum_{t=1999}^{2019} \beta_{2,t} \Delta\theta_{j,1999}^{2019} \text{ x } \mu_t + \nu_{j,t} \tag{2.9}$$

where μ_t are year fixed effects and $HPI_{j,t}$ is the house price index in area j in year t. The estimates from this regression can be found in Figure 2.8. This figure shows the dynamics of the growth in house prices over this time period. It captures the housing boom and bust, the Great Recession, and the recovery as well. On average, a 1 s.d. better labor market is associated with an index that is higher by about 75 points. It is important to keep this in mind when interpreting the results on wealth in the next section.

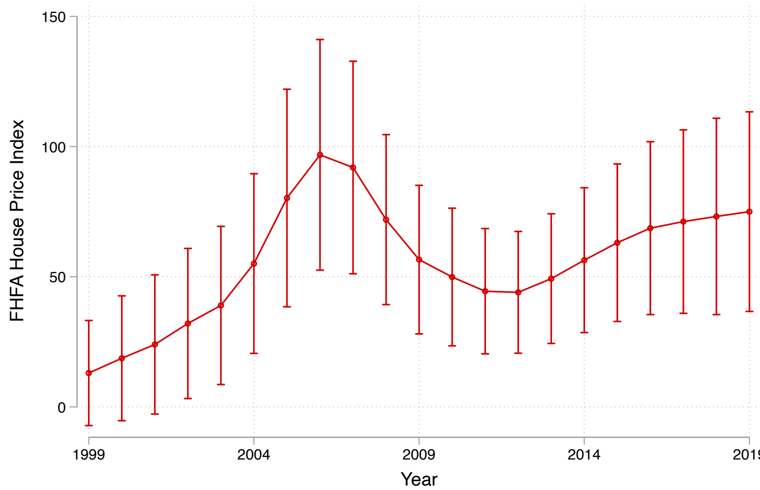


Figure 2.8: Association of 1 s.d. Better Labor Markets with House Prices, 1999-2019

2.4.1 Correlation of Labor Demand Growth with House Supply Elasticities

As per theory, a low house supply elasticity can exacerbate the effects of local labor market growth on house prices. The previous set of results provided evidence of this. Further, if labor demand growth is more likely to occur in areas that have a low house supply elasticity, then the dispersion in house prices is likely to grow over time. This seems anecdotally true between 1999 and 2019: for instance, places like San Francisco, which have a lower elasticity of house supply, had greater labor demand growth than places like Indianapolis, which have higher elasticities of housing supply. To see this, we can estimate a simple regression to get some measure on the correlation between the two:

$$\text{Elasticity}_j = \beta_0 + \beta_1 \Delta\theta_{j,1999}^{2019} + \psi \tag{2.10}$$

Results from this estimation are presented in Table 2.5. Indeed, there is a significant negative relationship between the two: increasing the elasticity by 1 unit (i.e., considering an area with a *higher* elasticity) is correlated with labor markets that perform worse by about 0.2 standard deviations. This can also be seen in Figure 2.9, which plots the data that is used to estimate Equation (2.10).

	Labor Demand Growth
Elasticity	-0.219^{*}
	(0.088)
N	273
R^2	0.0259

Table 2.5: Correlation Between Labor Demand Growth and House Supply Elasticities

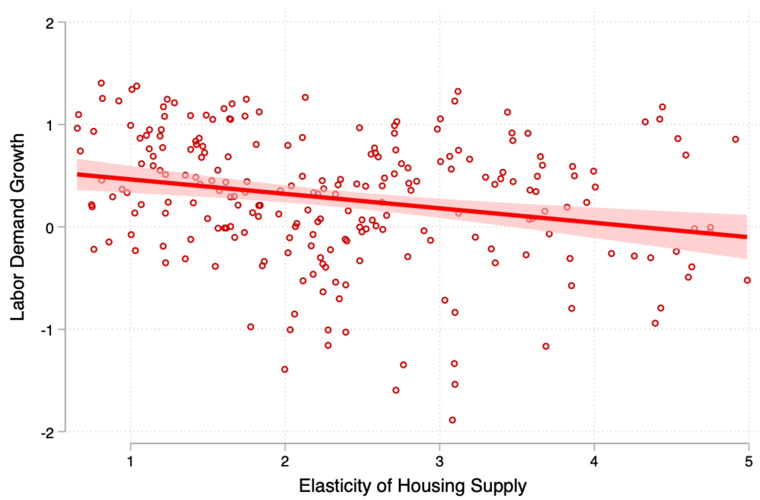


Figure 2.9: Growth in Labor Demand between 1999 and 2019 and House Supply Elasticity

This implies that in this period, part of the reason house prices were going rapidly was because labor market growth was concentrated in areas with a low elasticity of supply. Consequently, the housing wealth of households is likely to have been affected similarly as well. But was this spatial pattern of growth always true in the United States? In the next section, I repeat the exercises here but I consider labor market growth between 1980 and 1999 instead.

1980-1999: Suggestive Evidence

Growth in local labor markets looked different between 1980 and 1999 compared to the years after it. Figure 2.10 presents a map of the labor demand growth in this period, and Figure 2.11 presents a map of the growth in house prices.

Figure 2.10: Regional Heterogeneity in 1980-1999 Labor Demand Shock

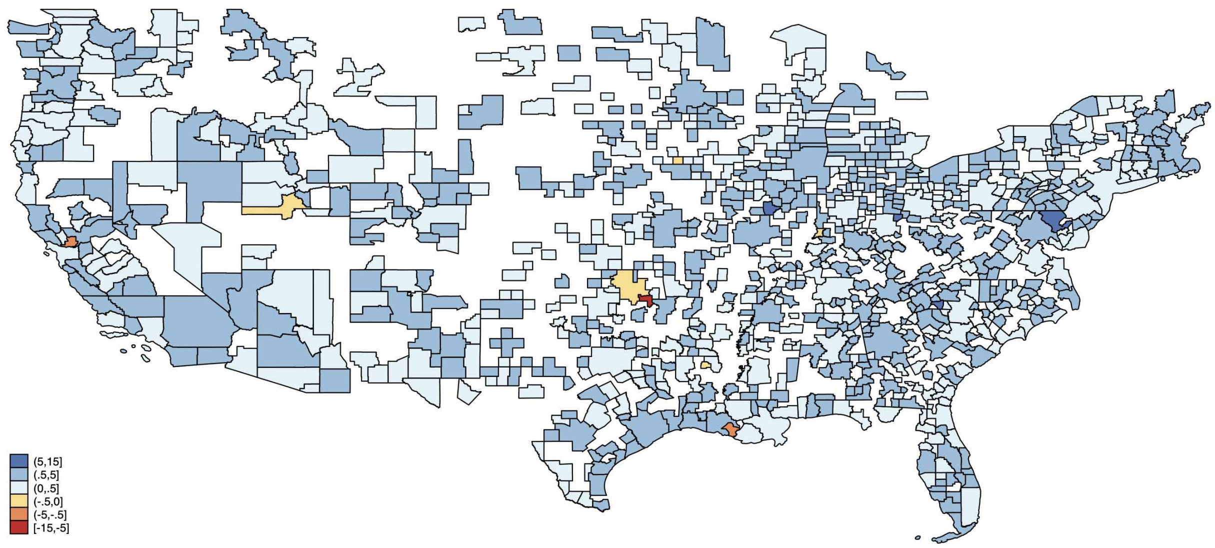
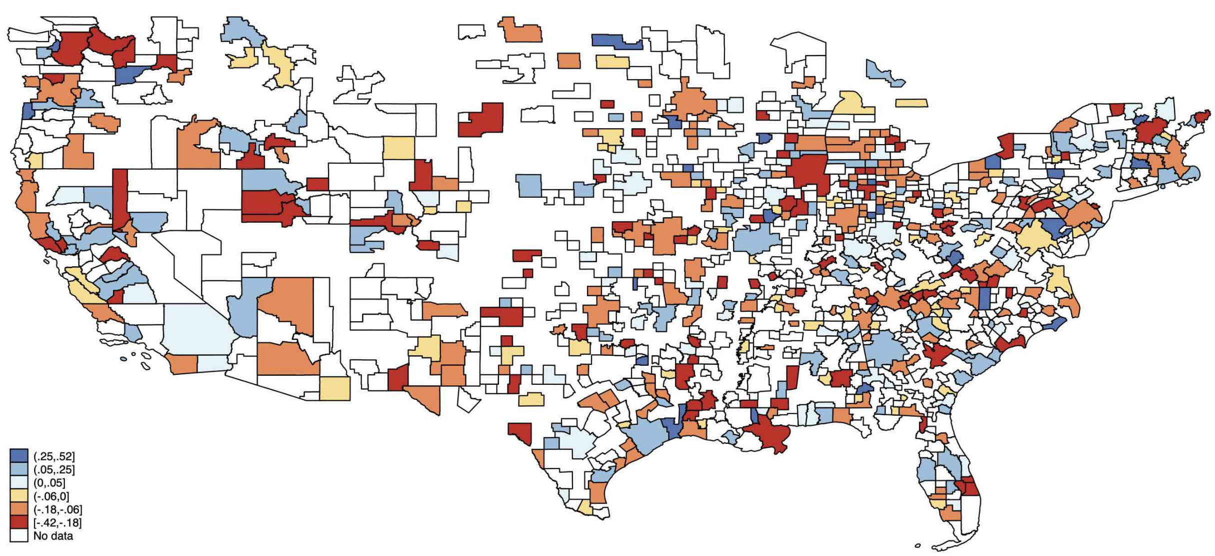


Figure 2.11: Regional Heterogeneity in 1980-1999 House Price Growth



Labor demand growth does have a positive relationship with house prices, but it isn't as strong as before. Table 2.6 provides the estimates from this regression. It implies that a 1 s.d. better labor market is associated with only a 1 percentage point higher growth in house prices. However, low supply elasticity areas still show the most growth in house prices, which agrees with theory. The interaction term is still in the right direction, but is smaller in magnitude and not statistically significant.

	1999-2019	**1980-1999**
Labor Demand Growth	0.148^{**}	0.010^{*}
	(0.032)	(0.038)
Elasticity	-0.043^{**}	-0.066^{**}
	(0.010)	(0.010)
Labor Demand Growth	-0.022^{*}	-0.012
x Elasticity	(0.010)	(0.023)
N	273	257
R^2	0.2476	0.1763

Table 2.6: The Effects of Labor Demand Growth and House Supply Elasticity on House Price Growth

This could be because of *where* labor market growth was strongest in this time period. If there was no correlation between house supply elasticities and labor demand growth, i.e., high supply elasticities grew equally well compared to areas with lower ones. Table 2.7 provides the results of estimating Equation (2.10) for this time period, and Figure 2.12 plots the results. This pattern might mean that wealth gains in these period was more evenly spread compared to before.

	1999-2019	**1980-1999**
Elasticity	-0.219^{*}	-0.042
	(0.088)	(0.039)
N	273	257
R^2	0.0259	0.0047

Table 2.7: Relationship Between Local Labor Demand Growth and House Supply Elasticity

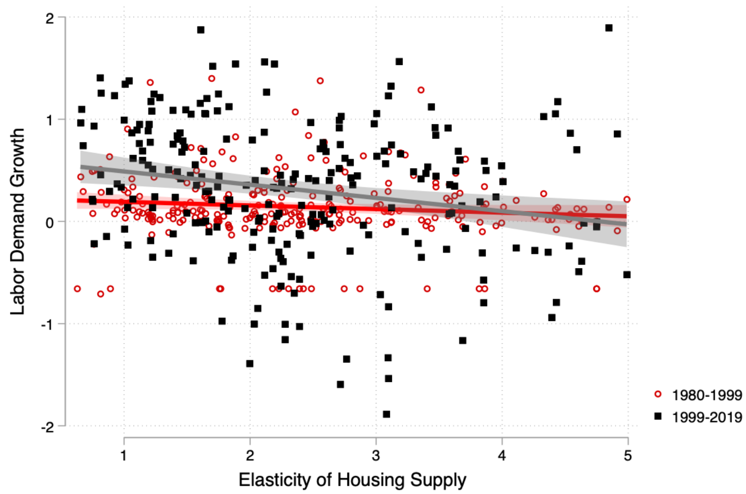


Figure 2.12: Relationship Between Labor Demand Growth and House Supply Elasticity

It might be claimed that the time periods considered here are somewhat ad-hoc. While that is true, we can still find similar patterns of labor demand growth even if we use decadal growth rates (i.e., 1980-1990, 1990-2000, and so on). The results from these are found in Appendix B.1.

This section presented evidence on the response of regional house prices to local labor demand, and how this varies by house supply elasticity. It also presented evidence that the distribution of labor market growth in the U.S. between 1999 and 2019 hasn't been random: areas that were hard to build in were also good labor markets to be in. However, this wasn't true between 1980 and 1999, where this relationship did not exist. Consequently, large increases in labor demand did not, on average, lead to large increases in house prices.

Next, I move on to investigating the wealth accumulation of households in response to the labor demand growth.

2.5 Empirics: The Effects of Local Labor Markets on Regional Wealth

What are the Once households are assigned the labor market growth of the parent, I regress this measure of parental labor market growth on the child's household wealth. It is useful to think about the regression as an event study regression of sorts. The event here is the child splitting off to form her own household, and the shock in question is the labor demand growth in the parent's area of residence in the ten years prior to splitoff. The identification of the effect of the labor market growth, then, is through difference-in-differences. The regressions I run are of the form, where T is the time of splitoff and j is the area of residence of the parent:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{2019}_{j,1999} + \mu_t + \sum_{t=1999}^{2019} \beta_{2,t}(\Delta\theta^{2019}_{j,1999} \text{ x } \mu_t) + \beta_3 X_{ijt} + \epsilon_i + \epsilon_{ijt} \tag{2.11}$$

where:

- Y_{ijt}: household level outcome
- μ_t: indicator for year
- X_{ijt}: household characteristics
- $\Delta\theta^{2019}_{j,1999}$: labor demand growth

All regressions include year fixed effects. $\beta_{2,t}$ is the effect of a 1 standard deviation increase in the strength of the local labor market on the mean wealth of houeholds in year t. The outcomes I examine include several measures of wealth, income, and home values.

It is important to note that I do *not* include income or occupation as part of the control variables in this regression. This is because these are all plausible mechanisms through which local labor markets might impact a household's wealth, and thus should not be included in the regression. In other words, including them would mean we shut off some of the channels through which the local labor markets might have an effect.

All regressions are run using longitudinal weights provided by the PSID. These are meant to make the data nationally representative. I also cluster standard errors at the CBSA level.

Finally, I Winsorize the wealth data at the 5th and 95th percentile. This is done because the wealth data in particular contains outliers that ideally should not have a disproportionate effect on the estimate, and is particularly important in this case because wealth is also allowed to be negative (this is why I cannot simply take logs). Winsorizing the data essentially means top and bottom-coding the data. This means I do not lose these observations, but rather just top-code them to ensure that the effects I estimate are not unduly influenced by households who have millions of dollars in wealth. In practice, the 95th percentile of wealth in the data is about \$1 million, and the bottom percentile is at \$80,000 of debt, i.e., -\$80,000 of wealth.

This can be thought of as an "event study" type specification, except that the shock occurs over a long time horizon (between 1999 and 2019). Essentially, we are looking at the evolution of the wealth holdings of an individual who resided in an area which, in 1999, received a long term labor demand shock. Instead of displaying the results in a table, I plot these estimates to give a better visualization of the results. Since the measure of labor demand growth I am using is a shift-share instrument, identification is through difference-in-differences.

However, an increase in labor demand in an area has multiple effects. First, it directly increases wages; second, it attracts people to the area, increasing local population and therefore housing demand, which in turn increases house prices; third, there could be an increase in the wealth holdings of households in the region, which can occur due to two mechanisms: the increase in expendable income could mean households automatically save more, and the increase in house prices could increase the housing wealth of incumbent homeowners. In this way, we find that local labor market growth likely has different effects on homeowners and renters, and it would be useful to know which of these groups is driving the results.

I do this by adding an interaction term with homeownership to Equation (2.5), which makes it a triple difference estimator. For a household i in area j in year t, I estimate:

(2.12)

$$Y_{ijt} = \beta_0+\beta_1\Delta\theta^{2019}_{j,1999}+\mu_t+\sum_{t=1999}^{2019}\beta_{2,t}(\mu_t \text{ x } \Delta\theta^{2019}_{j,1999})+\sum_{t=1999}^{2019}\beta_{3,t}(\Delta\theta^{2019}_{j,1999} \text{ x Homeowner}_t \text{ x } \mu_t)$$
$$+ \beta_4\text{Homeowner} + \beta_5 X_{ijt} + \epsilon_{ijt}$$

where Y_{ijt} is the outcome we are considering Homeowner captures the ownership status of a household.

2.5.1 Income

Do increases in local labor demand translate into increases in income? That seems to be the case. I estimate Equation 2.5 and Equation 2.5 for the income for the labor income of households and find that in fact, households in 1 s.d. better labor markets are associated with a higher labor income of \$4,000 per year. Figure 2.13 presents these results.

Figure 2.14 breaks down this association by homeownership, and finds that homeowners make about \$6,000 more per year in booming markets, while renters make \$2,000 more. This probably reflects the fact that homeowners tend to be of a different demographic (older, male, white) and might also work in different occupations within the same industry.

Figure 2.13: Association of 1 s.d. Better Labor Markets with Labor Income, 1999-2019

Figure 2.14: Association of 1 s.d. Better Labor Markets with Labor Income by Homeownership, 1999-2019

2.5.2 Net Worth

Figure 2.15 presents the results of estimating Equation (2.5). It shows that on average, households in 1 s.d. better labor markets accumulate \$20,000 more in net worth by 2019. This association is the greatest in 2007 (at the height of the housing boom), which suggests that housing wealth is probably a crucial component of this relationship. It also indicates that it would be informative to break this association into coming from homeowners and renters separately.

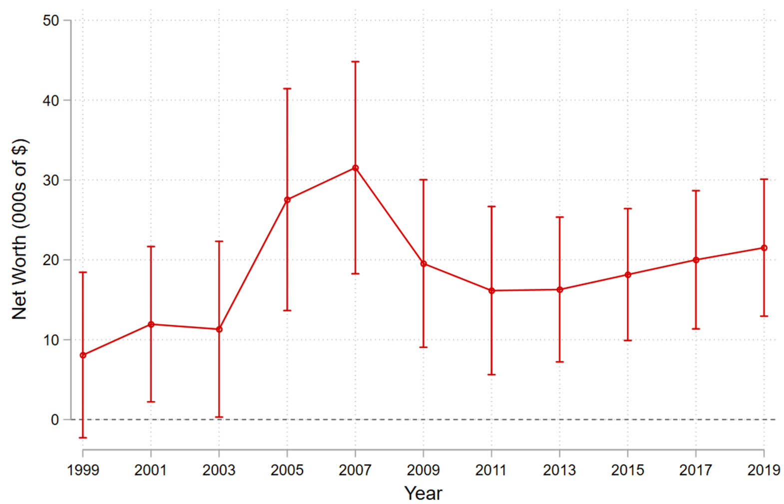


Figure 2.15: Association of 1 s.d. Better Labor Markets with Net Worth, 1999-2019

Figure 2.16 plots the results of estimating Equation (2.5). It should that by 2019, Homeowners living in one standard deviation better labor markets between 1999 and 2019 are able to accumulate roughly \$43,000 more net worth. Meanwhile, the same number for renters is close to zero. This show the tremendous inequality in net worth that is produced within the same labor market, due in large part to housing. The point estimates in this figure can be backed out by summing across the relevant coefficients in Table B.2 in Appendix B.4. For instance, the association of a 1 s.d. increase in local labor markets with the net worth of homeowner households in 2019 is calculated as $-1.508 + 0.797 + 15.356 + 28.396 = 43.041$, or \$43,041. The same point estimate for the renter households would be $-1.508+0.797 = -0.711$, or -\$711.

It also shows why looking only at Figure 2.15 masks substantial heterogeneity in terms of homeownership. It should also be noted that renter households tend to be disproportionately younger and black, and a little more likely to have a female head of household.

Further, the trend suggests that the households started accumulating wealth early, and better labor markets were associated with a higher net worth of almost \$50,000 in 2007, which was the height of the housing bubble. However, after the bust and the Great Recession, the increase in net worth drops to \$30,000, but recovers to around \$43,000 by 2019. This shows how important the housing boom and Great Recession were to the wealth of households. Perhaps even more crucially, it shows that the gains from the housing boom have persisted even ten years after the Great Recession.

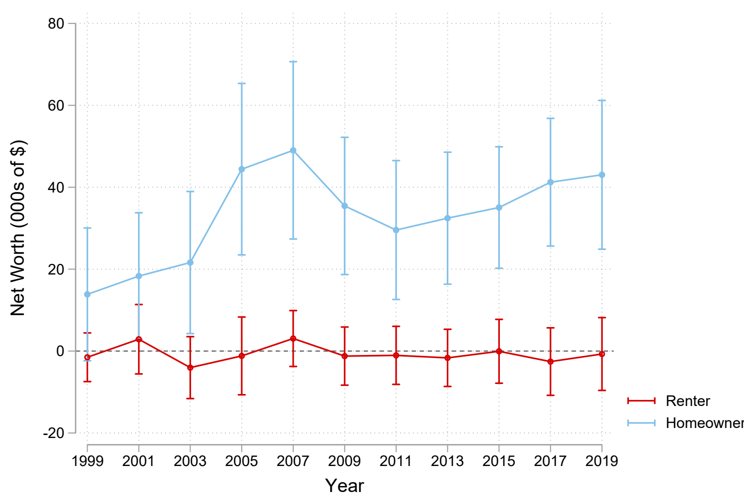


Figure 2.16: Association of 1 s.d. Better Labor Markets with Net Worth by Homeownership, 1999-2019

2.5.3 Home Equity and Home Values

Figures 2.18 and 2.17 present results of estimating equation (2.5) for homeowner households on their home equity and home values respectively. Both these graphs show a large and significant increase. Home equity increases by about \$25,000 by 2019, and home values increase by about \$40,000. This implies that most of the gains in net worth are due to an increase in home equity. Further, these households are able to afford more expensive homes as well.

Moreover, since these households are selected from the working age population, it means that they are likely still paying down their mortgage. This implies that once the mortgage is paid off, they will be even wealthier. In other words, the total benefits of being in a strong labor market have yet to be realized. Therefore, the estimates on net worth are likely to be lower bounds.

- Home equity increases by almost \$25,000, and home values increase by almost \$40,000.
- This implies there are long term benefits that will accrue to homeowners once their mortgage is paid down.

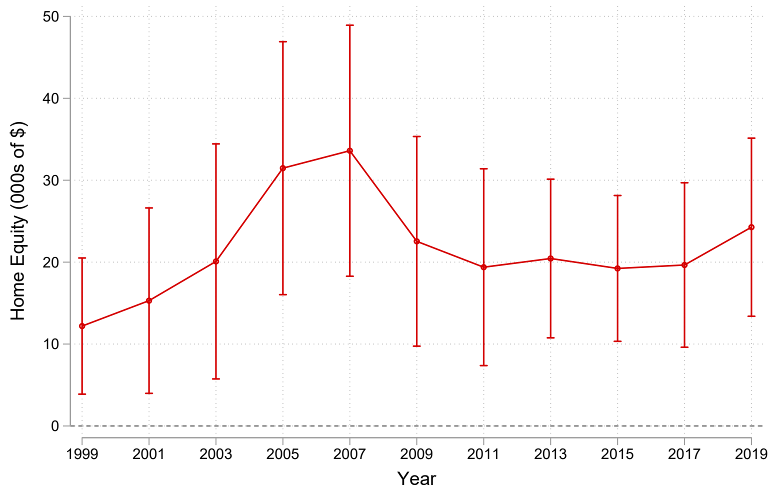


Figure 2.17: Association of 1 s.d. Better Labor Markets with Home Equity for Owners, 1999-2019

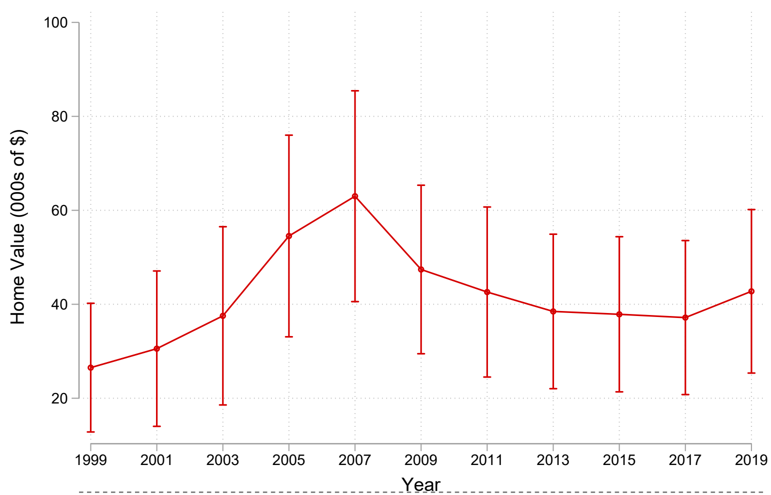


Figure 2.18: Association of 1 s.d. Better Labor Markets with Home Values for Owners, 1999-2019

2.5.4 Net Worth without Home Equity

Finally, Figure 2.19 presents the estimates from estimating Equation 2.5 for the net worth without home equity for the sample. I find that by 2019, homeowner households are able to accumulate about $12,000 additional non-housing wealth, which is still large, but smaller than the $25,000 that households accumulate through home equity.

The estimates also aren't statistically distinguishable from those of renters.

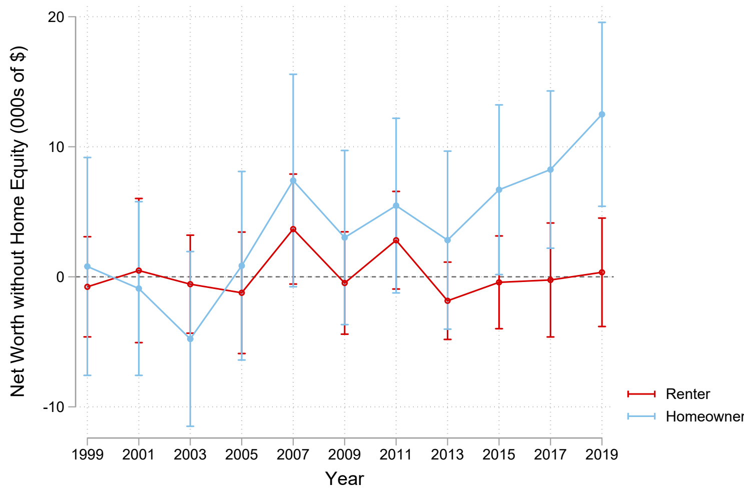


Figure 2.19: Association of 1 s.d. Better Labor Markets with Net Worth (without Home Equity) by Homeownership, 1999-2019

2.5.5 Interaction with House Supply Elasticity

The previous section established that house prices are most responsive to labor markets when the housing supply has a low elasticity. I examine this in a quadruple-difference framework by interacting a categorical measure of high vs. low elasticity with the triple difference estimation strategy in Equation (2.5). The results from this estimation are presented in Figure 2.20.

One can see that as expected, the association of a 1 s.d. better labor market with net worth is the highest in low supply elasticity housing markets – in 2019, homeowners in low supply elasticity areas are better off by more than \$50,000 while the comparable number for homeowners in high supply elasticity areas is only \$25,000. In other words, homeowners in housing markets with a lower supply elasticity see house prices go up much more in response to the same increase in labor demand. Consequently, their home equity increases and they are richer than their counterparts in high supply elasticity areas.

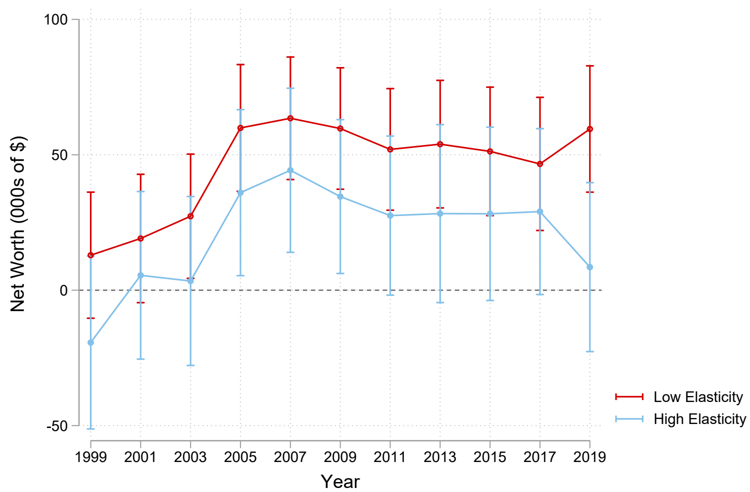


Figure 2.20: Association of 1 s.d. Better Labor Markets with Net Worth of Homeowners in Low and High Elasticity Housing Markets

2.5.6 1980-1999: Suggestive Evidence

The Panel Study of Income Dynamics (PSID) collects data on household wealth in 1984, 1989, 1994, and 1999 (after which it starts collecting wealth data in every interview wave). This allows for a deeper examination of wealth dynamics within these particular years. Using this, I run the regression in Equation (2.5) for this time period. Households are assigned the labor market growth in their area of residence in 1984 for this exercise. Results from this estimation are presented in Figure 2.22 (Net Worth), Figure 2.21 (Net Worth without Home Equity) and Figure 2.23 (Home Equity).

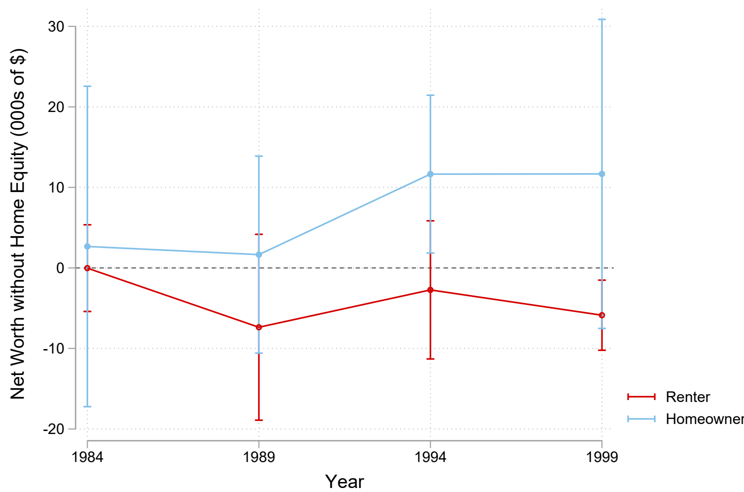


Figure 2.21: Association of 1 s.d. Better Labor Markets with Net Worth (Without Home Equity) by Parental Tenure, 1984-1999

Notably, homeowners in 1994 witnessed an increase in their net worth by approximately \$20,000, a finding with statistical significance. However, this growth appears to diminish by 1999, with homeowners experiencing a less significant increase of about \$12,000 in net worth, a result that lacks statistical significance. Even in this time period, no increase in net worth was observed among renters.

When we remove home equity from the equation, the net worth of homeowners continues to follow an upward trajectory. Specifically, homeowners in 1994 saw their net worth without home equity rise by about \$17,000. This growth slightly regressed to \$7,000 in 1999. In contrast, renters did not display any noticeable increase in their net worth during these years, maintaining a pattern consistent with the general net worth trends. Meanwhile, the data shows a moderate elevation in home equity, with an increase of roughly \$5,000 in 1994 and \$4,000 in 1999.

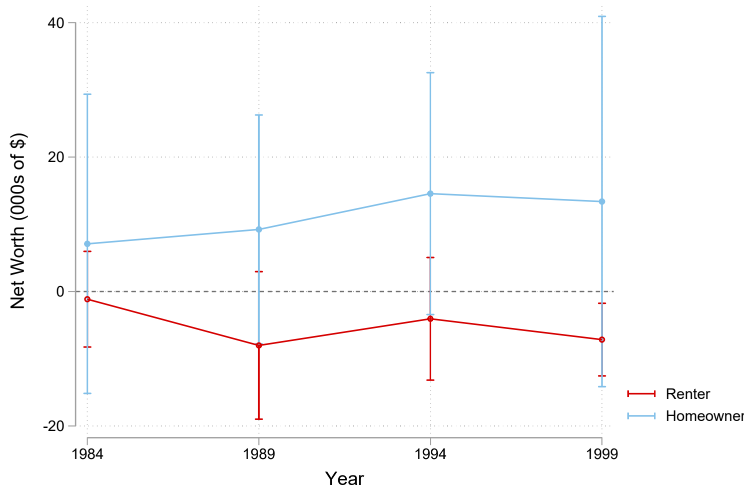


Figure 2.22: Association of 1 s.d. Better Labor Markets with Net Worth by Parental Tenure, 1984-1999

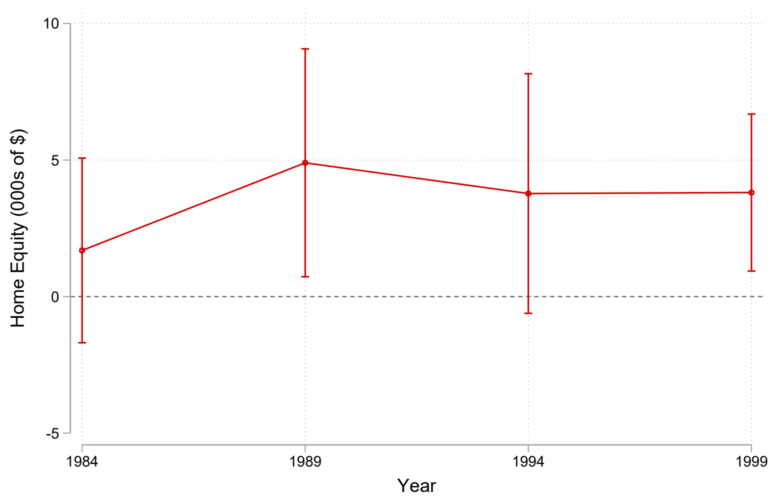


Figure 2.23: Association of 1 s.d. Better Labor Markets with Home Equity for Owners, 1984-1999

These findings collectively indicate that the wealth dynamics at play during this period were both lower in magnitude and qualitatively distinct. Specifically, there was no evidence of home values appreciating in response to changes in local labor markets. Thus, the wealth dynamics of this period stand in stark contrast to those of the later years, highlighting the evolving relationship between labor markets, housing markets, and wealth accumulation.

2.5.7 Summary

Between 1999 and 2019, a significant shift in the wealth distribution of U.S. homeowners was evident. Notably, for every one standard deviation improvement in the labor market during this period, homeowners saw an increase in their wealth by approximately $43,000. The majority of this wealth accumulation, about $25,000, was traced back to home equity, while non-housing wealth witnessed a more moderate increase, ranging between $10,000 to $15,000. An interesting pattern was observed concerning the regional dynamics of this wealth accumulation. The increase in net worth was also more prevalent for homeowners in markets with a low elasticity of housing supply (like San Francisco) compared to others.

This wealth accumulation trend, however, was not equally pronounced across all decades. For instance, the association between housing market wealth and labor markets was less robust between 1980 and 1999. Within this period, a one standard deviation improvement in the labor market correlated with a net worth increase of about $20,000. Contrary to the 1999-2019 period, a larger share of this wealth increase, approximately $12,000, was due to a rise in non-housing wealth.

The combined analysis of these temporal and regional patterns suggests a profound shift in the dynamics of wealth inequality, with housing wealth playing a dominant role in shaping wealth inequality between 1999 and 2019. This elevation in the significance of homeownership for wealth accumulation carries noteworthy policy implications, especially given the spatial distribution of labor market growth. Consequently, policy makers should consider these evolving dynamics when devising strategies to address wealth inequality or addressing inequities in the housing market.

2.6 Implications for Welfare and Wealth Inequality in the United States

In this section, I discuss what the increase in wealth means for welfare, and why the effects of local labor markets should matter for policy on inequitable access to housing and wealth inequality.

2.6.1 Consumption

The results of the paper show that the wealth of households increased significantly for homeowners living in better labor markets. However, what are the real benefits of this wealth? In Rao [2023], I explore how households can leave this wealth to their children. In this paper, I focus on how the households themselves can spend this wealth by focusing on consumption.

The PSID collects information on certain key categories of expenditure over the entire time period of this paper: food, health, education, childcare, transport, and housing.[7] I aggregate these expenditures to create a measure of overall consumption, and use local CPI measures as a deflator. This is important because the expenditures collected by the PSID are highly local.

Figure 2.24 presents the results of estimating Equation (2.5), and Figure 2.25 breaks it down by whether the household owns or not. I find that consumption increases by about \$3,000 - \$4,000 per year for a one standard deviation increase in labor demand growth, and that this effect is even great among homeowners, who are able to consume \$4,500 more if they live in 1 s.d. better labor markets. Renters also see their consumption go up, but by less than \$2,000.

These results should be interpreted in the light of the results on income, which showed that there is, roughly, a \$6,000 increase in income for homeowners, and a

[7] Other categories, such as trips or clothing are also collected, but only after 2005. For this reason, I do not include them in the calculations here.

$2,000 increase in income for renters. This implies that renters consume all their extra earnings, while homeowners are able to save some. Note that the measure of consumption here includes rental expenditure, which might explain why renters need to consume so much of the increase in their income.

Figure 2.24: Association of 1 s.d. Better Labor Market with Consumption

Figure 2.25: Association of 1 s.d. Better Labor Market with Consumption by Parental Tenure

2.6.2 Wealth Inequality

Building a model to quantify the effects of house supply elasticities on the level of wealth inequality is beyond the scope of this paper. However, I develop such a model in Rao [2023], which finds that between 1999 and 2019, the dispersion in labor market growth across areas, i.e., the fact that certain areas grow more than others, is responsible for about 0.02 points (40%) of the increase in the wealth Gini; however, heterogeneity in local house supply elasticities only accounts for a rise of 0.003 points (8%). Shutting off labor mobility would increase inequality by an additional 0.008 points (13%). Finally, an alternate version of the model which does not allow for homeownership would only increase wealth inequality by 0.02 points of the Gini, or about 40% as much as in the main model.

In particular, it finds that while house supply elasticities themselves only explain about 8% of the rise in inequality, they can still interact with the dispersion in local labor market growth to exacerbate their effects. This is particularly relevant because between 1980 and 1999, house prices were not very responsive to labor market conditions. Consequently, the effects of these labor markets on wealth inequality is likely to not have been large.

However, it is clear that the dynamics of wealth inequality were different across the two periods. The empirical results of the paper imply that equating labor market growth across regions is a useful strategy if the policymaker values a reduction in wealth inequality. Moreover, the spatial distribution of local labor market growth and whether it happens in areas with a low elasticity of housing supply is quantitatively relevant in determining household wealth accumulation and consumption.

2.7 Conclusion

This study presents a comprehensive examination of the interplay between local labor markets, housing markets, and wealth accumulation in the United States. Utilizing a rich dataset that encompasses the Panel Study of Income Dynamics (PSID) and Core Based Statistical Areas (CBSAs), the research underscores the importance of these relationships across two distinct periods: 1980-1999 and 1999-2019.

Between 1999 and 2019, housing markets in CBSAs with higher labor demand shocks exhibited a disproportionate increase in house prices, with a 1 standard deviation improvement in labor market conditions leading to an increase in house prices by 1.6 percentage points. In markets with a low elasticity of housing supply, such as San Francisco, the impact was even more pronounced, with a 10 percentage point escalation in house price growth rates. The confluence of these factors resulted in homeowners within these markets gaining significantly, with an average net worth increase of $43,000. Much of these gains stemmed from housing wealth, particularly pronounced in markets with a low housing supply elasticity. This increase in wealth and an additional $6,000 annual income enabled homeowners to elevate their yearly consumption by $4,500. In contrast, renters within these strong labor markets experienced no noteworthy wealth accumulation or consumption increases.

The dynamics were notably different in the earlier period of 1980-1999. There was no observable correlation between labor market growth and housing supply elasticity. While homeowners still managed to accumulate wealth in healthier labor markets, the amount was lesser, with a net worth increase of around $17,000, mostly originating from non-housing wealth sources ($12,000).

These findings indicate a significant shift in the mechanisms of wealth accumulation and inequality, with housing wealth playing an increasingly central role in recent decades. Consequently, there are many resulting implications for public policy. Policymakers can focus on addressing the widening wealth disparity between homeowners and renters and devise strategies to facilitate access to homeownership. As the relationship between local labor market growth and house prices strengthens, efforts must also be made to manage the intensified effects in areas with lower housing supply elasticity. These have persistent, long-term effects that also influence the wealth accumulation of the children of these households [Rao, 2023]. The results of this paper underscore the necessity for a continuous examination of evolving trends in housing and labor markets to inform more nuanced and effective economic policy and wealth inequality interventions.

APPENDICES

APPENDIX A

Appendices to Chapter 1

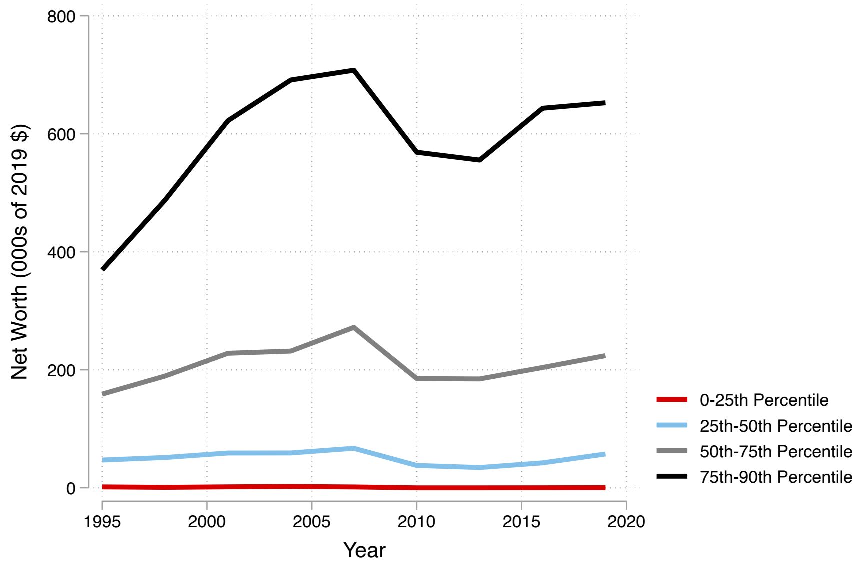
A.1 Wealth Inequality among the Bottom 90%

It is worth noting that while a vast literature has focused on the rise in the wealth shares of the top 1% [Saez and Zucman, 2016], there is also evidence of growing wealth inequality among the bottom 90% of households. Figure A.1 gives a sense of this divergence in the last few decades. It plots the median net worth of households as measured by the Survey of Consumer Finances (SCF) for households in four percentile groups: the bottom 25%, the 25th-50th percentiles, the 50th-75th percentiles, and the 75th-90th percentiles. It shows that the total wealth holdings of these groups are diverging away from each other. The divergence is particularly salient for two highest groups, although even the 25th-50th percentile group has been pulling away from the bottom 25%. This has also has an effect on inequality as measured by the Gini coefficient: the wealth Gini for the bottom 90% of households in United States went from 0.56 in 1999 to 0.63 in 2019, an increase of 0.07 units.[1]

I also find that the wealth of homeowners has evolved in a dramatically different way over this period compared to that of renters. Figure A.2 plots the evolution of median net worth for homeowners and renters between 1995 and 2019 as observed

[1] On the other hand, the income Gini for the bottom 90% of households went up from 0.37 to 0.39 over the same period, an increase of 0.02 units. All numbers calculated using PSID data.

Figure A.1: Median Net Worth in the United States by Percentile Groups



This figure plots the evolution of median net worth between 1995 and 2019. The numbers are calculated from the Survey of Consumer Finances (SCF). Median net worth is plotted according to four percentile groups: 0-25th percentile, 25th-50th percentile, 50th-75th percentile, and 75th-90th percentile. The trend suggests that the wealth of the top two percentile groups has been diverging away from the bottom two in this period.

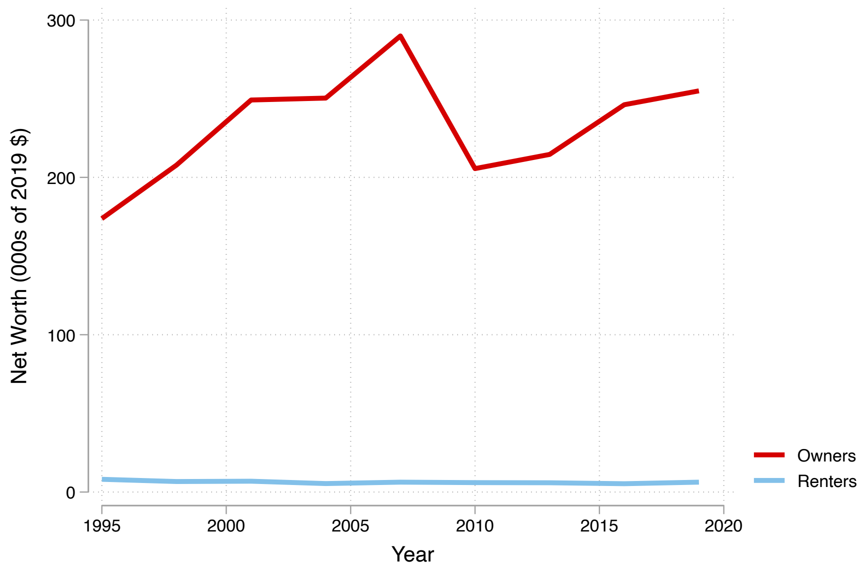
in the Survey of Consumer Finances. This figure shows how the wealth of owners has been growing over this period, while the wealth of renters has stagnated. At the beginning of the sample period, i.e., in 1995, the median net worth of homeowners is \$173,800, while that of renters is only \$8,000. At the end of the sample period in 2019, these numbers are \$255,000 and \$6,300 respectively.

A.2 Empirics: Regression Tables

This section presents results from estimating equation 1.4.2 in Table A.1. Due to concerns of space, I only show results for the main coefficients of interest, which show the marginal effect of a 1 s.d. higher labor demand growth in the area of the parent.

The graphs presented in Section 1.4 with the results can be backed out by summing

Figure A.2: Median Net Worth in the United States by Homeownership



This figure plots the evolution of median net worth between 1995 and 2019 for homeowners and renters. The numbers are calculated from the Survey of Consumer Finances (SCF). The trend suggests that the wealth of homeowners has grown, while the wealth of renters has stayed roughly constant over this period.

across the relevant coefficients. For instance, the association of a 1 s.d. increase in local labor markets with the net worth of the children of homeowning parents, 20 years after splitoff, is calculated as $-19.508 - 25.804 + 9.631 + 81.503 = 45.8$, i.e., \$45,800. The same point estimate for the children of renter parents would be $-19.508 - 25.804 = -45.312$, i.e., -\$43,312.

A.3 Results without Parental Area F.E.

Interpretability of results of vastly improved if we remove parental area fixed effects from the regressions, although the results move further away from causality if we do so. Without parental area fixed effects, we are comparing children who split off from areas that were doing good in a particular year to areas that were doing bad. In this way, we recover the story in the introduction of Detroit vs. San Francisco and the different narratives therein.

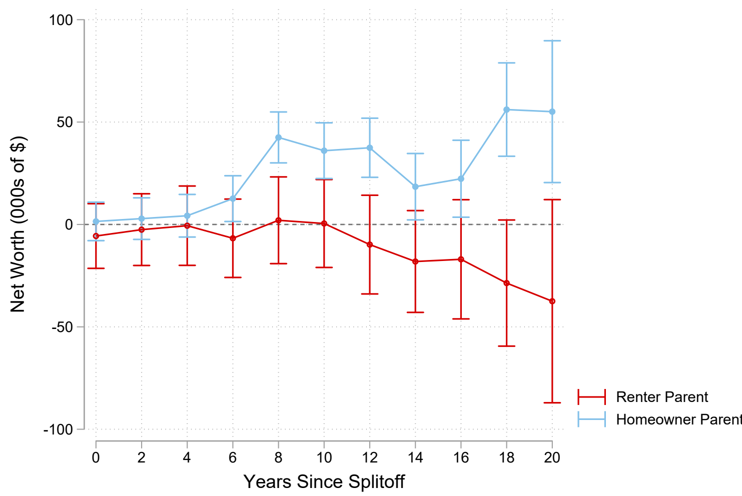
Table A.1: Regression Coefficients Used for Point Estimates in Graphs

		Net Worth
Labor Demand Growth		-19.508**
		(8.735)
Years Since Splitoff x Labor Demand Growth	**2**	1.597
		(11.547)
	4	5.304
		(12.302)
	6	-0.303
		(12.240)
	8	10.876
		(13.061)
	10	9.184
		(13.225)
	12	-3.890
		(14.277)
	14	-13.314
		(14.693)
	16	-9.962
		(16.647)
	18	-18.766
		(17.509)
	20	-25.804
		(25.965)
Homeowner Parent x Labor Demand Growth		9.631
		(9.203)
Years Since Splitoff x Homeowner Parent x Labor Demand Growth	**2**	-0.500
		(13.302)
	4	-3.633
		(13.994)
	6	10.608
		(14.074)
	8	27.976*
		(15.038)
	10	26.270*
		(15.465)
	12	42.746***
		(16.579)
	14	33.963**
		(17.354)
	16	34.078*
		(19.627)
	18	74.403***
		(21.308)
	20	81.503***
		(31.515)
N		**13,443**
R-squared		**0.197**

This table presents selected coefficients from estimating equation 1.4.2. These are the numbers that are used to produce the graphs in Section 1.4. For instance, the association of a 1 s.d. increase in local labor markets with the net worth of the children of homeowning parents, 20 years after splitoff, is calculated as $-19.508 - 25.804 + 9.631 + 81.503 = 45.8$, i.e., \$45,800.

The results show an even stronger association between better parental labor market growth and net worth in this case, with households being better off by $55,000, 20 years after split off.

Figure A.3: Association of Better Parental Labor Markets with Net Worth of Child, No Area F.E.



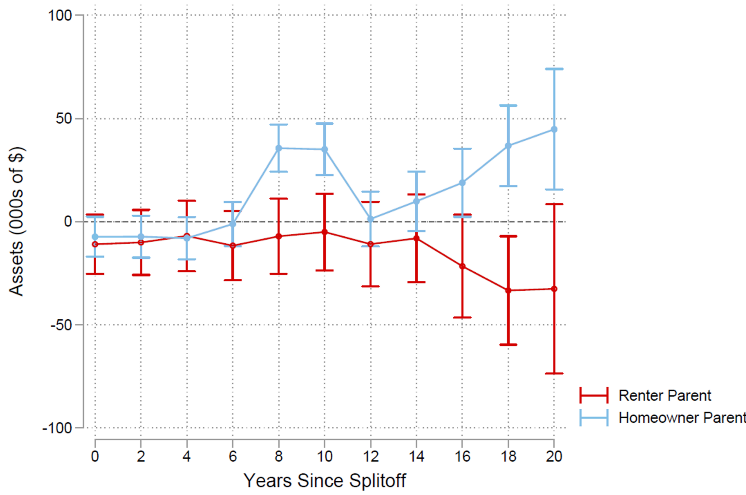
This figure plots the association of a 1 s.d. better parental labor market with the net worth of a child without accounting for parental area fixed effects. it indicates that for the children of homeowner parents, better parental labor markets are associated with an increase in net worth of almost $55,000. This number is perhaps more intuitive to interpret because it compares, e.g., a child who split off from San Francisco to one who split off from Detroit.

A.4 Association of Better Parental Labor Markets with Other Measures of Wealth

A.4.1 Assets and Debt (No Home Equity)

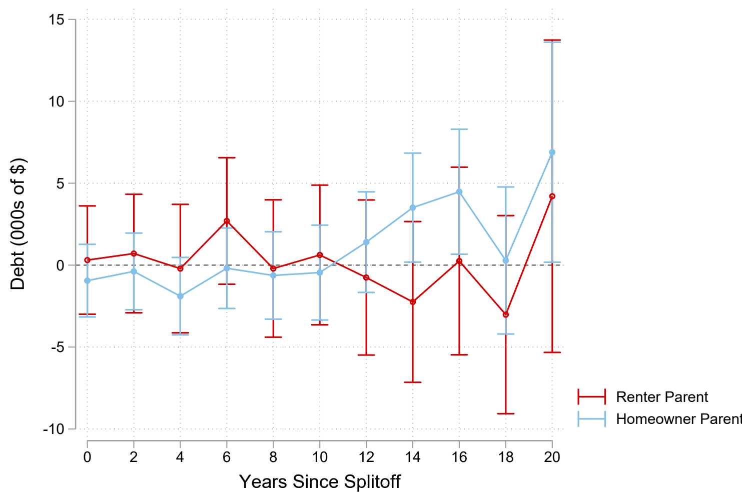
I am also able to split total net worth (without home equity) into assets and debts – effects on these are plotted in Figure A.4 and Figure A.5 respectively. It is worth noting that almost all of the effect comes from assets, and there is no effect of the labor demand shock on debt. This is true even of college debt. This points to an explanation involving savings rates as perhaps children are subsidized by their parents through intervivos transfers (which are not observed in the PSID) and can therefore save a larger amount of their income.

Figure A.4: Association of Better Parental Labor Markets with Child's Assets (without Home)



This figure plots the association of a 1 s.d. better parental labor market with the child's asset holdings.

Figure A.5: Association of Better Parental Labor Markets with Child's Debt (without Mortgage)

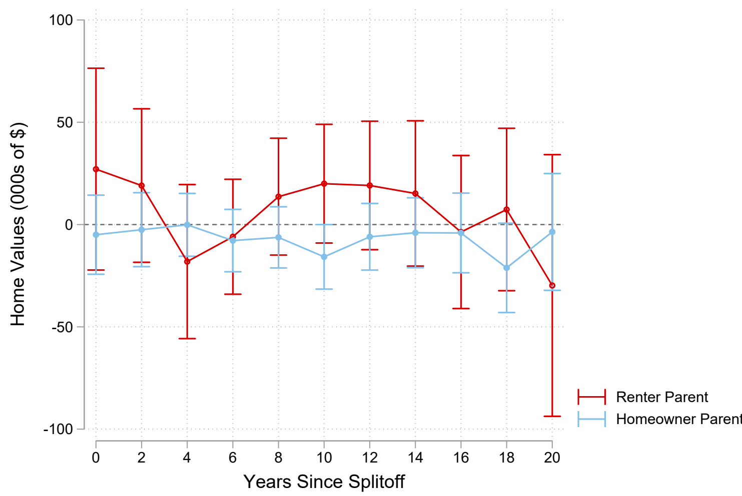


This figure plots the association of a 1 s.d. better parental labor market with the child's debt holdings.

A.4.2 Home Values

Figure A.6 plots the association of a 1 s.d. better parental labor market with the home value of a child. It indicates that among homeowner children, there is no salient effect of better parental labor markets on home values. This echoes the earlier result on home equity. Conditional on being a homeowner, there is no association of better parental labor markets on home values of the child.

Figure A.6: Association of Better Parental Labor Markets with Child's Home Value (Owners Only)



This figure plots the association of a 1 s.d. better parental labor market with the home value of a child. It indicates that among homeowner children, there is no salient effect of better parental labor markets on home values. This echoes the earlier result on home equity. Conditional on being a homeowner, there is no association of better parental labor markets on home values of the child.

A.4.3 College Debt

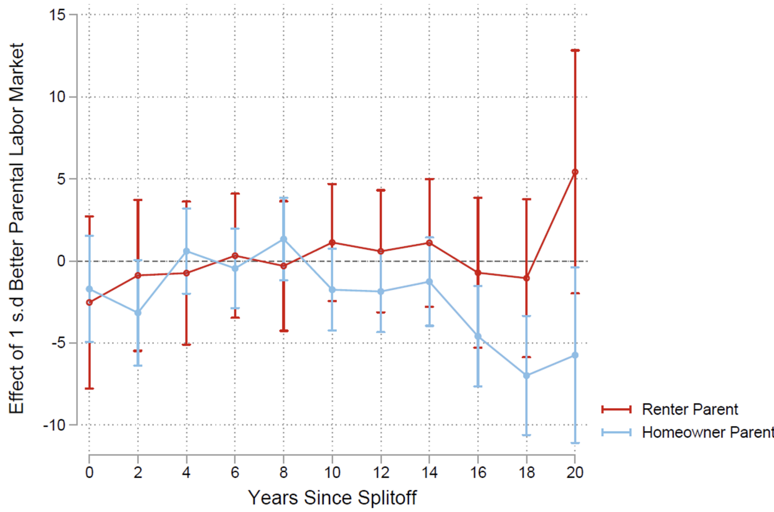
FIgure A.7 plots the association of a 1 s.d. better parental labor market with the college debt. It indicates that the children of homeowner children had somewhat lower debt if their parents lived in better labor markets.

There is no robust effect on any of the debt variables that I look at, although qualitatively, it does appear that children of homeowning parents take on less college debt, which is also consistent with the literature. However, there isn't enough power in the data to get at these differences in a statistically meaningful way, and so I shy away from discussing them too seriously.

A.4.4 Association with Wealth without IRA accounts

There is a debate about whether IRA accounts are wealth that is bequeathable or spendable by households. However, the existence of wealth in an IRA account is

Figure A.7: Association of Better Parental Labor Markets with Child's College Debt



This figure plots the association of a 1 s.d. better parental labor market with the college debt. It indicates that the children of homeowner children had somewhat lower debt if their parents lived in better labor markets.

likely to affect a household's wealth accumulation through its life cycle, which means that it is an important source of wealth to include in any calculations on household measures of wealth.

However, in this section I show that my results are robust to their exclusion as well. Figure XX provides the results of this estimation. Overall, there is still a robust association, with a 1 s.d. better parental labor market growth being associated with a higher child net worth by $40,000, 20 years after split off.

A.5 Sensitivity to Timing of Labor Market Growth

What period of labor market growth in the parent's area of residence is important for the wealth accumulation of children in adult life? The choice of considering labor market growth right before the splitoff event was made so that there was a uniform measure of the labor market growth under consideration with respect to the "event" under consideration, i.e., the splitoff of the child's household from the parent's household. However, there might be other time periods in a child's life when

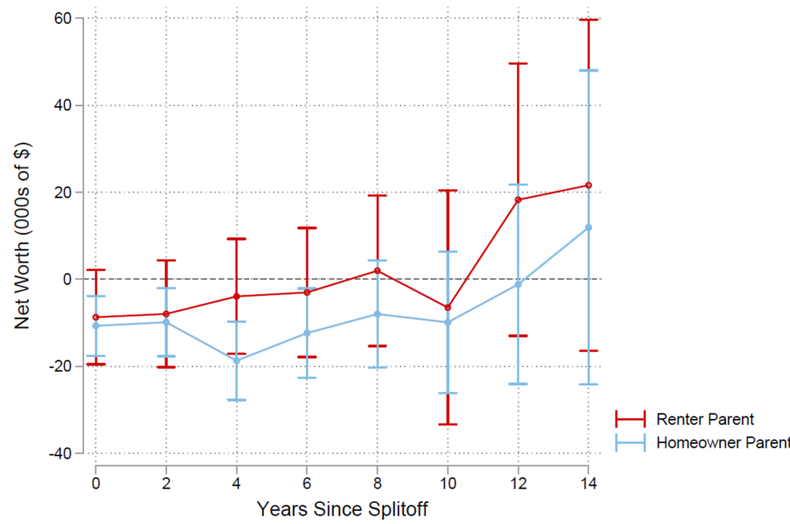


Figure A.8: Association of Better Parental Labor Markets (When Child Aged 0-10 years old) with Child's Net Worth by Parental Tenancy

the parental labor market is salient.

To investigate this, I consider two different periods in a child's life. The first is early childhood, from birth until the child is 10 years old. The second is late childhood, when the child is between 8 and 18 years of age, and closer to the splitoff event. The caveat is that as we go further back in time, fewer parents are part of the PSID sample, and it becomes harder to ascertain the characteristics of the parents. To avoid these sample size issues while maintaining a robust post-splitoff time period, I consider splitoffs that happen only after 2005.

I discuss the results of these alternate time periods below.

A.5.1 Growth in First Ten Years of Child's Life (Ages 0-10)

Parental labor market growth in the first ten years of a child's life has little effect on the child's wealth accumulation. The results are shown in Figure **??**. There is some evidence of a positive association towards the later years, but there is no differential effect between the children of homeowner and renter parents.

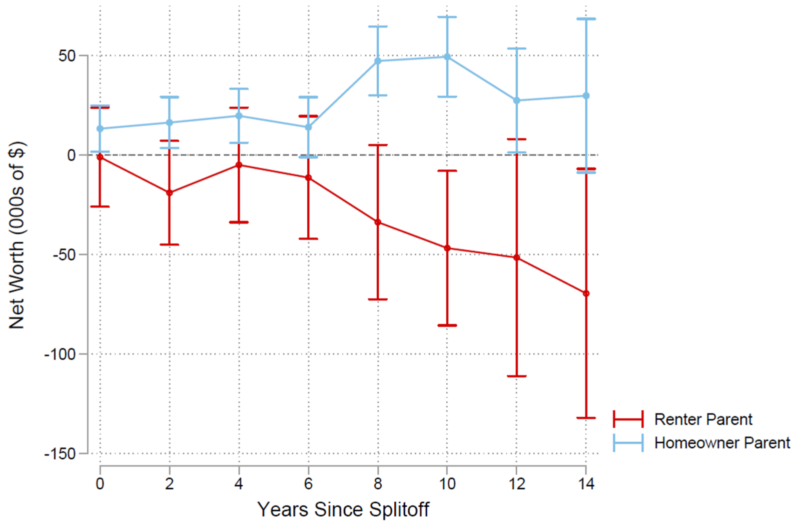


Figure A.9: Association of Better Parental Labor Markets (When Child Aged 8-18 years old) with Child's Net Worth by Parental Tenancy

A.5.2 Growth in Teenage Years of Child's Life (Ages 10-18)

Parental labor market growth when the child is between 8 and 18 years of age has a similar association to the baseline parental labor market growth that I consider in the paper. The results are shown in Figure **??**. The children of homeowner parents from better labor markets accumulate almost $30,000 more net worth 14 years after splitoff, while the children of renter parents, if anything, are worse off. This makes sense, since the period we are considering is closer to the splitoff event (recall the average age at splitoff is 24).

A.6 Association of Labor Demand Growth with the Local Economy

Conceptually, it is also useful to think of the "first stage" of the event-study specification where the growth in labor market affects parental labor markets and housing markets, and through them, parental wealth. In the second stage, this change in parental wealth affects children's wealth. However, PSID only consistently collects wealth starting in 1999, which would mean I could only examine splitoffs starting in 2009 onwards, and this would dramatically reduce both sample sizes and the time horizon of the analysis. In light of this, I directly regress parental local labor demand growth on children's outcomes in the main specification. This breaks convention from the literature, which has largely treated the shift-share measure of local labor market growth as an instrumental variable.

In this section, I present evidence that the labor demand growth measure is in fact strongly correlated with the local economy. I use data on average annual payrolls from the CBP (the same dataset used to calculate local labor demand growth) and the FHFA house price index to investigate the effect of the labor demand growth on changes in these variables over time. Specifically, I run the regression:

$$\Delta \mathrm{Y}_{j,T} = \beta_0 + \beta_1 \Delta\theta_{j,T} + \mu_j + \lambda_t + \epsilon_{j,t}$$

where $\Delta \mathrm{Y}_{j,T}$ is the percentage change in either average wages or house prices between T and $T+10$, and $\Delta\theta_{j,T}$ is labor market growth between T and $T+10$. These regressions also include year and area fixed effects, which means that the identifying variation comes from changes within areas over time. Results from this regression are presented in Table A.2. They imply that a 1 s.d. better growth in labor demand over a 10 year period is associated with a 4 percentage point increase in wages and a 3 percentage point increase in house prices. The raw data is also plotted in Figure A.10a (house prices) and Figure A.10b (average wages).

I also run a similar regression for household level income and net worth as observed in the PSID:

$$Z_{i,t} = \beta_0 + \beta_1 \Delta\theta_{j,T} + \beta_2 \mu_t + \sum_{t=0}^{10} \beta_{3,t} \Delta\theta_{j,T} \mu_t + \beta_2 X_{i,t} + \epsilon_{j,t}$$

where Z is either household income or net worth, μ_t is a dummy that captures time from T, and X is a vector of household characteristics including a quadratic in age, marital status, race, gender, family size, as well as area and time fixed effects. To fix ideas, for a period of labor market growth between 1999 and 2009 (denoted by $\Delta\theta_{j,1999}$), $Z_{i,t}$ would capture net worth at each point in time in this period: in 1999, 2001, ..., 2009. In this way, the regression gives the evolution of net worth of a household as the labor demand growth is happening. The regression merely aggregates up these periods of labor demand growth. Note that in the regression, I do not focus on the subpopulation of households who show up in the main regression: i.e., these are not only parent households, but in fact every household in the dataset. This is because the sample restriction makes the "parent-only" sub-population too sparse to work with. In this sense, this shouldn't be interpreted as a strict "first-stage" regression, even though it captures how the wealth of households in a local economy evolves as there is a growth in labor demand.

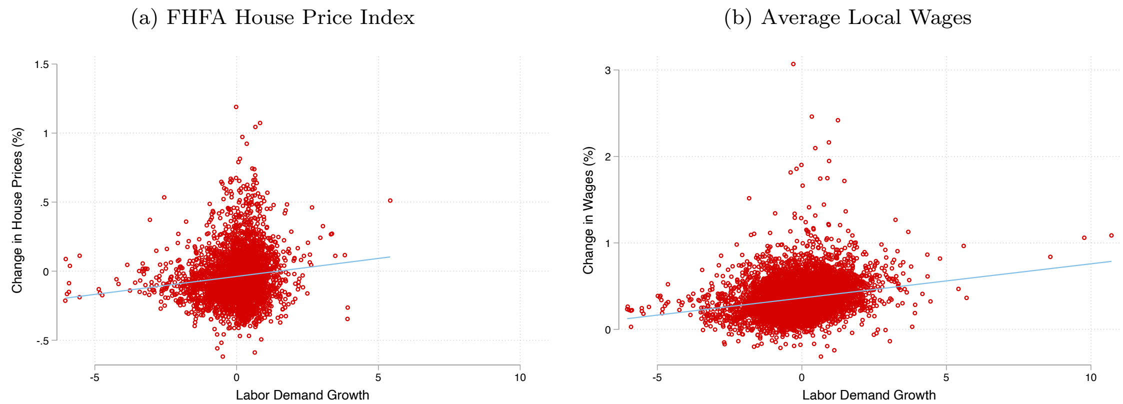
Figure A.11 captures the increase in household income and net worth over the 10-year labor demand growth in response to a 1 s.d. better labor market. Both outcomes show a positive relationship with labor demand growth, which is as expected.

	Δ Wage	**Δ House Price**
$\Delta\theta$	0.040	0.029
	(0.005)	(0.003)
R^2	0.030	0.033
N	9330	3183

Table A.2: Effect of Labor Demand Growth on Local Wages and House Prices

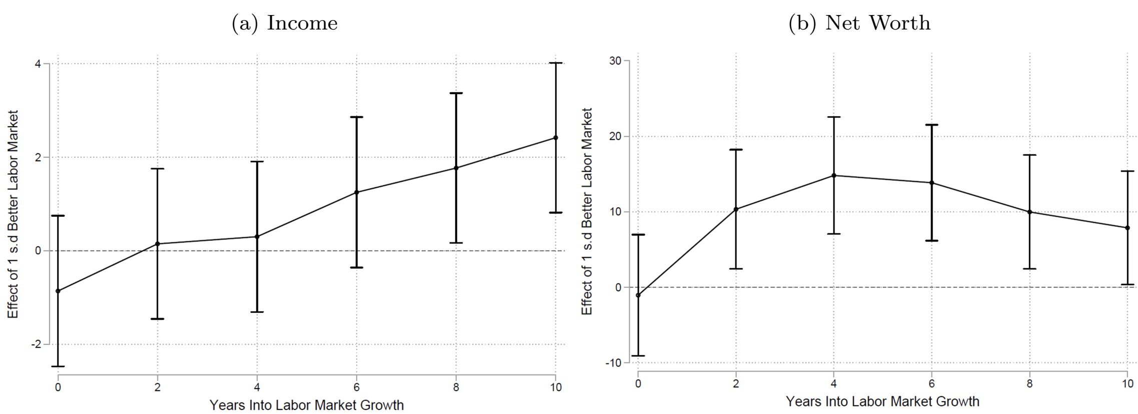
It is also important to think about the underlying variation that drives any result from the regression. Specifically, what is the local variation in labor markets over time after removing year and area fixed effects? This left over or residual variation allows me to estimate effects in the regression, and is essentially the performance of an area over time relative to its own average. So, if the Detroit metro area was doing

Figure A.10: Association of Parental Labor Markets with Local House Prices and Wages



This figure presents a scatter plot of local labor demand growth and local outcomes. Both house prices and average wages in an area are positively correlated with growth in labor demand, which is what we would expect. This is the underlying growth that is driving the local economy and feeding into individual outcomes.

Figure A.11: Association of Better Parental Labor Markets with Parent Outcomes



This figure presents the association of a 1 s.d. increase in parental labor market growth with the labor income (left) and net worth (right) of the parent. Since these are only available from 1999 onwards, these figures comprise of all parent households who experience these markets between 1999 and 2019. Both labor income and parental wealth rise significantly as areas grow over this period.

relatively well (i.e., relative to it's own average performance) in the ten year period between 1989 and 1999, then it will have a positive residual. On the other hand, since Detroit did very badly between 1999 and 2009, it's residual for this period would be negative. However, different areas in the data have different patterns of growth, and I investigate this in further detail in Appendix A.7.

A.7 Identifying Variation and Distribution of Labor Demand Growth

It is worth investigating the underlying variation in the key explanatory variable, $\Delta\theta_{j,T}$, which is the local growth in labor demand across all industries in the area. Recall that this is the amount that an area's labor market employment has grown due to national level growth in industries, weighted by the share (i.e., importance) of that industry to the area. Specifically, I consider a 10 year growth period between $T - 10$ and T, where T is the year in which a child splits off from her parents and forms her own household.

Since all regressions I run include parental area and year fixed effects, the variation which identifies the coefficients of this regression is the variation of these 10 year labor demand growth measures within each area over time. This variation is the residual in the regression of the labor demand growth $\Delta\theta_{j,T}$ on area and time fixed effects:

$$\Delta\theta_{j,T} = \beta_0 + \beta_1\mu_T + \beta_2\lambda_j + \epsilon_{j,T}$$

where $\Delta\theta_{j,T}$ is the labor demand growth between $T - 10$ and T. I run this using the "Bartik" measure of labor demand growth and calculate residuals. I call this the "residual" regression. Next, I present the trend in these residuals by area. Specifically, these are plotted for some major CBSAs in Figure A.12. The residuals represent the relative performance of an area over time, so that a positive value means that an area outperformed its average, while a negative one means that labor demand growth was slower (or even negative) than average. The graph suggests that most areas did relatively well in the earlier periods, with only Boulder, CO showing poor growth between 1989 and 1999 (which is the 1999 coefficient). Most areas also show a downward shift around the time of the Great Recession, followed by varied levels of recovery. In general, these cities can be divided into following three broad patterns in their trends.

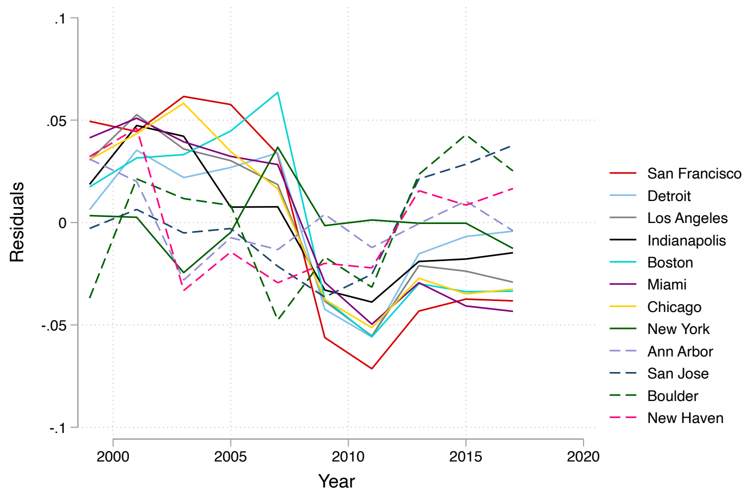
First, we notice that most big areas follow a pattern where they do relatively well in earlier periods, followed by a big downward spike at the Great Recession, and then a slow recovery (Figure A.13). However, there are some areas where there is not much of a trend in labor market growth, e.g., New York and Ann Arbor (Figure A.15), and others who did relatively okay in the before the Great Recession, but grew rapidly in the Recovery, e.g., San Jose, Boulder, and New Haven (Figure A.14).

There patterns help interpret the results in the main specifications. Essentially, we are comparing kids who split off when an area was doing better vs. when it was doing worse, which means we would be comparing a child who split off from Detroit parents in 1999 against someone who split off in 2011, and studying their differences. Alternatively, we are comparing someone who split off from New York parents in 2003 vs. 2007.

These patterns also reflect the spatial distribution of labor demand growth itself. Figures A.16, A.17, and A.18 present the spatial distribution of labor market growth between 1989 and 1999, between 1999 and 2009, and between 2007 and 2017 respectively. Between 1989 and 1999, most areas experienced strong growth in their labor markets. However, this slow down between 1999 and 2009, mostly due to the Great Recession. In fact, many areas in this period, particularly in the Midwest, experienced negative labor demand growth. Finally, labor demand growth between 2007 and 2017 captures both the effects of the Great Recession and the recovery. Most areas have recovered by the end of this period (although not all, most notably in the so called "Rust Belt").

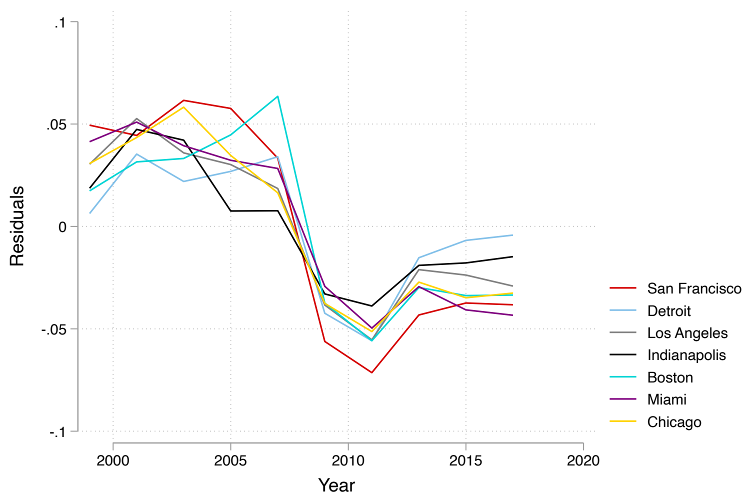
To get a sense of why the frequency might matter, I plot the spatial distribution

Figure A.12: Identifying Variation Over Time in Selected CBSAs



This figure plots the identifying variation that is leveraged to estimate the main regression in the paper. Specifically, it plots residuals from estimating the “residual” regression, which regresses the 10 year labor demand growth in an area between 1989 and 2017 on year and and area fixed effects. An estimate above zero implies the area was doing better than its own average performance over time, while an estimate below zero implies the opposite. The figure shows a variety of patterns, but the most striking is the big downward spike corresponding to the Great Recession.

Figure A.13: Identifying Variation Over Time in Selected CBSAs: Strong Initial Growth



This figure plots the identifying variation that is leveraged to estimate the main regression in the paper for selected areas that showed strong growth in the early periods and weaker growth post-Great Recession. Specifically, it plots residuals from estimating the “residual” regression, which regresses the 10 year labor demand growth in an area between 1989 and 2017 on year and and area fixed effects. An estimate above zero implies the area was doing better than its own average performance over time, while an estimate below zero implies the opposite.

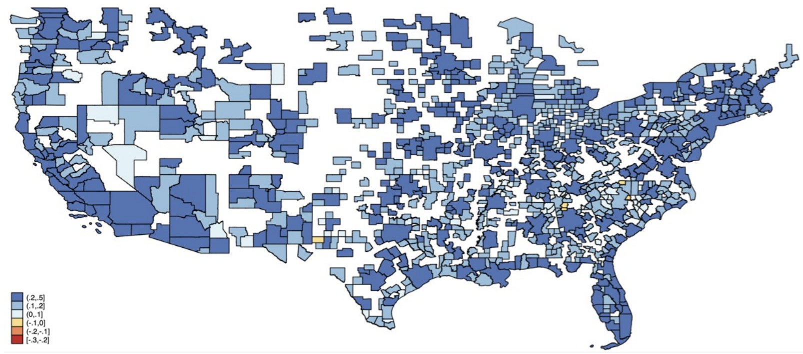
Figure A.14: Identifying Variation Over Time in Selected CBSAs: Weaker Initial Growth

This figure plots the identifying variation that is leveraged to estimate the main regression in the paper for selected areas that showed comparatively weaker growth in the early periods and stronger growth post-Great Recession. Specifically, it plots residuals from estimating the "residual" regression, which regresses the 10 year labor demand growth in an area between 1989 and 2017 on year and and area fixed effects. An estimate above zero implies the area was doing better than its own average performance over time, while an estimate below zero implies the opposite.

Figure A.15: Identifying Variation Over Time in Selected CBSAs: Constant Growth

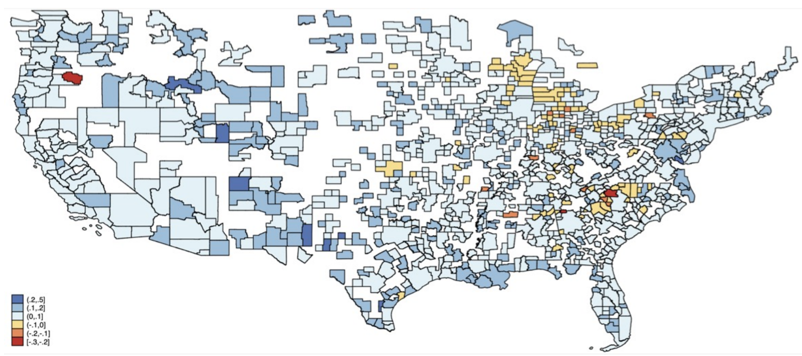
This figure plots the identifying variation that is leveraged to estimate the main regression in the paper for selected areas that showed a consistent level of growth across periods. Specifically, it plots residuals from estimating equation the "residual" regression, which regresses the 10 year labor demand growth in an area between 1989 and 2017 on year and and area fixed effects. An estimate above zero implies the area was doing better than its own average performance over time, while an estimate below zero implies the opposite.

Figure A.16: Spatial Distribution of Labor Demand Growth Between 1989 and 1999



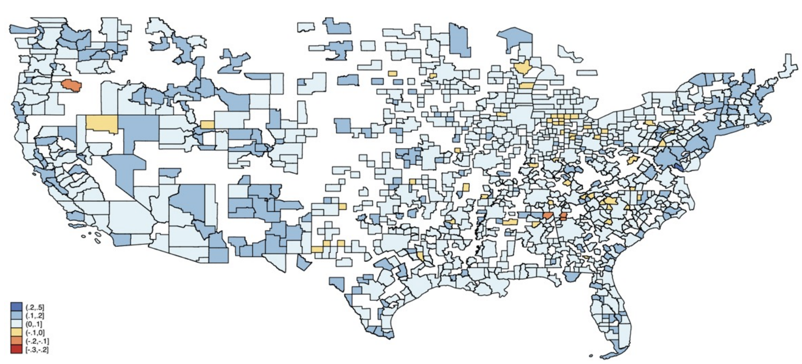
This figure plots labor demand growth between 1989 and 1999 across the United States. We see that most areas grew very strongly in this time period. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

Figure A.17: Spatial Distribution of Labor Demand Growth Between 2001 and 2011



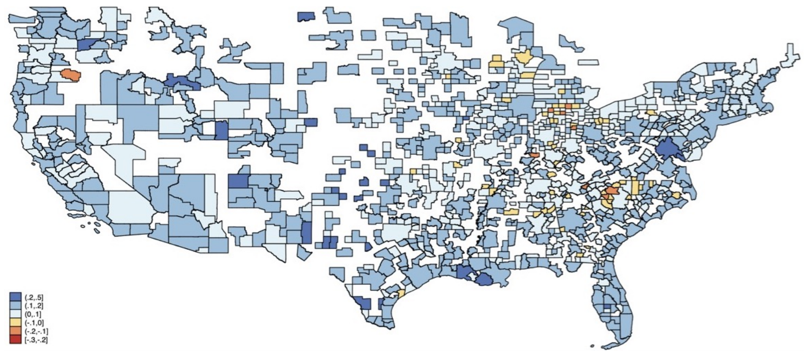
This figure plots labor demand growth between 2001 and 2011 across the United States. We see a greater heterogeneity in growth in this period, primarily due to the heterogeneous effects of the Great Recession. Areas in the so-called Rust Belt particularly did poorly in this time period. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

Figure A.18: Spatial Distribution of Labor Demand Growth Between 2007 and 2017



This figure plots labor demand growth between 2007 and 2017 across the United States. We see that areas have started recovering from the Great Recession in this period, although some scarring effect still remains, particularly in the Rust Belt. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

Figure A.19: Spatial Distribution of Labor Demand Growth Between 1999 and 2009



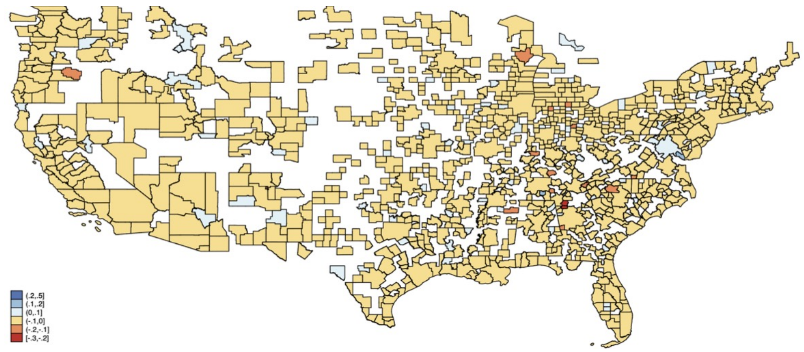
This figure plots labor demand growth between 1999 and 2009 across the United States. We see that some areas are still growing strongly across this period, while others exhibit negative growth due to the Great Recession. This heterogeneity is because while the Great Recession negatively impacted all areas, some areas grew very strongly between 1999 and 2007. Since the 10 year growth measure is spread over a long period, it takes some time for the negative effects to show up in most areas. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

of labor demand growth calculated over a shorter period (Figure A.20) vs. a longer one (Figure A.19). The shorter period considers growth between 2007 and 2009 (the Great Recession), while the longer one considers growth between 1999 and 2009 (a longer horizon which includes the Great Recession). The two year measure contains a substantially higher number of areas with negative growth compared to the ten year measure. This is to be expected given that when the period under consideration is of low frequency (i.e., a 10 year growth instead of a 2 year growth), the measure "smoothens out" short term spikes. However, the low frequency measure is appropriate measure to use here because this paper concerns the accumulation of wealth, which is a gradual process for most households.

A.8 Endogeneity Concerns with the Timing of Split-Off Event

There are also other endogeneity concerns about the labor demand growth itself. For instance, it might be that the age at splitoff might be affected by parental labor markets. This effect could go either way: one could imagine a child putting off leaving home because times are bad and parents need help. On the other hand, good

Figure A.20: Spatial Distribution of Labor Demand Growth Between 2007 and 2009



This figure plots labor demand growth between 2007 and 2009 across the United States. We see that most areas exhibit negative growth due to the Great Recession. The short run measure captures the heterogeneity across space well in times of general recessions but, by design, does not account for longer term trends in labor markets. Darker shades of blue imply stronger, more positive growth markets; darker shades of yellow imply more weaker, negative growth markets. Please print in color for a better reading experience.

parental labor markets might also delay splitting off because the child can spend more time at home looking for a better job. It is also easy to imagine education differences at the time of splitting off for similar reasons.

To see the distribution of these two variables in particular in my sample, I divide households into two groups: those above and below the average level of labor demand growth in the year they split off. I then plot the density of these variables. The results can be seen in Figure A.21.

The distributions mostly overlap each other, which means that at least mechanically, there seems to be no systematic difference between those who parents had above or below average labor markets before the child split off. Balance regressions also indicate no significant difference between these variables.

A.9 Other Data Sources Used for Model

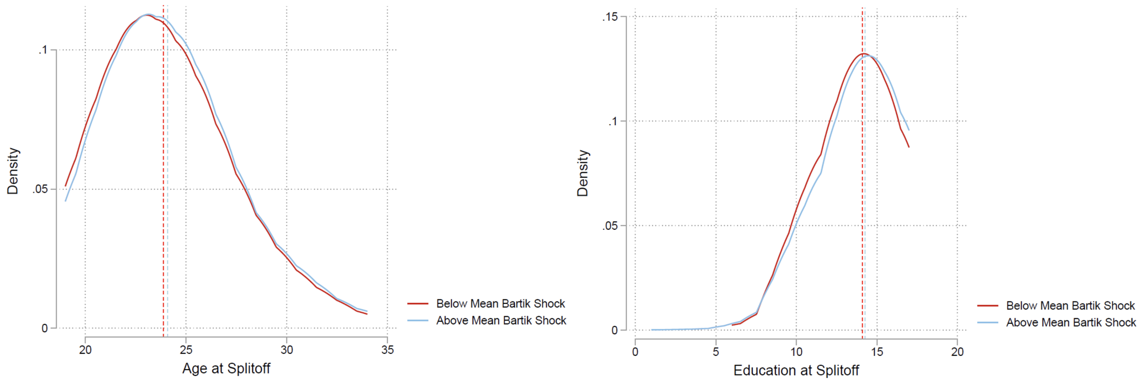
A.9.1 FHFA House Price Index

The FHFA HPI is a broad measure of the movement of single-family house prices, and serves as an accurate indicator of house price trends at various geographic levels. The FHFA HPI is a weighted, repeat-sales index, meaning that it measures average

Figure A.21: Distribution of variables that could be affected by parental labor markets

(a) Age at Splitoff

(b) Education at Splitoff



This figure presents the distribution of age and density of splitoff for those splitting off from areas above and below the mean level of local labor demand growth. The figures show that the distributions are very similar in both instances, which assuages concerns that local labor demand growth endogenously affects the splitoff itself.

price changes in repeat sales or refinancings on the same properties, and is available 1975 onwards. For the purposes of this paper, I use data from 1999 onwards to calibrate the model to an "initial" equilibrium.

A.9.2 Saiz [2010] House Supply Elasticity

A key parameter of interest is the house supply elasticity, which determines the responsiveness of prices to population changes. Data for this comes from Saiz [2010], who uses local land availability measures to construct a measure of house supply elasticity that is plausibly exogenous to local labor market conditions. Essentially, this measure captures how hard it is to build housing in an area due to its geography – for instance, areas where the slope of the land is steep (such as on hills) or areas which have a significant amount of water (such as beaches), are inherently difficult places to build housing in. To fix ideas, a place like San Francisco is hard to build in, while a place like Indianapolis is relatively easy to build in. These are important parameters for the model in Section 1.5, since they are a defining feature of a housing market.

These elasticities control how housing prices react to an increase in labor demand. Suppose an area had perfectly elastic housing market – this would mean that building more housing was essentially costless. In that case, an increase in local labor demand would have no effect on house prices, even if it has an effect on housing demand. Alternatively, if an area has a perfectly inelastic market, it's impossible to build more housing in the area, and the pass through of the increase in labor demand to house prices will be very large.

APPENDIX B

Appendices to Chapter 2

B.1 Robustness to Period of Local Labor Market Growth

How has the relationship between house supply elasticities and local labor market growth evolved over time? The paper presents results for two time periods: 1980-1999 and 1999-2019. However, in this section, I also present results for local markets using a decade-specific definition of the shift-share labor demand growth (as is common in the literature, e.g., Moretti [2013], Goldsmith-Pinkham et al. [2017], Zabek [2017]). In particular, I consider labor market growth between 1980-1990, 1990-2000, 1999-2009, and 2009-2019.

The results from estimating a regression of the labor demand growth on for these alternate definitions are presented in Table B.1. One can see that there is little correlation between labor demand growth and house prices in the first two periods, but a positive and significant relationship between them in the following two periods. This lines up with the initial definitions of the periods in consideration, and shows that there is no heterogeneity within them.

	1980-1990	1990-2000	1999-2009	2009-2019
Labor Demand Growth	0.008	-0.005	0.110*	0.022*
	(0.026)	(0.017)	(0.039)	(0.010)
N	525	766	903	907
R^2	0.0004	0.027	0.033	0.015

Table B.1: Relationship Between House Price Growth and Labor Demand Growth Across Decades

B.2 Robustness Checks within the PSID

B.2.1 Controlling for Labor Income

Labor income is not included as a control when estimating Equation (2.5), since growth in labor markets affects income, and income affects wealth. Therefore, controlling for income would "shut off" a channel of wealth accumulation. However, I also estimate the regression while including labor income and the results are unchanged. The results are presented in Figure B.1.

Figure B.1: Association of 1 s.d. Better Labor Markets with Net Worth after Controlling for Labor Income, 1999-2019

B.2.2 1999 Households Only

The sample of the PSID is slightly different every year as some households split off from others and add to the PSID sample size. In order to account for this, I run the regression in Equation (2.5) but only with the households that are present in the sample in 1999. The results can be seen in Figure B.2 (Net Worth) and Figure 2.19 (Net Worth without Home Equity). The numbers are similar to the ones in the main regression.

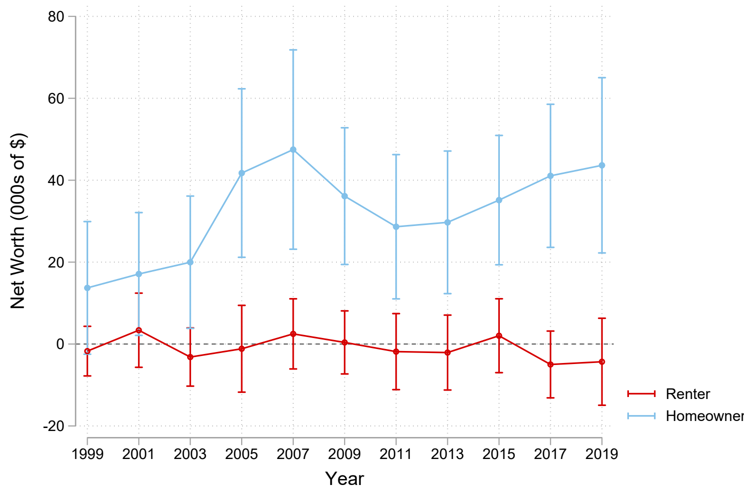


Figure B.2: Association of 1 s.d. Better Labor Markets with Net Worth for Households Present in 1999, 1999-2019

B.2.3 Incumbent Homeowners in 1999

In the main PSID sample, there are changes in homeownership over time as households buy and sell their houses. This might bias the estimates as people might sell or buy for a variety of reasons. In this section, I run the regression in Equation (2.5) for the subsample of households who are already homeowners in 1999. The results are somewhat higher for this subsample, as in 2019, homeowners in better labor market have $50,000 more in net worth, compared to $43,000 for the full sample.

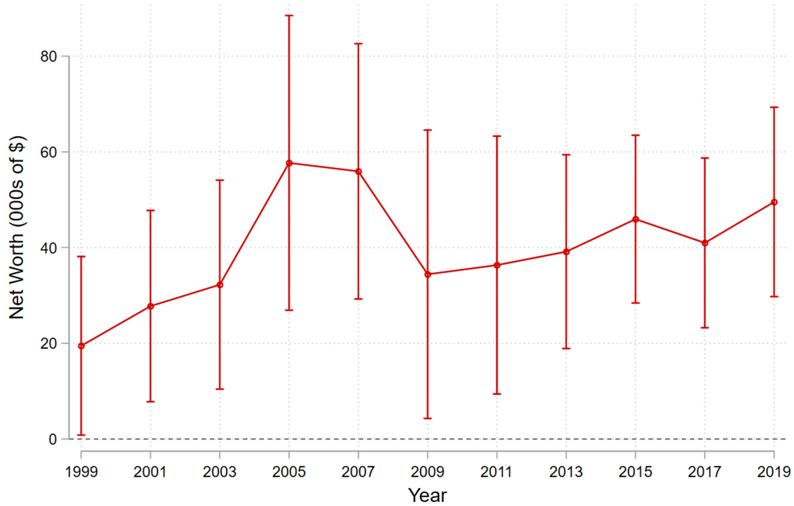


Figure B.3: Association of 1 s.d. Better Labor Markets with Net Worth of Incumbent Homeowners in 1999

B.3 Effects of Local Labor Market Growth on Debt

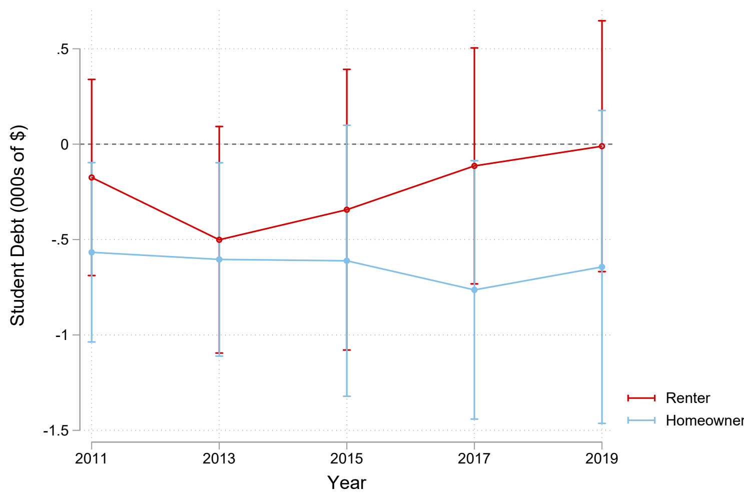


Figure B.4: Association of 1 s.d. Better Labor Markets with Debt by Parental Tenure, 1999-2019

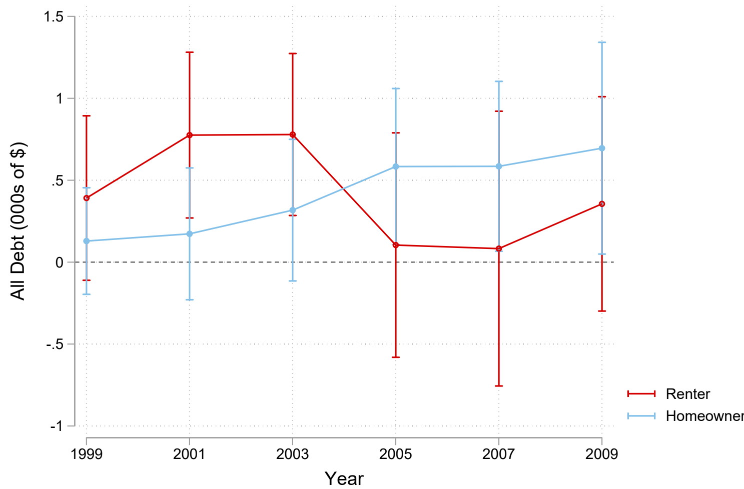


Figure B.5: Association of 1 s.d. Better Labor Markets with Student Debt by Parental Tenure, 1999-2019

No effect on debt.

B.4 Results of Regression

This section presents results from estimating Equation (2.5) in Table B.2. Due to concerns of space, I only show results for the main coefficients of interest, which show the marginal effect of a 1 s.d. higher labor demand growth in the area of residence of the household.

The graphs presented in Section 2.5 with the results can be backed out by summing across the relevant coefficients. For instance, the association of a 1 s.d. increase in local labor markets with the net worth of homeowner households in 2019 is calculated as $-1.508 + 0.797 + 15.356 + 28.396 = 43.041$, or \$43,041. The same point estimate for the renter households would be $-1.508 + 0.797 = -0.711$, or \$711.

		Net Worth
Labor Demand Growth		-1.508
		(3.031)
Year x Labor Demand Growth	**2001**	4.403
		(3.981)
	2003	-2.529
		(4.324)
	2005	0.330
		(5.369)
	2007	4.578
		(4.381)
	2009	0.288
		(4.296)
	2011	0.462
		(4.573)
	2013	-0.148
		(4.668)
	2015	1.458
		(4.825)
	2017	-1.056
		(4.751)
	2019	0.797
		(4.817)
Homeowner		15.356
x Labor Demand Growth		(6.732)
Homeowner x Year	**2001**	0.067
x Labor Demand Growth		(5.484)
	2003	10.303
		(5.590)
	2005	30.235
		(7.645)
	2007	30.585
		(8.060)
	2009	21.306
		(7.221)
	2011	15.247
		(8.964)
	2013	18.756
		(8.624)
	2015	19.75
		(7.768)
	2017	28.443
		(8.591)
	2019	28.396
		(9.683)
N		65834
R^2		0.349

Table B.2: Regression Coefficients Used for Point Estimates

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