The Intergenerational Wealth Effects of Local Labor Markets*

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Abstract

Between 1999 and 2019, income and house prices have diverged across local areas in the United States as some cities have seen persistent growth in their labor markets while others have not. These divergent trends across labor and housing markets have an effect on wealth, especially housing wealth, which persists across generations. This paper asks how the local markets of parents shape their children's wealth and affect wealth inequality. I find that children who grew up in better local labor markets have, on average, $45,000 higher net-worth as adults. This association is only true for the children of homeowner parents. To measure the aggregate effect of this divergence on wealth inequality, I build a parsimonious, multi-region model, and find that dispersion in local labor market growth accounts for 40% of the rise in wealth inequality amongst the bottom 90% of households.

JEL Codes: TBD

Keywords: Wealth Inequality, Local Housing Markets, Household Finance, Asset Prices, Local Labor Markets, etc.

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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. However, the public debate on the topic has focused on the top 1% (Saez and Zucman (2016)) of the population, while paying little attention to the wealth of the bottom 90%. It is important to consider these groups separately because their wealth portoflios 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. 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, Detroit has seen real wages decline by 2%, while real house prices have decreased by 12.5%; on the other hand, San Francisco has seen real wages increase by 50%, and real house prices increase by 99%. These trends, in turn, affect the wealth holdings of households experiencing them. For homeowners in these areas, they affect their housing wealth as well. So, 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.[2]

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

[2]The effects of local labor markets can also persist across generations. For instance, Lovenheim (2011) finds that an increase in the housing wealth of parents increases college attendance. This is in addition to how parental wealth can affect children's outcomes: see Killewald et al. (2017) (children's education) and Brandsaas (2021) (help with downpayments).

[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 2.

that children of parents who experienced better labor markets do, in fact, accumulate more wealth, but only for the children of *homeowner* parents. Children of renter parents do not show a significant response in their wealth accumulation, and if anything, are negatively affected.

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 as well as their homeownership rates. However, there is no differential trend in their labor earnings. In order to quantify some of the channels through which these divergent patterns might affect wealth inequality, I build a parsimonious, multi-region model 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 amongst the bottom 90% of households between 1999 and 2019. 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. So, 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 Detroit was doing relatively well, and the other right in the aftermath of the Great Recession in 2009, by which point Detroit 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.

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.

Finally, I also investigate the mediating channels that point towards how these child households are able to accumulate their wealth. As mentioned before, I focus on gifts or inheritances, labor income, and child homeownership. 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 $10,000. 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.

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 the data. In order to make a first pass at quantifying some of these channels, I build a parsimonious model 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.

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

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

In the model, local labor and housing markets are intrinsically linked because households live and work in the same area. The key mechanism is as follows: if local labor market productivity increases, wages in the area rise. This leads to an increase in housing demand because incumbent residents would want to purchase more housing and also because the improved labor markets attract new residents into the area, which bids up the price of housing. In this way, local markets have multiple effects on household wealth: first, they have a direct effect through savings rates; second, they have an indirect effect due to the pass through of the increased wages onto house prices and rents. Finally, at the end of the period, households die after leaving bequests to the next generation – crucially, homes are part of the bequests that homeowner parents make, which makes local increases in productivity especially salient for them. I model bequests as a luxury good, following work by De Nardi (2004) and Straub (2019). This is the incentive for households to save and purchase housing. 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 quantitative 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, 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. 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)). 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 intergenerational pass through: local labor markets that parents experience when the child is growing up.[8]

The paper proceeds as follows. Section 3 decomposes the change in mean wealth between 1999 and 2019 into coming from homeowner or renter households. Section 2 introduces the data used for the various analyses conducted in the paper, while Section 4 presents the main empirical results of the paper. Section 5 introduces the model of local labor and housing

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

[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.

markets to quantify various channels that might affect wealth inequality, and Section 6 concludes.

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.

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 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 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 **??**.

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 D 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.

2.2.1 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.

2.3 Final Dataset

Finally, the two datasets are merged to create the final dataset I use for the empirical analyses in the paper. Specifically, I 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 Detroit 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 4.

2.4 Descriptive Statistics about the Sample

It is useful to consider where households are splitting off from, and when. Table 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 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.

In total, between 1999 and 2019, this yields 13,443 household x time data points for the main regression.

Meanwhile, Figure 1 provides the spatial distribution of where these households are splitting off from. The most common areas captured by the data are Detroit, Chicago, and New York, although there is good coverage across the country in terms of a few observations (approximately 5) each in most CBSAs. Overall, splitoffs from about 315 CBSAs are a part of the sample.

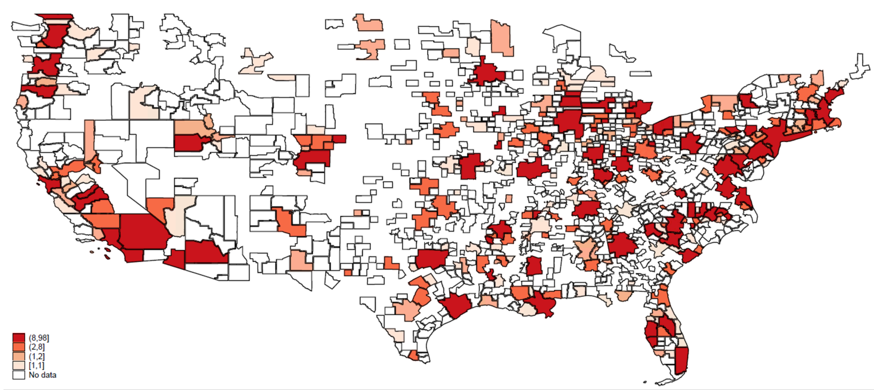
A caveat to note is that the skewed dispersion of households across space means that the regression naturally weighs larger areas more heavily, although this concern is somewhat alleviated because I use longitudinal weights provided by the PSID in all regressions.

Table 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

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.

Figure 1: Spatial Distribution of Sample



This figure presents the spatial distribution of where the reference person of a household in the main sample grew up. Most reference persons in the PSID data grew up in bigger areas (Detroit, New York, Chicago, San Jose, etc.) although in general the observations come from a wide variety of areas. This skewed dispersion means that the regression naturally weighs larger areas more heavily, although this concern is somewhat alleviated because I use longitudinal weights provided by the PSID in all regressions. The longitudinal weights are provided to make the data nationally representative.

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.

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

The mean level of wealth in the United States amongst the bottom 90% of households increased between 1999 and 2019. Using the Panel Study of Income Dynamics (PSID), I find that amongst this group, the average net worth (including home equity) was $142,299[9] in 1999. This went up to $168,022 by 2019, a real increase of almost $26,000.

Figure 2 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,

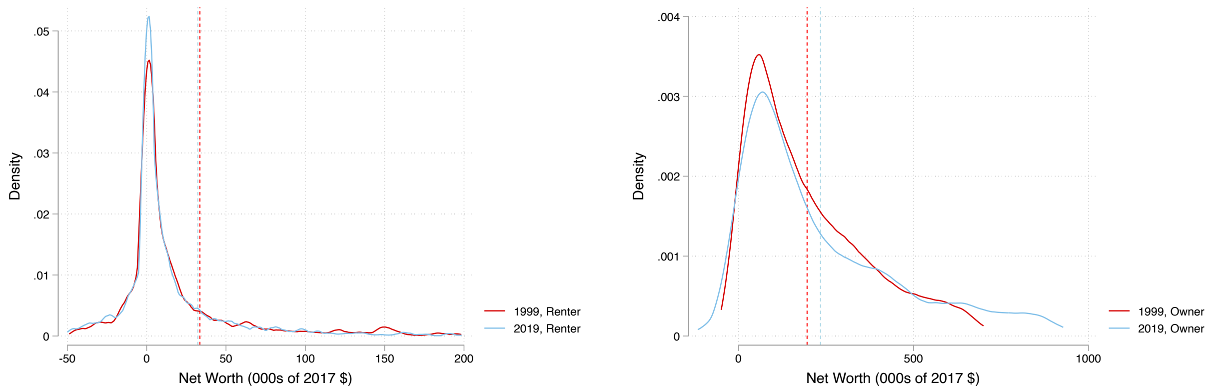
$$N_{R,0} + N_{O,0} = N = N_{R,1} + N_{O,1} \implies \Delta Q_R = -\Delta Q_O$$

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

[9] All prices are in real 2017 dollars.

Figure 2: Distribution of Wealth of Renters and Homeowners in 1999 and 2019

(a) Renters **(b)** Owners



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$$\Delta\bar{W} = \bar{W}_1 - \bar{W}_0 \tag{1}$$

$$= \left(Q_{R,1}\frac{1}{N_{R,1}}\sum_{i=1}^{N_{R,1}} W_{i,R,1} + Q_{O,1}\frac{1}{N_{O,1}}\sum_{i=1}^{N_{O,1}} W_{i,O,1}\right) - \left(Q_{R,0}\frac{1}{N_{R,0}}\sum_{i=1}^{N_{R,0}} W_{i,R,0} + Q_{O,0}\frac{1}{N_{O,0}}\sum_{i=1}^{N_{O,0}} W_{i,O,0}\right) \tag{2}$$

$$= Q_{R,0}\Delta\bar{W_R} + Q_{O,0}\Delta\bar{W_O} + \Delta Q_O(\bar{W_{O,1}} - \bar{W_{R,1}}) \tag{3}$$

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 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 3) by the left hand side to get:

Table 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

$$1 = \frac{Q_{O,0}\Delta \bar{W_O}}{\Delta \bar{W}} + \frac{Q_{R,0}\Delta \bar{W_R}}{\Delta \bar{W}} + \Delta Q_{O,0}\frac{(\bar{W_{R,1}} - \bar{W_{O,1}})}{\Delta \bar{W}} \tag{4}$$

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 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:

$$1 = \underbrace{(1.377)}_{\text{Due to change in wealth of owners}} + \underbrace{(-0.0133)}_{\text{Due to change in wealth of renters}} + \underbrace{(-0.364)}_{\text{Due to change in ownership rate}} \tag{5}$$

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.

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.[10] It is worth noting that there is a "first stage" of this regression in the background, where the local labor markets of parents 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.

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. (2017), 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

[10] 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.

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 Volker 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.

Further, Goldsmith-Pinkham et al. (2017) 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.

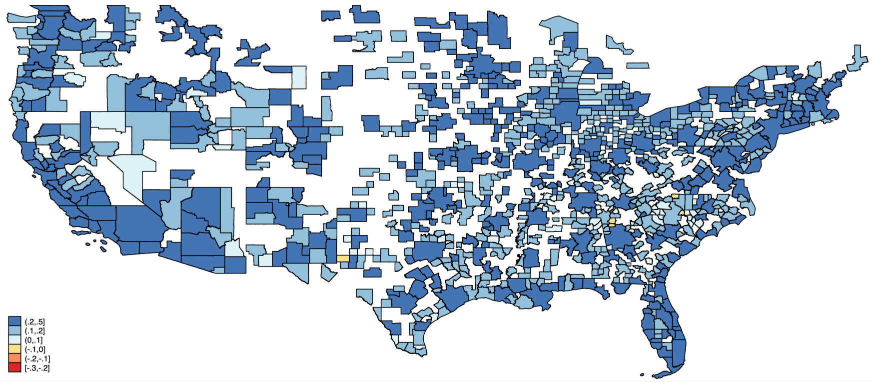
Specifically, I define parent's labor market growth as $\Delta\theta^{par}_{j,T}$, for a parent in CBSA j at time of the child splitting off, T as:

$$\Delta\theta^{par}_{j,T} = \underbrace{\sum_{k \in ind}}_{\text{summing over industries}} \underbrace{\left(\frac{L_{k,-j,T} - L_{k,-j,t-l}}{L_{k,-j,T-l}}\right)}_{\text{national growth rate}} \underbrace{\frac{L_{k,j,T-l-5}}{L_{j,T-l-5}}}_{\text{share of industry in area}} \tag{6}$$

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.

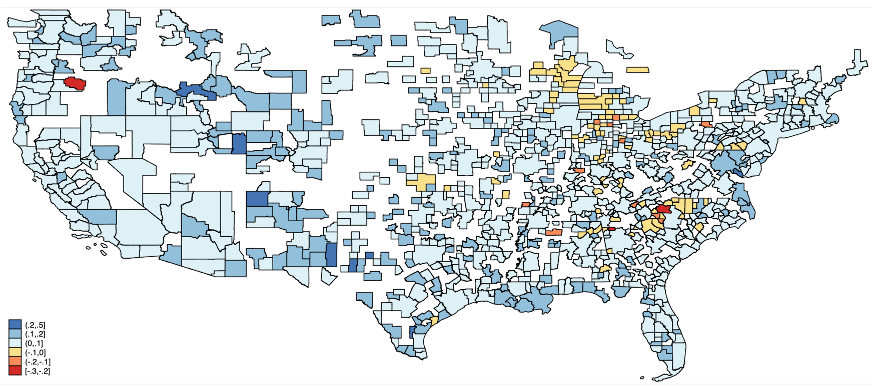
In practice, how are these Bartik measures spread across the United States? Figures 3 and 4 present the spatial distribution of labor market growth between 1989 and 1999 and between 2001 and 2011. Between 1989 and 1999, most areas experienced strong growth in their labor markets. However, this slow down between 2001 and 2011, mostly due to the

Figure 3: 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.

Figure 4: 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.

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 F.

The main idea is to examine differences in children's outcomes T onwards according to the parent's labor market condition at T. In the next section, I formalize the notion of these regressions.

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:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T}) + \beta_4 X_{ijt} + \beta_5 X^{par}_{T} + \epsilon_{ijt} \tag{7}$$

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. This is because these are all plausible mechanisms through which parental labor markets might impact a child'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 parental 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 parental area (or area where the household grew up) level.

Finally, I Winsorize the wealth data at the 1st and 99th 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 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.

4.2.1 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. (2017), 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. (2017), 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.

4.2.2 Association of Labor Demand Growth with 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. Due to this reason, parental local labor demand growth is directly regressed on children's outcomes in the main specification, and not used as an instrumental variable, as is more common in the literature.

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 following 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 3. 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 **??** (house prices) and Figure **??** (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.

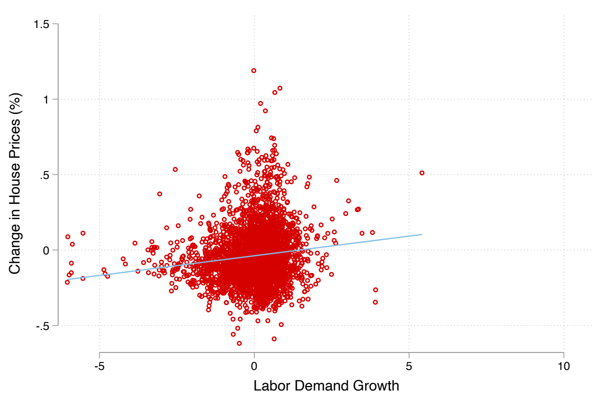
Figure 6 captures the increase in household income and net worth over the 10-year labor demand growth in response to a 1 s.d. better labor market. Both outcomes show a positive relationship with labor demand growth, which is as expected.

	Δ Wage	**Δ House Price**
$\Delta\theta$	0.040	0.029
	(0.005)	(0.003)
R^2	0.30	0.33
N	9330	3183

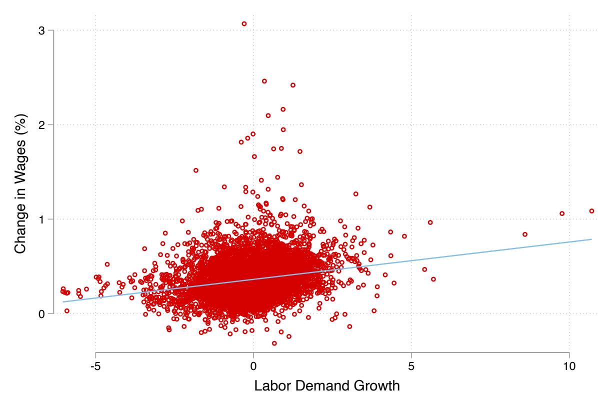
Table 3: Effect of Labor Demand Growth on Local Wages and House Prices

Figure 5: Association of Parental Labor Markets with Local House Prices and Wages

(a) FHFA House Price Index



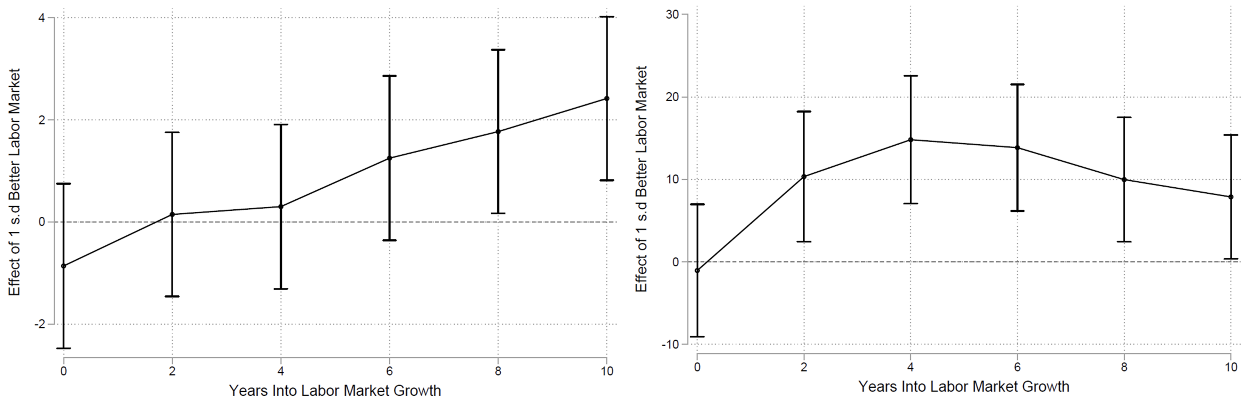
(b) Average Local Wages



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 6: Association of Better Parental Labor Markets with Parent Outcomes

(a) Income **(b)** Net Worth



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.

Finally, 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 Detroit was doing 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 F.

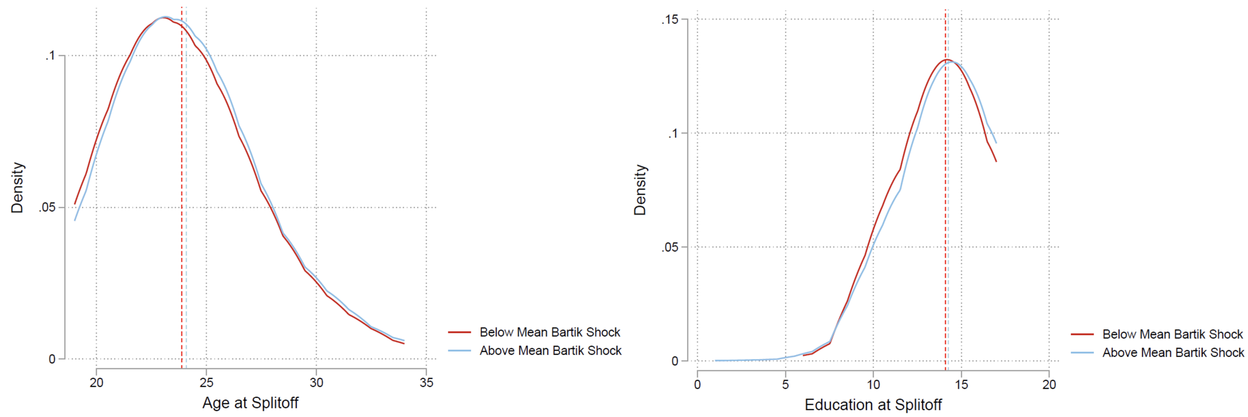
4.2.3 Endogeneity Concerns with the Timing of Split-Off Event

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 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

Figure 7: 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.

the year they split off. I then plot the density of these variables. The results can be seen in Figure ??.

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.

4.2.4 Heterogeneity of Results by Parental Income

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:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T}) + \beta_3(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T} \textbf{ x } \text{Own}^{\text{par}}) + \beta_4 X_{ijt} + \beta_5 X^{par}_{T} + \epsilon_{ijt} \quad (8)$$

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.

4.3 Effect on Wealth Portfolio of Splitoff Households

In this section, I present results from running the difference-in-difference regression in Equation 4.2 and the triple difference regression in Equation 4.2.4 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 B.

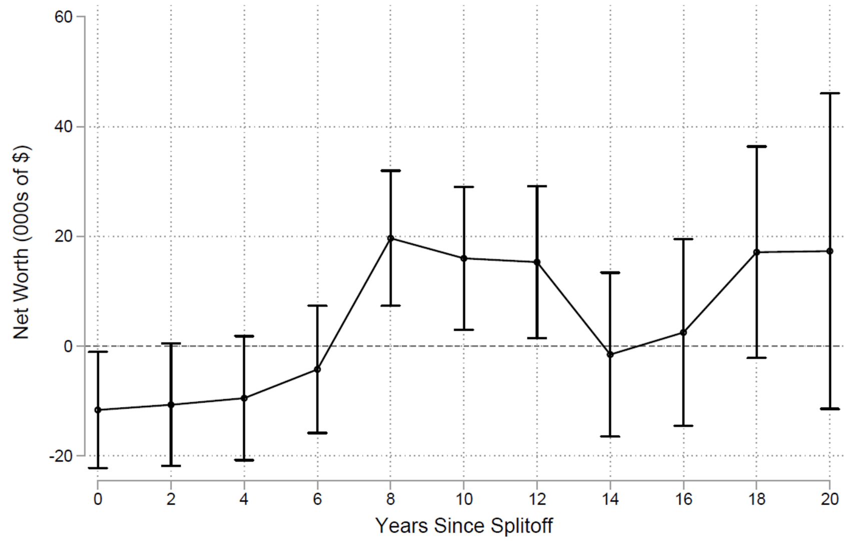
For each outcome, I calculate the association of a 1 standard deviation increase in the strength of parental labor markets with the outcome every year from splitoff, separately by parental homeownership. At the end of the sample, I observe children who have been splitoff from their parents for 20 years, 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.

4.3.1 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 8. 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., twnty 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 9 shows that this masks substantial heterogeneity in the patterns of

Figure 8: Association of Better Parental Labor Markets with Child's Net Worth



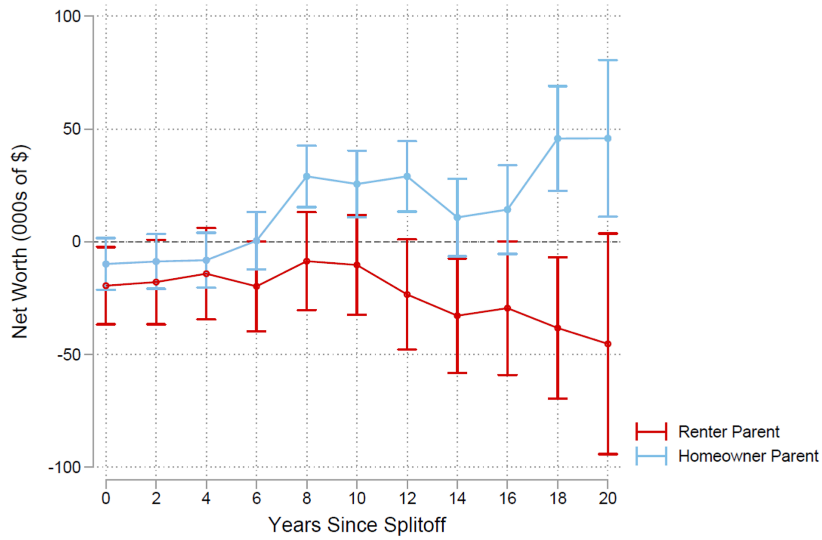
This figure presents the association of a 1 s.d. increase in parental labor market growth with the net worth of a child, t years after splitting off. There is no significant pattern of associations between parental labor market growth and wealth accumulation overall, although in general the association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

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 4.5 in Appendix B. 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 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

Figure 9: 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 8. 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.

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.

4.3.2 Net Worth without Home Equity

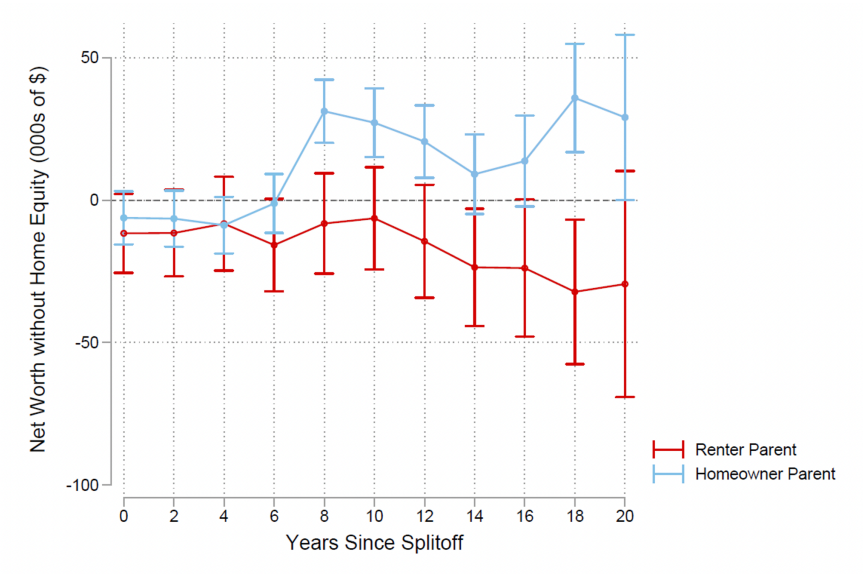
It is useful to investigate what part of the wealth portfolio of the child is driving these effects. To do this, I break down the net worth of the child as consisting of a non-housing part, and a housing part. The latter is simply home equity (calculated as home value minus outstanding mortgage), and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

Figure 10 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 9. 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.

Figure 10: Association of Better Parental Labor Markets with Child's Net Worth (without Home Equity)



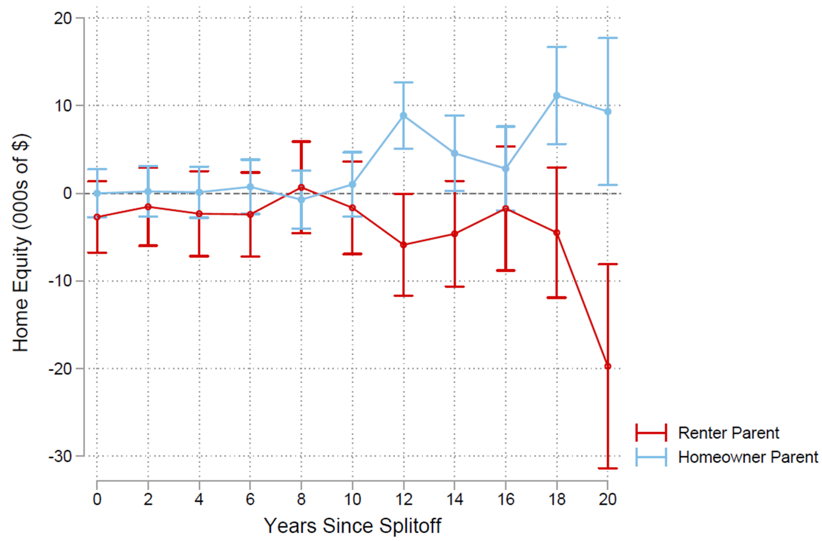
This figure presents the association of a 1 s.d. increase in parental labor market growth with the net worth (without home equity) of a child, t years after splitting off. There is no significant association between parental labor market growth and wealth accumulation overall, as seen in the left panel. 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.

4.3.3 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 11 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.

Figure 11: 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.

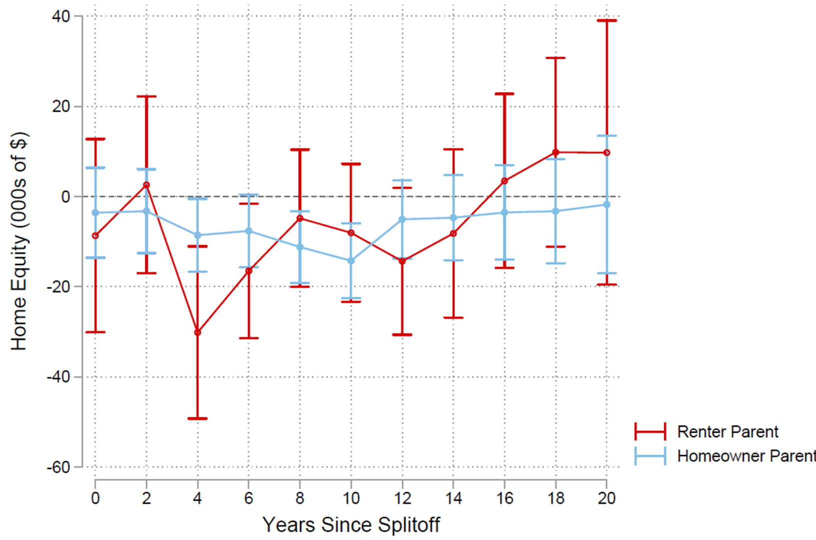
However, these results include both renter and homeowner children. As discussed above, home equity is zero for renter children. So, I run another analysis considering only homeowner children to see how much the selection into homeownership affects the results. The estimates from this regression are plotted in Figure 12. They show that all the results from Figure 11 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.

4.4 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,

Figure 12: 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. 11), conditional on owning a home, there is no effect on home equity.

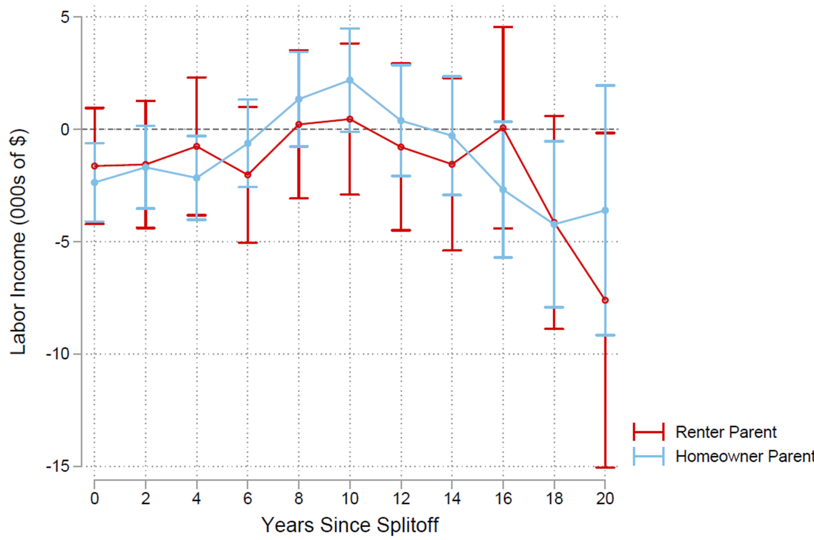
which helps them accumulate wealth in other ways (instead of saving up and spending on a home). Finally, parents can make gifts or leave an inheritance for their child, which directly influences her wealth.

4.4.1 Income

Figure 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).

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 ??) and so it makes

Figure 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 9.

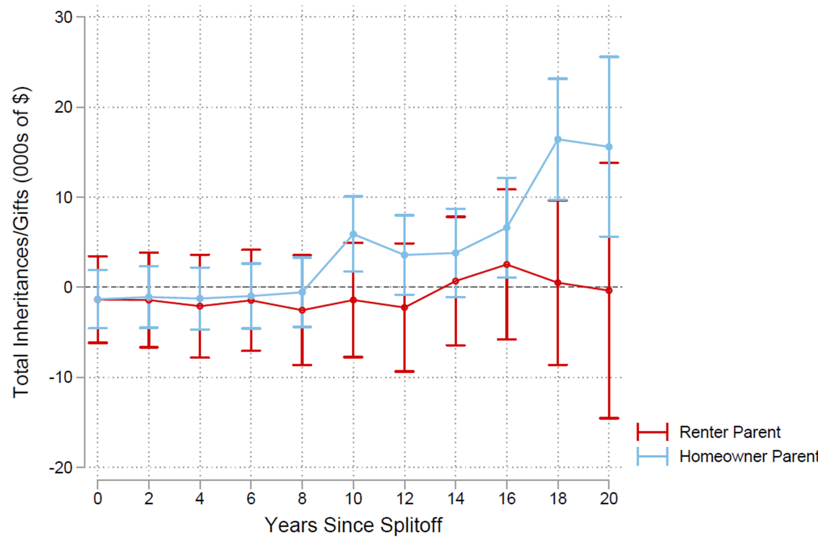
sense that it wouldn't impact income, either.

4.4.2 Inheritance

Another way parents could affect a child's wealth is through direct intervivos gifts or inheritances and bequests. Figure 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

Figure 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 9.

average life expectancy in the U.S., they are likely still alive, and only just starting to leave inheritances.

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

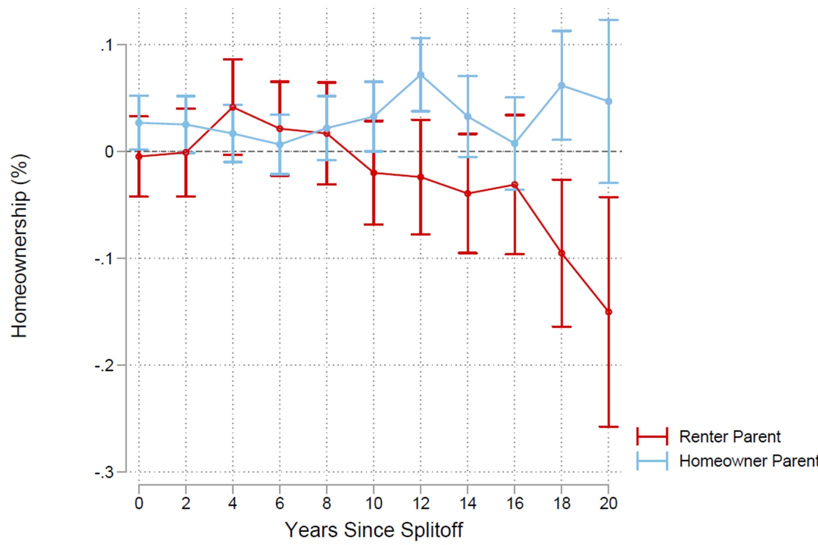
4.4.3 Homeownership

Finally, it could also be 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 12 and Figure 11.

Figure 15 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 15: 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 9.

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.

4.5 Supplementary 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:

$$Y_{ij} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \beta_{2,t-T}\text{Own}^{\text{par}} + \beta_3(\Delta\theta^{\text{par}}_{j,T} \text{ x } \text{Own}^{\text{par}}) \\ + \mu_{t-T} + \beta_4 X_{ij} + \beta_5 X^{par}_T + \epsilon_{ij} \quad (9)$$

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

4.6 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:

	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

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. Additionally, they are also associated with greater rates of homeownership by about 5 percentage points (p.p.). 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 D 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).

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, at the expense of 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 allows me 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.

5 Local Markets and Wealth Inequality in a Parsimonious Model

I begin by studying local labor and housing markets within a stylized 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 intergenerational transfers.

The model incorporates multiple regions, each with its own labor and housing market that must clear separately. Households in the model live 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 are not allowed to be negative. Along with the fact that households only live for one period, this means that expectations of the future are irrelevant in the model, and households do not have to smooth consumption.

I calibrate the model to an initial (steady state and static) equilibrium in T_0 by matching local house prices, local employment by area, deciles of the local wage distribution, and 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.[11] 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.

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.

5.1.1 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.

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

Note that given local labor markets, each productivity type is allowed to have a different wage in each area.

5.1.2 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.

5.1.3 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.

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.

5.2.1 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[12], 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.).

5.2.2 Homeowners

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

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

[12]This follows work by De Nardi (2004) and Lockwood (2018).

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

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 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.

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.

5.4 Population Shares

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

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

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.

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:

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

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 5.2.

2. Firms maximize profits by solving the equations in Section 5.5

3. Labor, housing, and capital markets clear:

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

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

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

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

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 16 shows the calibration for homeownership rates across wage deciles. The homeownership rate increases almost linearly through the deciles.

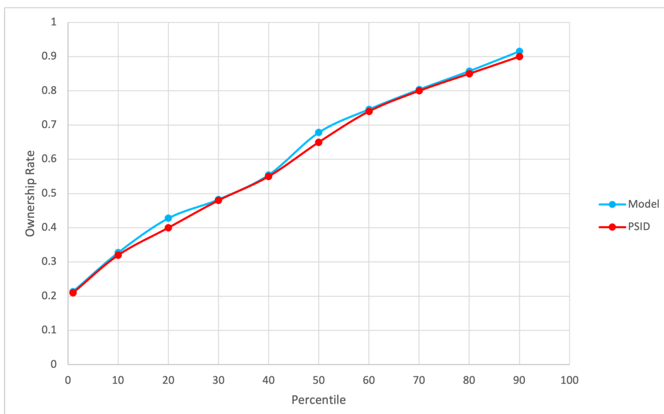


Figure 16: Calibration of Homeownership in Initial Equilibrium

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 17 shows the matching for local employment.

Housing Markets I use house supply elasticities from Saiz (2010) for the parameter 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 18 shows the the exact matching of the FHFA price index in the initial equilibrium.

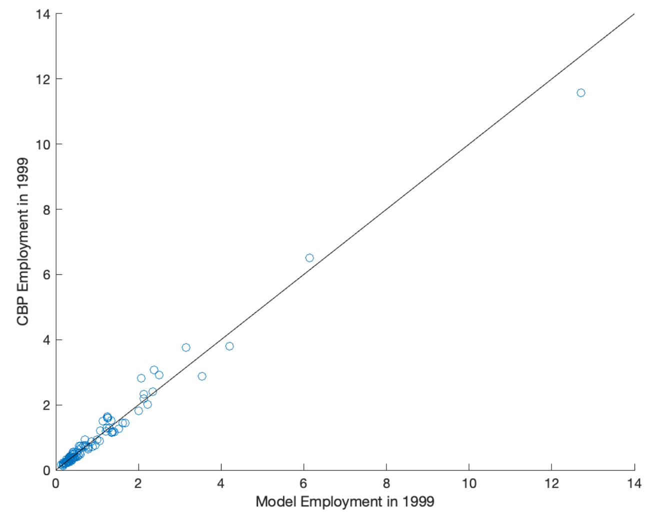


Figure 17: Calibration of Employment in Initial Equilibrium

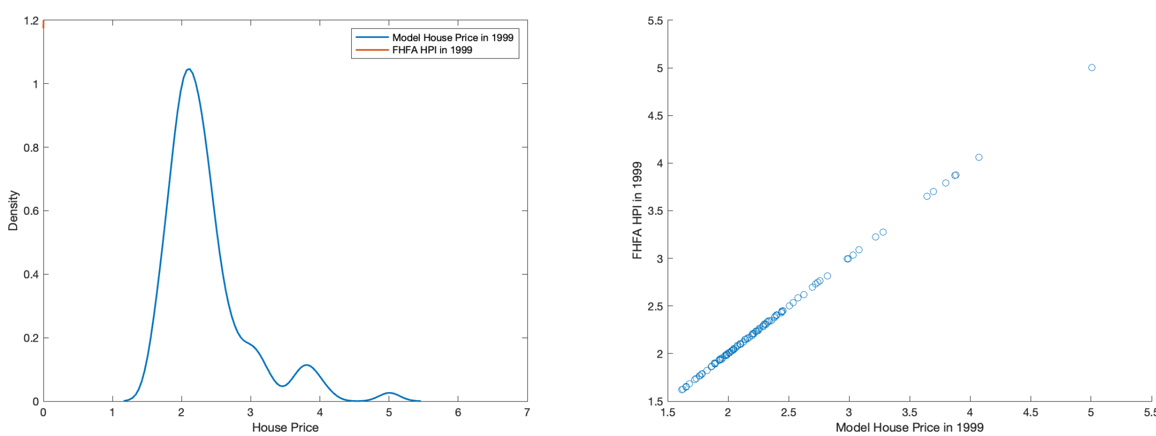


Figure 18: Calibration of House Prices in Initial Equilibrium

Summary Table 4 provides a summary of the parameters I use in the calibration. Appendix G describes the data sources I use in the model in greater detail.

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

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 4: Summary of Parameters

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.

5.10 Results from Main Model

5.10.1 House Prices

Figure 19 shows the house prices distribution that results from the model in the final equilibrium. 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.

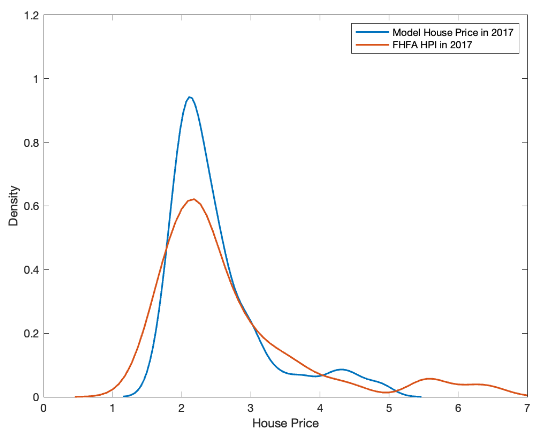


Figure 19: Comparing Model-Generated House Price Distribution to FHFA HPI in 2017

Figure 20 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 18).

5.10.2 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.

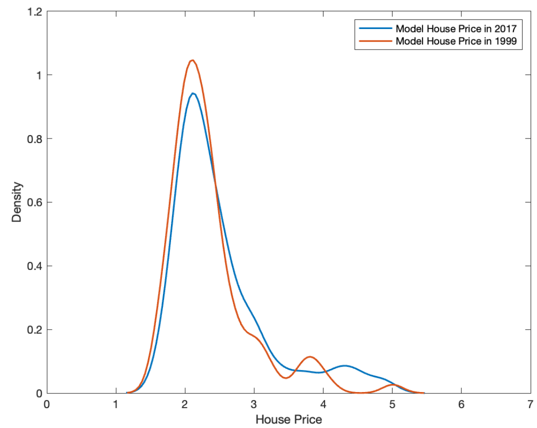


Figure 20: Comparing Model-Generated House Price Distribution in 1999 and 2017

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 3, where a change in homeownership rates is the second more important component of the overall change in mean wealth between 1999 and 2019.

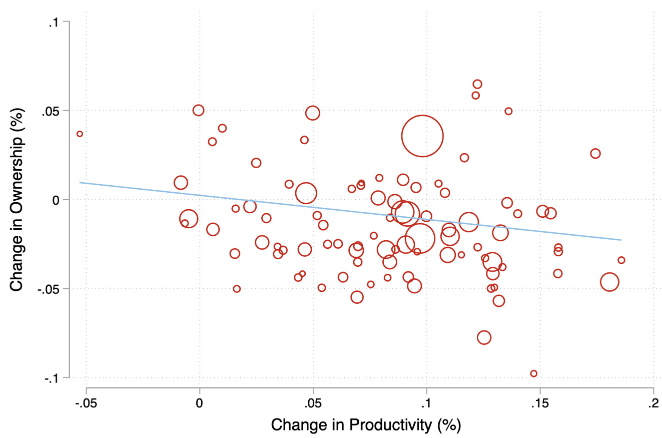


Figure 21: Ownership and Homeownership in the Model

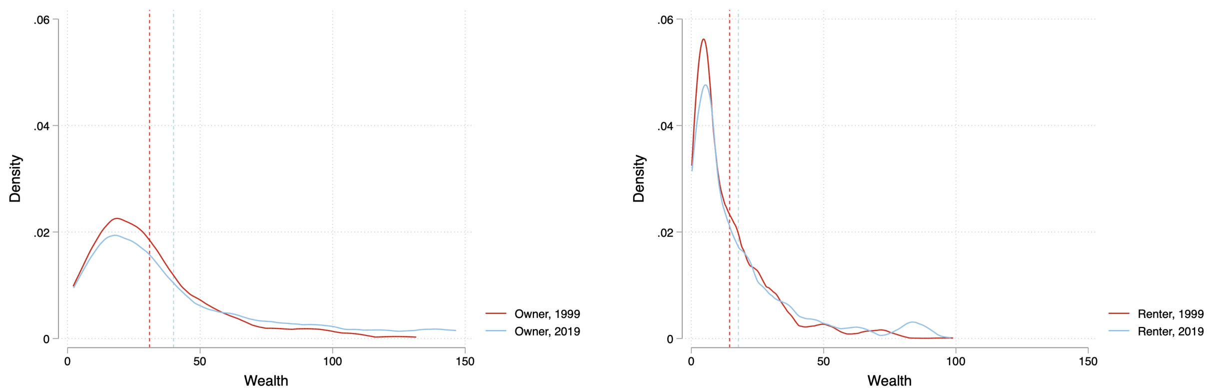


Figure 22: Wealth Distributions of Owners and Renters

5.10.3 Wealth Inequality in the Model

Figure 22 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 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,

	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 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 6: 90/50 Ratio in Model and PSID Data

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. These can be found in Table 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 amongst 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.

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

Table 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.

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.

5.12.1 What if all labor markets grew equally?

San Francisco and Detroit 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 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 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 8 and Table 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 cities like Detroit and San Francisco grow at different rates and not the same rate is responsible for 40% of the increase in wealth inequality amongst the bottom 90% of households in the United States.

5.12.2 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 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 10.

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

Table 10: Increase in Gini Coefficients in Model Without Homeownership

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

Table 11: Increase in 90/50 Ratio 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 to homeownership. Moreoever, this percentage increases to 80% if we consider the increase in the 90/50 ratio (Table 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.

5.12.3 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 12 (changes in Gini coefficients) and Table 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 12).

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

Table 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 13: Increase in 90/50 Ratio in Model With Perfectly Elastic Housing Markets

5.12.4 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 14 (Gini coefficients) and Table 15 (90/50 ratios).

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 ratio increases by 1.20 compared to 1.06 in the main model. This indicates that labor mobility across the United

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

Table 14: Increase in Gini Coefficients in Model Without Geographic Mobility

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

Table 15: Increase in 90/50 Ratio in Model Without Geographic Mobility

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.

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. 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 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. Using this model, I find that dispersion in labor market growth across areas can explain approximately 40% of the increase in wealth inequality amongst 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.

References

Aladangady, A. (2017). Housing wealth and consumption: Evidence from geographically-linked microdata. *American Economic Review 107*(11), 3415–46.

Bartik, T. J. (1991). Boon or boondoggle? the debate over state and local economic development policies.

Becker, G. S. and N. Tomes (1986). Human capital and the rise and fall of families. *Journal of labor economics 4*(3, Part 2), S1–S39.

Blanchard, O. J. and L. F. Katz (1992). Regional evolutions. *Brookings papers on economic activity 1992*(1), 1–75.

Borusyak, K., P. Hull, and X. Jaravel (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies 89*(1), 181–213.

Bound, J. and H. J. Holzer (2000). Demand shifts, population adjustments, and labor market outcomes during the 1980s. *Journal of labor Economics 18*(1), 20–54.

Brandsaas, E. E. (2021). *Essays in Macroeconomics and Household Finance*. The University of Wisconsin-Madison.

Callaway, B., A. Goodman-Bacon, and P. H. Sant'Anna (2021). Difference-in-differences with a continuous treatment. *arXiv preprint arXiv:2107.02637*.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics 129*(4), 1553–1623.

Daysal, N. M., M. F. Lovenheim, and D. Wasser (2022). " the intergenerational transmission of housing wealth. Technical report.

De Nardi, M. (2004). Wealth inequality and intergenerational links. *The Review of Economic Studies 71*(3), 743–768.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980–2000. *The American Economic Review 106*(3), 479–524.

Engelhardt, G. V. and C. J. Mayer (1998). Intergenerational transfers, borrowing constraints, and saving behavior: Evidence from the housing market. *Journal of Urban Economics 44*(1), 135–157.

Fisher, J. D., D. S. Johnson, T. M. Smeeding, and J. P. Thompson (2022). Inequality in 3-d: Income, consumption, and wealth. *Review of Income and Wealth 68*(1), 16–42.

Gale, W. G. and J. K. Scholz (1994). Intergenerational transfers and the accumulation of wealth. *Journal of Economic Perspectives 8*(4), 145–160.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2017). Bartik instruments: What, when, why and how. *Unpublished Working Paper*.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277.

Greaney, B. (2020). The distributional effects of uneven regional growth.

Guren, A. M., A. McKay, E. Nakamura, and J. Steinsson (2021). Housing wealth effects: The long view. *The Review of Economic Studies 88*(2), 669–707.

Hornbeck, R. and E. Moretti (2018). Who benefits from productivity growth? direct and indirect effects of local tfp growth on wages, rents, and inequality. Technical report, National Bureau of Economic Research.

Karabarbounis, L. and B. Neiman (2014). The global decline of the labor share. *The Quarterly journal of economics 129*(1), 61–103.

Killewald, A., F. T. Pfeffer, and J. N. Schachner (2017). Wealth inequality and accumulation. *Annual review of sociology 43*, 379.

Kotlikoff, L. J. and L. H. Summers (1981). The role of intergenerational transfers in aggregate capital accumulation. *Journal of political economy 89*(4), 706–732.

Lockwood, L. M. (2018). Incidental bequests and the choice to self-insure late-life risks. *American Economic Review 108*(9), 2513–50.

Lovenheim, M. F. (2011). The effect of liquid housing wealth on college enrollment. *Journal of Labor Economics 29*(4), 741–771.

Lovenheim, M. F. and C. L. Reynolds (2013). The effect of housing wealth on college choice: Evidence from the housing boom. *Journal of Human Resources 48*(1), 1–35.

Mazumder, B. (2018). Intergenerational mobility in the united states: What we have learned from the psid. *The Annals of the American Academy of Political and Social Science 680*(1), 213–234.

Mian, A., K. Rao, and A. Sufi (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics 128*(4), 1687–1726.

Moll, B., L. Rachel, and P. Restrepo (2021). Uneven growth: automation's impact on income and wealth inequality. Technical report, National Bureau of Economic Research.

Moretti, E. (2013). Real wage inequality. *American Economic Journal: Applied Economics 5*(1), 65–103.

Notowidigdo, M. J. (2011). The incidence of local labor demand shocks. Technical report, National Bureau of Economic Research.

Pfeffer, F. T. and A. Killewald (2019). Intergenerational wealth mobility and racial inequality. *Socius 5*, 2378023119831799.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of political Economy 90*(6), 1257–1278.

Rosen, S. (1979). Wage-based indexes of urban quality of life. *Current issues in urban economics 3*, 324–345.

Saez, E. and G. Zucman (2016). Wealth inequality in the united states since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics 131*(2), 519–578.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics 125*(3), 1253–1296.

Spilerman, S. and F.-C. Wolff (2012). Parental wealth and resource transfers: How they matter in france for home ownership and living standards. *Social Science Research 41*(2), 207–223.

Straub, L. (2019). Consumption, savings, and the distribution of permanent income. *Unpublished manuscript, Harvard University*.

Topel, R. H. (1986). Local labor markets. *Journal of Political economy 94*(3, Part 2), S111–S143.

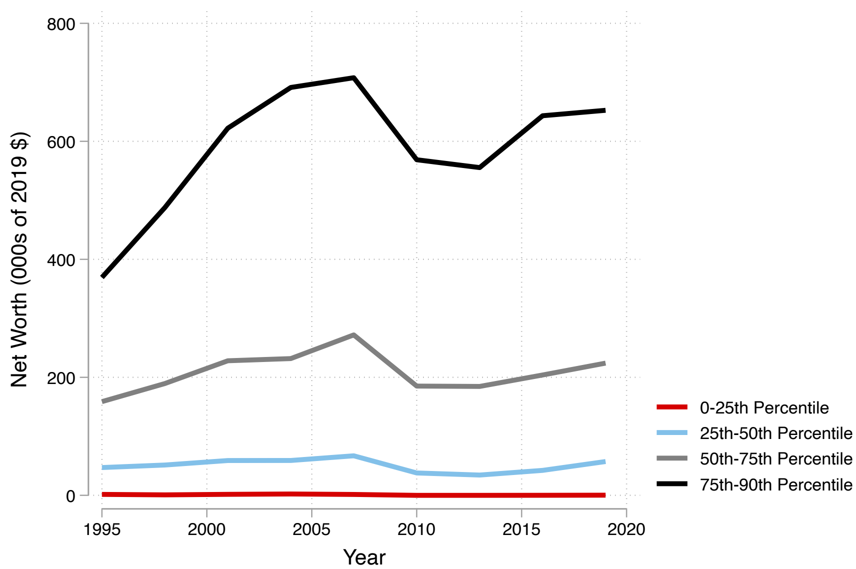
Wolff, E. N. and M. Gittleman (2014). Inheritances and the distribution of wealth or whatever happened to the great inheritance boom? *The Journal of economic inequality 12*(4), 439–468.

Zabek, M. (2017). Local ties in spatial equilibrium.

A Wealth Inequality amongst the Bottom 90%

It is worth noting that while a lot 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 amongst 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]

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



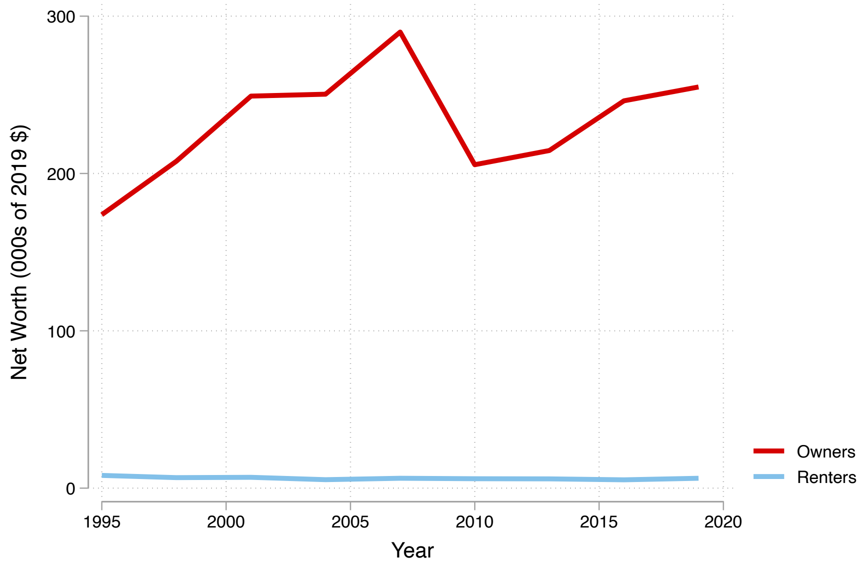
This figure plots the evolution of median net worth between 1995 and 2019. The numbers are calculated from the Survey of Consumer Finances (SCF). Median net worth is plotted according to four percentile groups: 0-25th percentile, 25th-50th percentile, 50th-75th percentile, and 75th-90th percentile. The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

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 in the Survey of Consumer Finances. This figure shows how the wealth of owners has been growing over this period, while the wealth of

[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.

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.

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.

B Empirics: Regression Tables

This section presents results from estimating Equation 4.2.4 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 4 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 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.

C 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

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

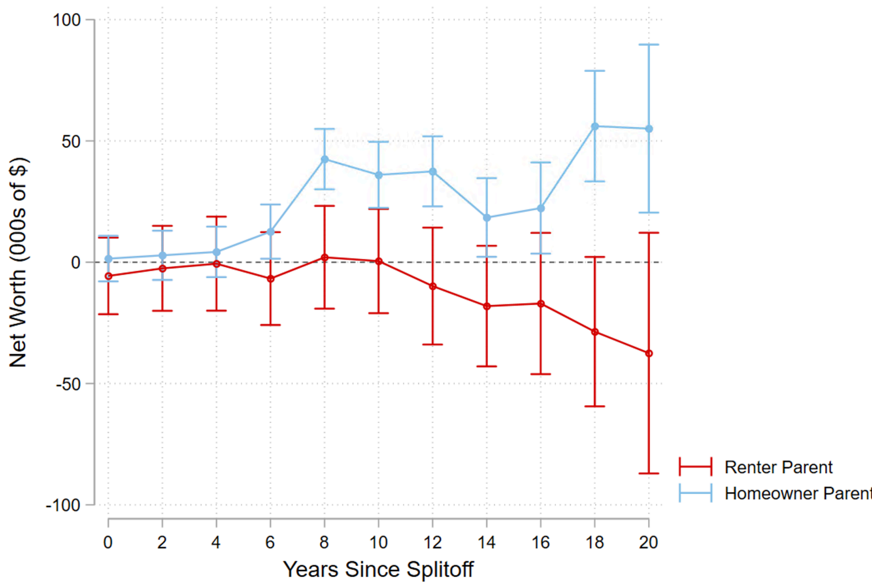
		Net Worth
Labor Demand Growth		-19.508**
		(8.735)
Years Since Splitoff x Labor Demand Growth	2	1.597
		(11.547)
	4	5.304
		(12.302)
	6	-0.303
		(12.240)
	8	10.876
		(13.061)
	10	9.184
		(13.225)
	12	-3.890
		(14.277)
	14	-13.314
		(14.693)
	16	-9.962
		(16.647)
	18	-18.766
		(17.509)
	20	-25.804
		(25.965)
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 4.2.4. These are the numbers that are used to produce the graphs in Section 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.

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.

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.



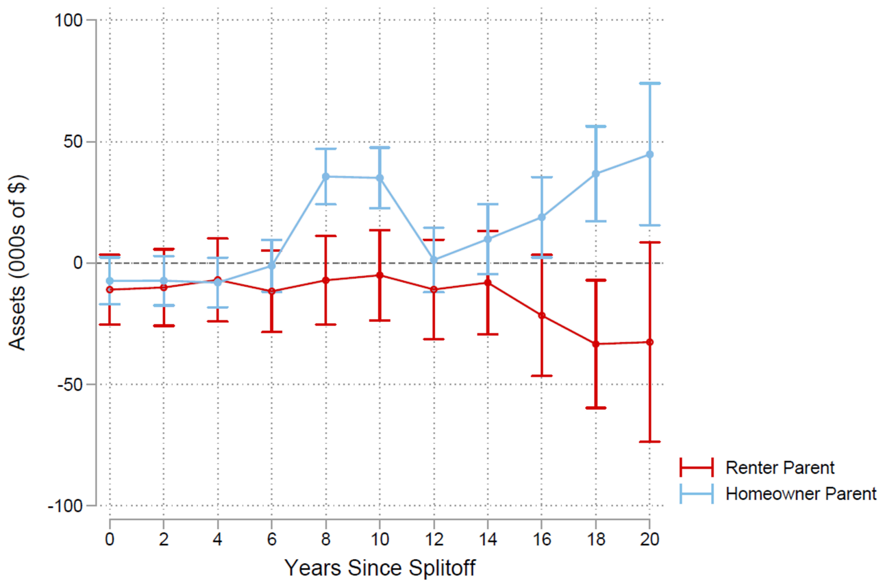
This figure plots the association of a 1 s.d. better parental labor market with the net worth of a child without accounting for parental area fixed effects. it indicates that for the children of homeowner parents, better parental labor markets are associated with an increase in net worth of almost $55,000. 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.

D Association of Better Parental Labor Markets with Other Measures of Wealth

D.1 Assets and Debt (No Home Equity)

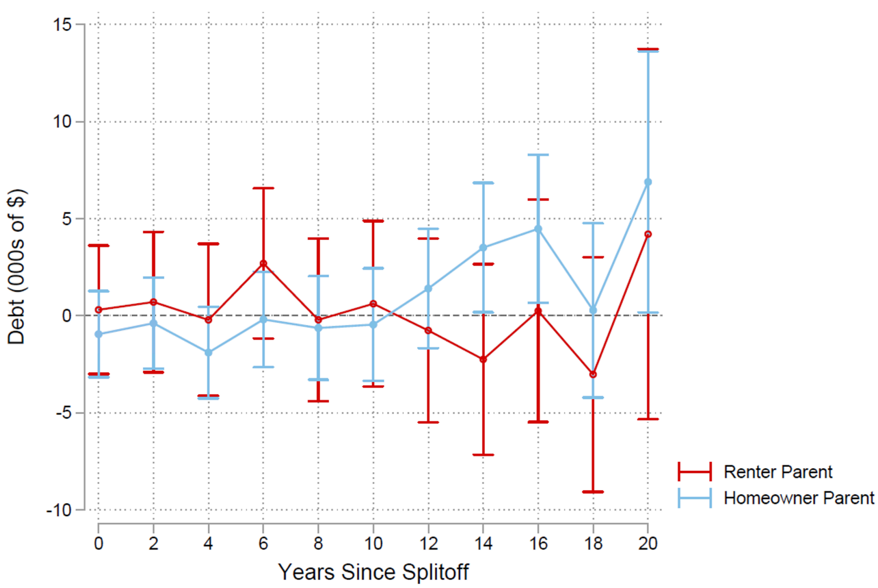
I am also able to split total net worth (without home equity) into assets and debts – effects on these are plotted in Figure A.4 and Figure A.5 respectively. It is worth noting that almost all of the effect comes from assets, and there is no effect of the labor demand shock on debt. This is true even 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)

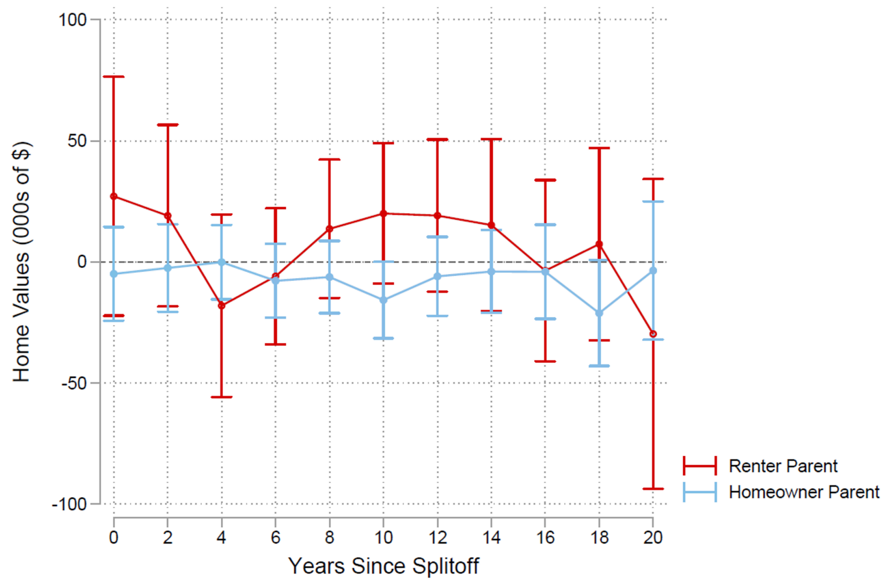


This figure plots the association of a 1 s.d. better parental labor market with the child's debt holdings.

D.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 amongst 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 amongst 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.

D.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.

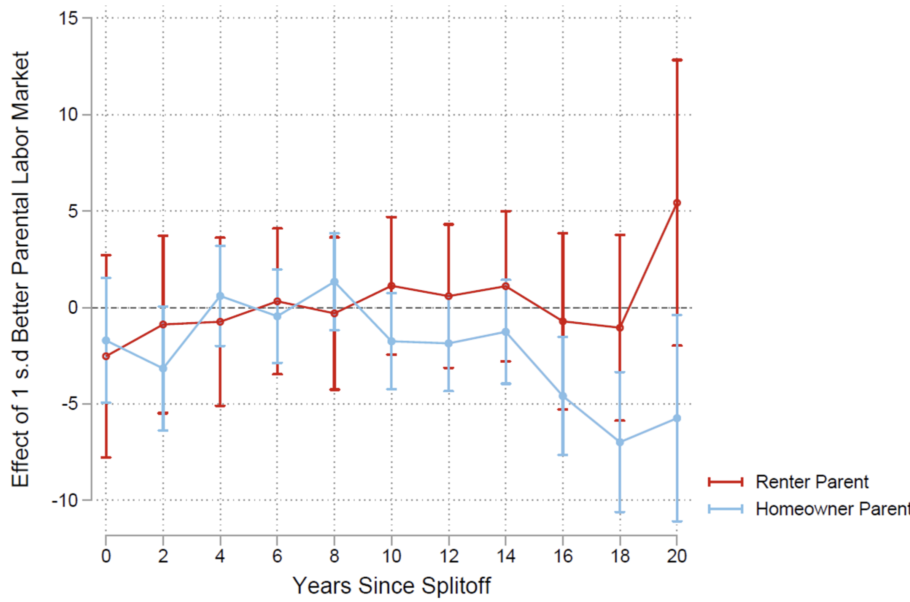
There is no robust effect on any of the debt variables that I look at, although qualitatively, it does appear that children of homeowning parents take on less college debt, which is also consistent with the literature. However, there isn't enough power in the data to get at these differences in a statistically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

D.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 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.

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.

E Association by Parental Ownership of Financial Stock

F Identifying Variation and Distribution of Labor Demand Growth

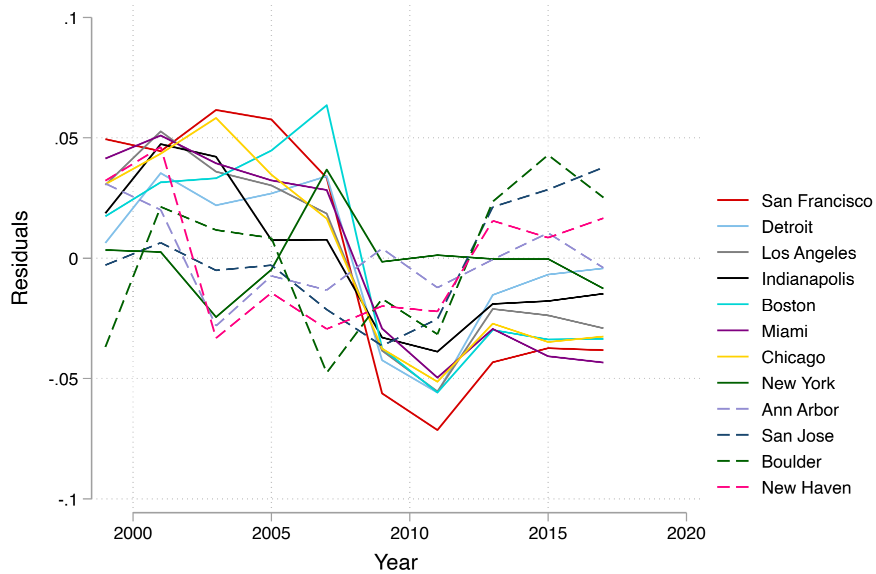
It is worth investigating the underlying variation in the key explanatory variable, $\Delta\theta_{j,T}$, which is the local growth in labor demand across all industries in the area. Recall that this is the amount that an area's labor market employment has grown due to national level growth in industries, 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:

$$\Delta\theta_{j,T} = \beta_0 + \beta_1\mu_T + \beta_2\lambda_j + \epsilon_{j,T} \tag{10}$$

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. Next, I present the trend in these residuals by area. Specifically, these are plotted for some major CBSAs in Figure A.8. The residuals represent the relative performance of an area over time, so that a positive value means that an

Figure A.8: 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 Equation 10, 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.

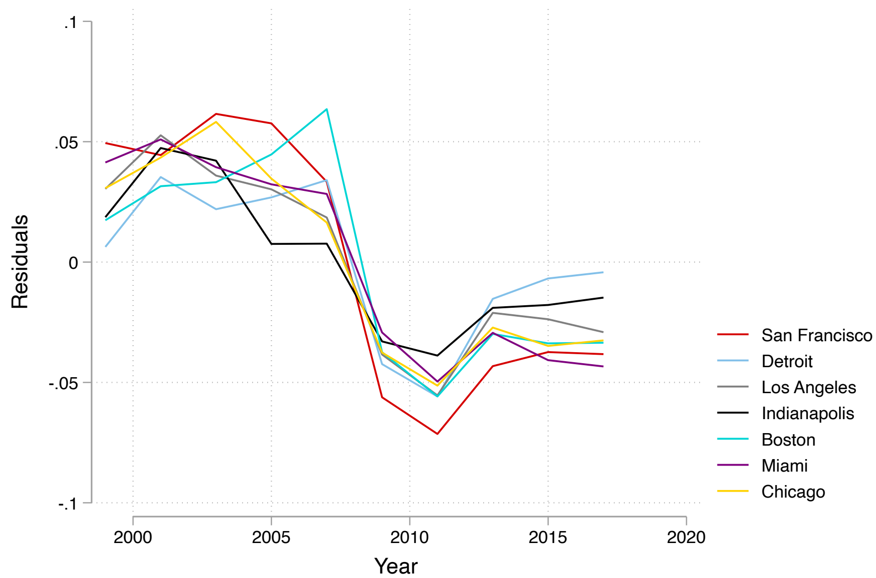
area outperformed its average, while a negative one means that labor demand growth was slower (or even negative) than average. The graph suggests that most areas did relatively well in the earlier periods, with only Boulder, CO showing poor growth between 1989 and 1999 (which is the 1999 coefficient). 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.9). 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.11), 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.10).

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.

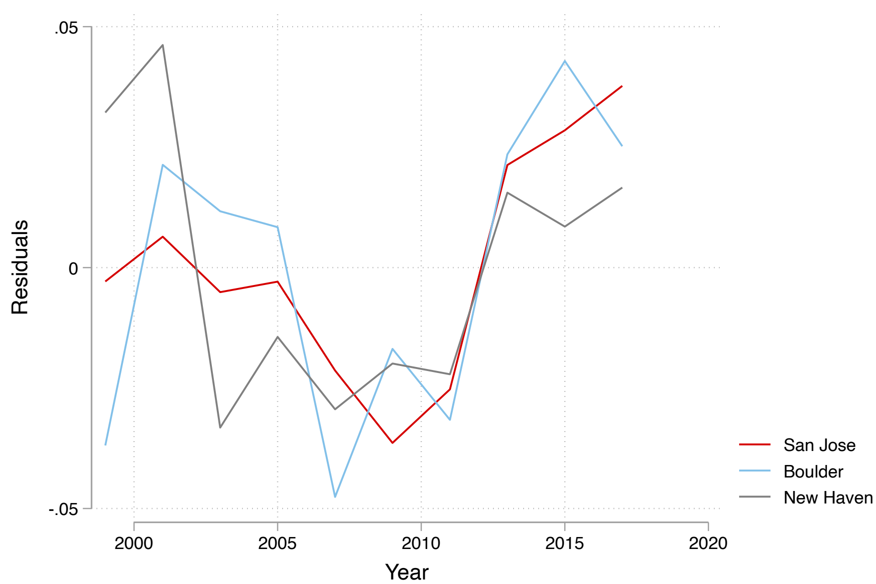
These patterns also reflect the spatial distribution of labor demand growth itself. Figures A.12, A.13, and A.14 present the spatial distribution of labor market growth between 1989 and 1999, between 1999 and 2009, and between 2007 and 2017 respectively. Between 1989 and 1999, most

Figure A.9: 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 Equation 10, 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.10: 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 Equation 10, 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.11: Identifying Variation Over Time in Selected CBSAs: Constant Growth

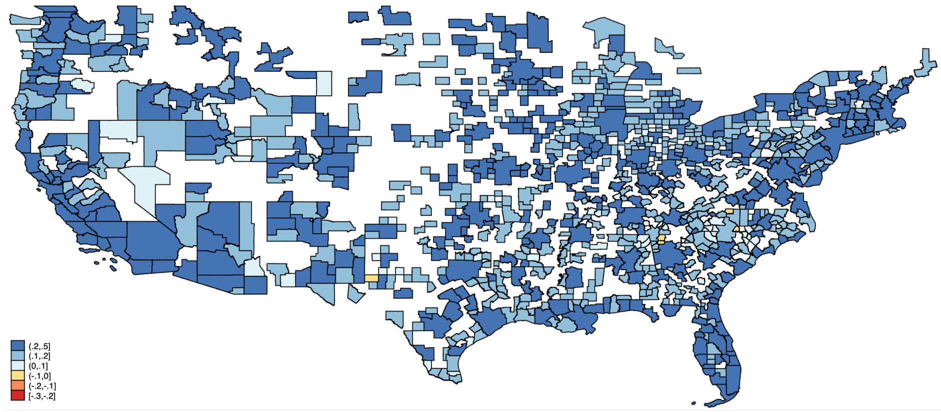
This figure plots the identifying variation that is leveraged to estimate the main regression in the paper for selected areas that showed a consistent level of growth across periods. Specifically, it plots residuals from estimating Equation 10, which regresses the 10 year labor demand growth in an area 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.

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 of labor demand growth calculated over a shorter period (Figure A.16) vs. a longer one (Figure A.15). 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.

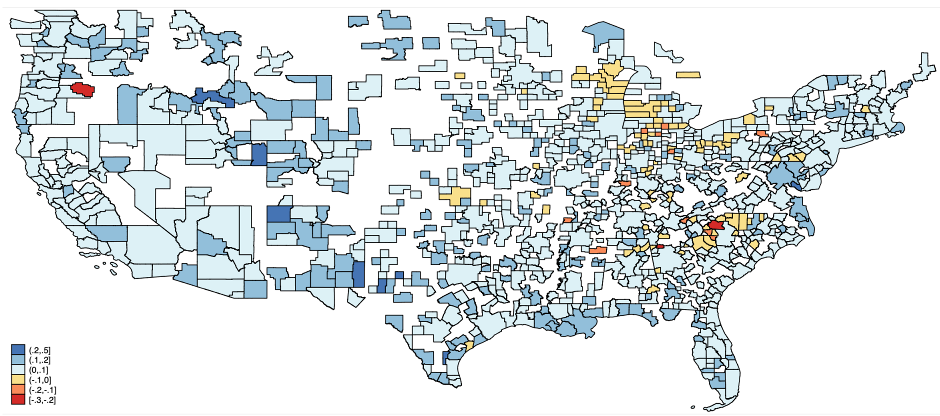
G Other Data Sources Used for Model

Figure A.12: Spatial Distribution of Labor Demand Growth Between 1989 and 1999



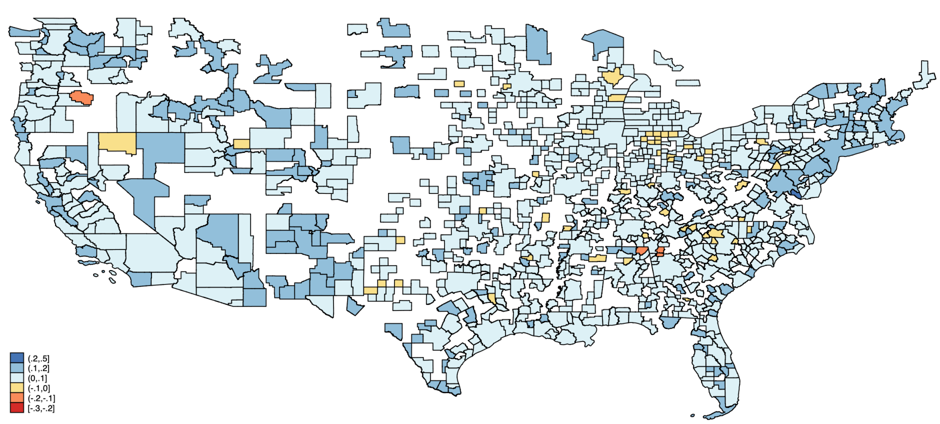
This figure plots labor demand growth between 1989 and 1999 across the United States. We see that most areas grew very strongly in this time period.

Figure A.13: Spatial Distribution of Labor Demand Growth Between 2001 and 2011



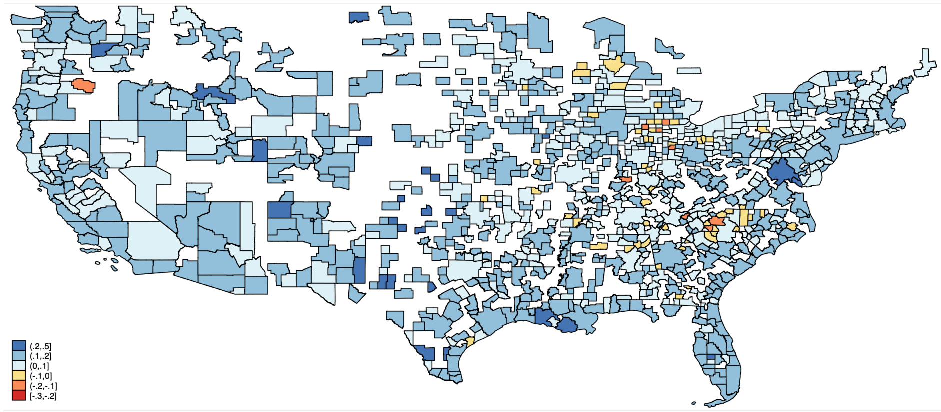
This figure plots labor demand growth between 2001 and 2011 across the United States. We see a greater heterogeneity in growth in this period, primarily due to the heterogeneous effects of the Great Recession. Areas in the so-called Rust Belt particularly did poorly in this time period.

Figure A.14: Spatial Distribution of Labor Demand Growth Between 2007 and 2017



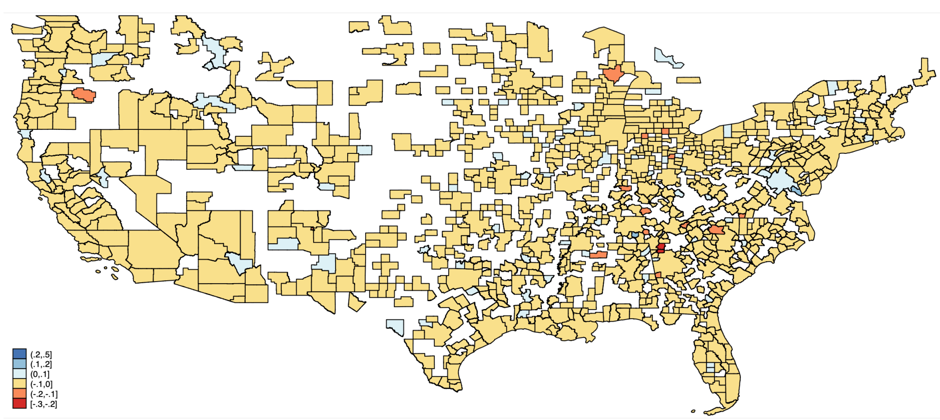
This figure plots labor demand growth between 2007 and 2017 across the United States. We see that areas have started recovering from the Great Recession in this period, although some scarring effect still remains, particularly in the Rust Belt.

Figure A.15: 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.

Figure A.16: 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.

G.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 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.

G.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 **??**, 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.