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. There is a knock on effect of this divergence on wealth, especially housing wealth, which persist across generations. This paper asks how local markets of parents shape their children's wealth and affect wealth inequality. I find that a 1 s.d. better labor market experience of parents is associated with a $30,000 higher net worth of the children, twenty years after the children split off to form their own household. This is only true for children of homeowning parents. To measure the aggregate effect of this divergence on wealth inequality, I build a parsimonious model with multiple areas 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

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1 Introduction

The recent increase in wealth inequality within the United States (documented by Saez and Zucman (2016), amongst others) has led to debates about its extent and causes both within economics and public policy. Moreover, 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%. Taken together with the earlier facts about housing wealth, 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. Specifically, I build an intergenerational dataset of households in the U.S. using the Panel Study of Income Dynamics (PSID), 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. 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. I find that children of parents who experienced better labor markets do, in fact, accumulate more wealth, but all of the effect comes from the children of *homeowner* parents. Children of renter parents do not show any response in their wealth accumulation, and if anything, are negatively affected. I also find that there is an increase in gifts or inheritances received by the children of homeowning parents, but 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 model of local labor and

[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, and moreover also has a positive effect on college quality, especially for lower wealth households (Lovenheim and Reynolds, 2013). This is, of course, in addition to how parental wealth (as opposed to only parental housing wealth) can affect children's outcomes: Killewald et al. (2017) studies the effects on children's education, while Brandsaas (2021) examines the role of parental help in paying the down-payment for a home.

housing markets with homeownership and location choice. 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 reaction of local housing markets to local labor markets 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.

I use data from a variety of sources to provide some baseline empirical facts about the association of local labor markets experienced by parents with the wealth accumulation of their children. I define local areas as Core Based Statistical Areas (CBSAs) because they capture large urban centers where households live and work in the same CBSA. The strength of labor markets in these areas is measured using employment statistics by county from the County Business Patterns (CBP) dataset. I use the Panel Study of Income Dynamics (PSID)[3] to capture wealth holdings at the household level. As such, the PSID is the only household level survey in the United States that allows me to observe the wealth of households over time[4], link across generations, and observe the area in which the parents and children live[5]. I merge this dataset with information about the parent's local labor market growth in the ten year priors to the child splitting off. 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. Using this final dataset, I am able to follow children as they split off from their parents' home and form their own household, and study how the wealth accumulation of children varies with the strength of the local labor markets their parents were exposed to.

The main empirical strategy employs an event study style specification. The "event" 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. [6] Formally, the regression compares children who split off from a parent in an area when it had experienced a one standard deviation better growth in local labor demand to children who split off when the area wasn't doing as well. To fix ideas, one can think of 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.

[3]The PSID has been the primary data source in the literature on wealth mobility (Mazumder (2018)).

[4]Regular measures of wealth were only collected by the PSID starting in 1999. Before this interview round, wealth data was only collected in 1984, 1989, and 1994, which motivates the timeline that I focus on. However, starting in 1999, PSID collects data on wealth every two years, with the latest data release being in 2019.

[5]The location of households is available in the restricted-use version of the dataset.

[6]However, note that this isn't a conventional event study because as such, there is no "pre" period, since household wealth of the child is not observed before split-off. 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.

Local labor markets can also have distinct effects depending on parental homeownership, because this determines the extent and channels through which local markets could affect wealth. It is therefore useful to break down the association found in the "event study" exercise by parental homeownership. 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 the children of households who experience better labor markets accumulate significantly more wealth after they split off from their parental home – twenty years after splitting off (i.e., when these children are on average 45 years of age), kids of parents who experienced one standard deviation better labor markets have a higher net worth by almost $30,000. This effect only exists for children of homeowner parents, which suggests that the effect of local labor and housing markets on housing wealth is particularly salient for the parent. I find that almost the entire effect on the child's wealth is driven by the *non-housing* part of the wealth portfolio of the child, which is higher by $20,000, twenty years after splitting off. On the other hand, there is no effect on the home equity of children.

However, I find that these children are about 5 percentage points more likely to be homeowners themselves, and receive additional inheritances or gifts of around $10,000. Surprisingly, there is no effect on the labor income of children, and so almost all the differences in net worth I observe are driven by gift receipt. 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%. Appendix A provides some descriptive evidence of the increase in wealth inequality in this population. 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 these using the data. In order to make a first pass at quantifying some of these channels, I build a parsimonious, two-period model with multiple areas, each with its own labor and housing markets, where households can choose homeownership and location.

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 both 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.[7] In this way, local markets have multiple effects on wealth: first, they have a direct effect through savings rates, which drives up their wealth; second, they have an

[7]Technically, this is true only as long as housing supply is not perfectly elastic.

indirect effect on wealth due to the pass through of the increased wages onto house prices, i.e., there is an additional benefit that accrues to homeowners in the area due to the general equilibrium effect of labor markets on housing markets. Finally, at the end of the period, households die after leaving bequests to the next generation – crucially, homes are part of the bequests that parents make, but of course only if the parents are homeowners. 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. I then feed in local increases in productivity in 2019, and solve for the "final" equilibrium. The main quantitative exercise is to compare the initial and final equilibria under different conditions.

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 about 72% of the increase observed in the data. I also conduct various quantification exercises to measure how much the various channels mentioned below contribute to the rise in wealth inequality amongst the bottom 90% of households between 1999 and 2019. 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 an increase of about 0.02 points of the gini (about 40%) of the increase in the wealth Gini; allowing homeownership in the model is responsible for an increase of about 0.03 points (60%). However, heterogeneity in local house supply elasticities only accounts for a rise of 0.003 points (8%). Finally, shutting off labor mobility would increase inequality by an additional 0.01 points (13%).

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, which in turn people have differing preferences over. Spatial equilibrium models have been the foundation of many subsequent papers that also look at differences in wages and amenities across areas in order to get at inequality in real wages across the United States (Topel (1986), Moretti (2013), Diamond (2016), Notowidigdo (2011), Zabek (2017)). However, this literature has largely treated increases in house prices that follow labor demand shocks as increases in rent, while house price appreciation also mean that the wealth of homeowners increases. My findings indicate that the fact that some of the people living in an area own their residence is quantitatively relevant in determining how they react to labor market shocks, and depends on how much house prices change in that area.

Second, this paper relates to the literature on the documentation, determinants, and causes of wealth inequality. Saez and Zucman (2016) focus on the very top of the wealth distribution and find a salient role for taxes in determining wealth inequality, while Moll et al. (2021) focus on how automation and skill biased technological change affect wealth inequality. Other studies, such as Fisher et al. (2022) and Killewald et al. (2017), among others, document the increase in wealth inequality in the United States. The latter also points out the crucial role of housing wealth in the rise in inequality. However, this literature does not delve into the role of local labor and housing markets in determining wealth inequality.

Third, the paper relates to the literature on intergenerational transfers. Homeownership in particular plays an important role in bequests and intergenerational wealth-building. It 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. Moreover, 90% of wealth transfers come from parents or grandparents (Wolff and Gittleman, 2014). If most wealth is passed on from one generation to the next in this way, then understanding the factors that might make these transfers more persistent, or more unequal, is important for policy makers who want to target wealth inequality. 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 (see, among others, Becker and Tomes (1986) Kotlikoff and Summers (1981), De Nardi (2004), Pfeffer and Killewald (2019)). Further, Illiquid assets play a major role in bequests and are considered a good potential predictor of bequest expectations (Kao et al., 1997), which suggests that housing may have a strong influence on bequest expectations. However, none of these papers consider the role of local labor and housing markets, especially how divergence within these markets can lead to an increase in intergenerational wealth inequality.

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 differs from Greaney (2020) in three key dimensions. First, I focus on direct household level measurement of wealth portfolios, which is absent in Greaney (2020). Second, and most importantly, I analyze how the labor markets faced by parents affect the wealth accumulation of children as they split off, something that is not the subject of Greaney (2020). Finally, the focus of my paper is not on the fundamentals of local housing markets per se, but to quantify how changes in local labor market conditions affect wealth in general, and how these advantages can persist across generations.

The paper proceeds as follows. Section 2 decomposes the change in mean wealth between 1999 and 2019 into coming from homeowner or renter households. Section 3 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 markets to quantify various channels that might affect wealth inequality, and Section 6 concludes.

2 Decomposing the Change in Mean Wealth

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[8] in 1999. This went up to \$168,022 by 2019, a real increase of almost \$26,000. 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:

$$\Delta\bar{W} = \Delta\tilde{W_O} + \Delta\tilde{W_R} + \frac{\Delta N_O}{N}(\bar{W}_{O,2019} - \bar{W}_{R,2019}) \tag{1}$$

where $W_{O,2019}$ is the wealth of owners in 2019, $N_{O,2019}$ is the number of owners in period 2019, and so on, and:

$$\Delta\tilde{W_O} = \frac{N_{O,1999}}{N}\Delta\bar{W_O} = \frac{N_{O,1999}}{N}(\bar{W}_{O,2019} - \bar{W}_{O,1999}) \tag{2}$$

$\Delta\tilde{W_R}$ is defined similarly. In words, Equation (2) is the change in mean wealth of owners between 1999 and 2019, *holding the proportion of owners in the population constant.*

To aid interpretation, we can divide both sides of Equation (1) by the left hand side to get:

[8] All prices are in real 2017 dollars.

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

Table 1: Mean Wealth for Bottom 90% Households in PSID (in 000s of 2019 dollars)

$$1 = \frac{\Delta \tilde{W_O}}{\Delta \bar{W}} + \frac{\Delta \tilde{W_R}}{\Delta \bar{W}} + \frac{\Delta N_R}{N} \frac{(\bar{W_{R2}} - \bar{W_{O2}})}{\Delta \bar{W}} \tag{3}$$

The first term on the right hand side captures the mean change in the wealth of owners over time, keeping constant the ownership rate. The second term captures a similar change in the mean wealth of renters, keeping constant the ownership rate. The third term is the change in the ownership rate, keeping constant the difference in the mean wealth of owners and renters. Table 1 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:

$$1 = \underbrace{(1.377)}_{\text{Due to change in wealth of owners}} + \underbrace{(-0.0133)}_{\text{Due to change in wealth of renters}} + \underbrace{(-0.364)}_{\text{Due to change in ownership rate}} \tag{4}$$

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.

3 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.

3.1 County Business Patterns (CBP)

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

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 **??**.

3.2 Panel Study of Income Dynamics (PSID)

The Panel Study of Income Dynamics (PSID) is a household survey that began in 1968, and in 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.

For the purposes of this paper, I subtract retirement wealth from all measures. The only form of retirement that the PSID explicitly collects is money in IRA accounts. I exclude this measure since this money cannot be used by a household in their working life and is only available in their retirement. Descriptive statistics for these can be found in Appendix B.

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.

3.3 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.

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.[9] 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

[9]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.

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 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:

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

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.

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:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T}) + \beta_4 X_{ijt} + \beta_5 X^{par}_{T} + \epsilon_{ijt} \tag{6}$$

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. These will be mentioned while discussing the results.

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.

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.

4.2.2 Effect of Labor Demand Growth on 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 does in fact affect 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 2. They imply that a 1 s.d. better growth in labor demand over a 10 year period is associated with a 4 percentage point increase in wages and a 3 percentage point increase in house prices. The raw data is also plotted in Figure 1 (house prices) and Figure 2 (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 3 captures the evolution of household income over the 10-year labor demand growth for a 1 s.d. better labor market, while Figure 4 captures the same for net worth. Both these figures 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 2: Effect of Labor Demand Growth on Local Wages and House Prices

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.

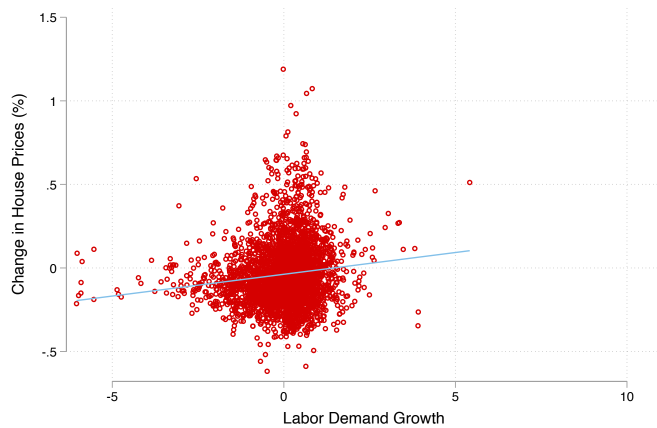


Figure 1: Labor Demand Growth and FHFA House Price Index

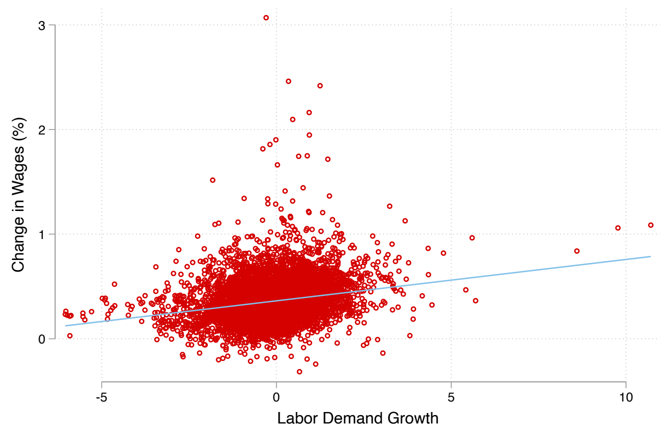


Figure 2: Labor Demand Growth and Local Average Wage

It is also easy to imagine education differences at the time of splitting off for similar reasons.

To see the distribution of these two variables in particular in my sample, I divide households into two groups: those above and below the average level of labor demand growth in the year they split off. I then plot the density of these variables. The results can be seen in Figure 5.

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.

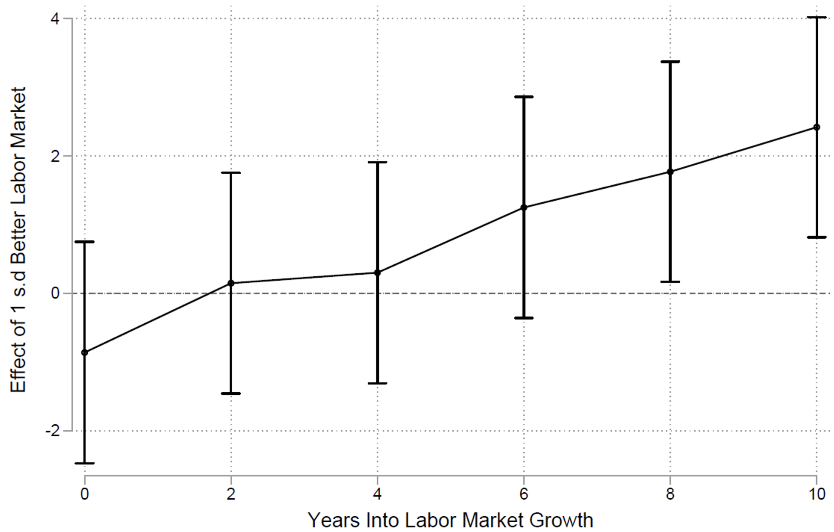


Figure 3: Labor Demand Growth and Labor Income of Households

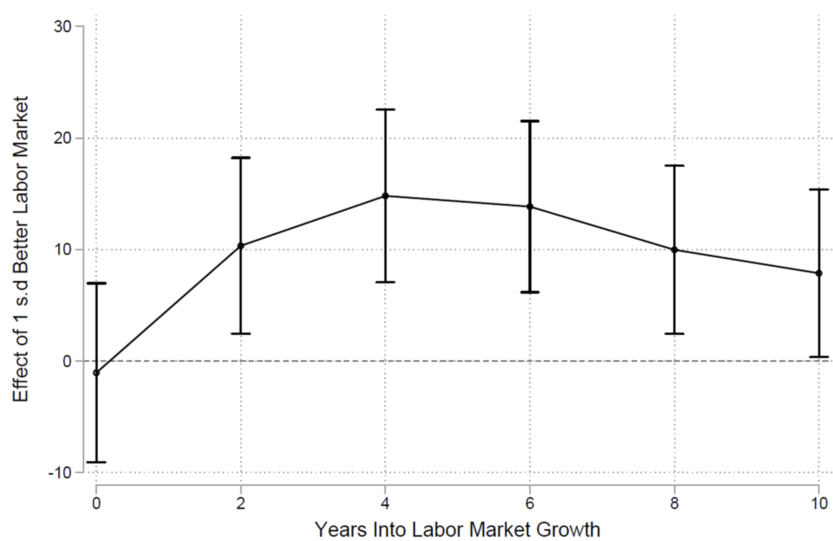
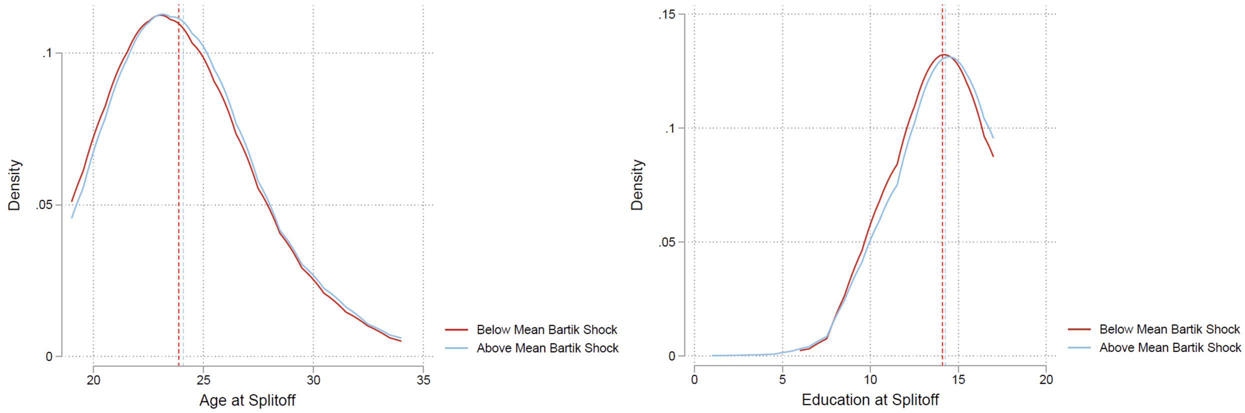


Figure 4: Labor Demand Growth and Net Worth of Households

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



(a) Age at Splitoff

(b) Education at Splitoff

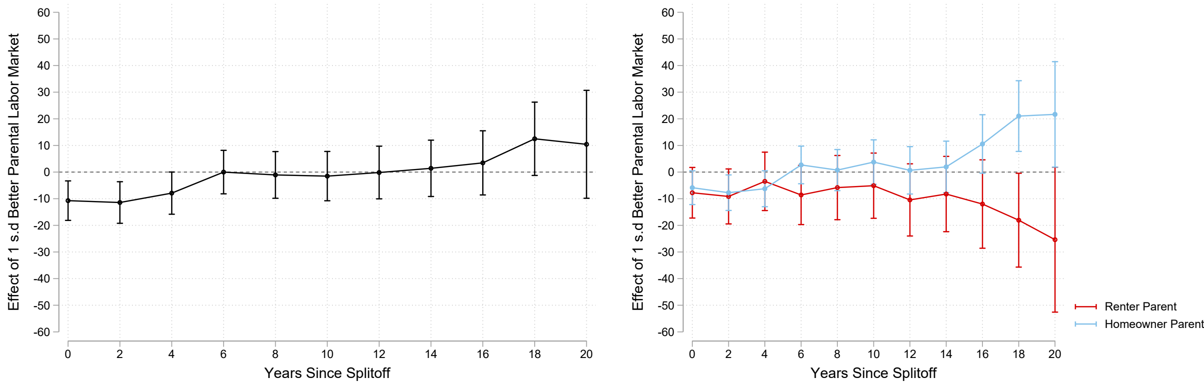
Figure 5: Distribution of variables that could be affected by parental labor markets

an interaction of the labor demand growth with parental homeownership:

$$Y_{ijt} = \beta_0 + \beta_1 \Delta\theta^{\text{par}}_{j,T} + \mu_{t-T} + \beta_{2,t-T}(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T}) \\ + \beta_3(\mu_{t-T} \textbf{ x } \Delta\theta^{\text{par}}_{j,T} \textbf{ x } \text{Own}^{\text{par}}) + \beta_4 X_{ijt} + \beta_5 X^{par}_T + \epsilon_{ijt} \quad (7)$$

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 might not be very plausible, 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.

An alternate reason to do this is to just look at heterogeneity in the effect of labor markets by ownership group. This tells us 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 effect might be hiding this heterogeneity, and performing the triple difference estimation allows us to uncover total effects.



(a) All Parents

(b) By Parental Homeownership

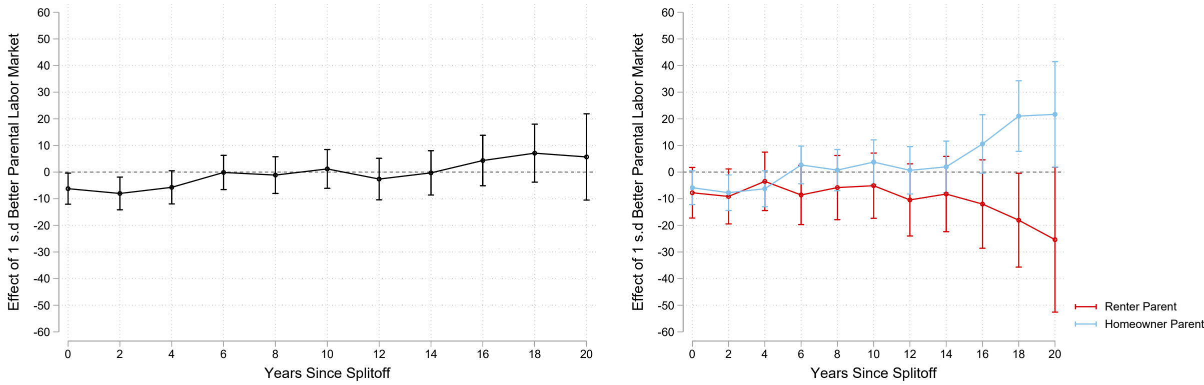
Figure 6: Effect of Parental Labor Markets on Child's Net Worth

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. A table would present coefficients for multiple time periods and be harder to read. Specifically, I calculate the effect of a 1 standard deviation increase in the strength of parental labor markets on wealth every year from splitoff. 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. As mentioned before, I substract the part of this wealth that comes from IRA accounts. The results are plotted in Figure 6. I find that overall, although there is an upward trend in wealth, the effect of the labor demand growth is not significantly positive. However, the figure on the right hand side shows that this is only because there is substantial heterogeneity in the patterns of wealth accumulation in terms of parental homeownership. Children of homeowner parents accumulate much more wealth than their renter parent counterparts, and in fact, a 1 s.d. better parental labor market increases their wealth by about $30,000, on average, 20 years after splitoff.



(a) All Parents **(b)** By Parental Homeownership

Figure 7: Effect of Parental Labor Markets on Child's Net Worth (without Home Equity)

4.3.2 Net Worth without Home Equity

A similar figure is plotted for net worth without home equity in Figure 7. This figure closely follows the one for wealth including equity. 20 years from split off, the effect of a 1 s.d. better parental labor market is $20,000. If anything, children of renter parents actually react negatively to better parental labor markets, although this is not statistically significant. In this way, net worth without home equity accounts for about 67% of the effect described in the previous section.

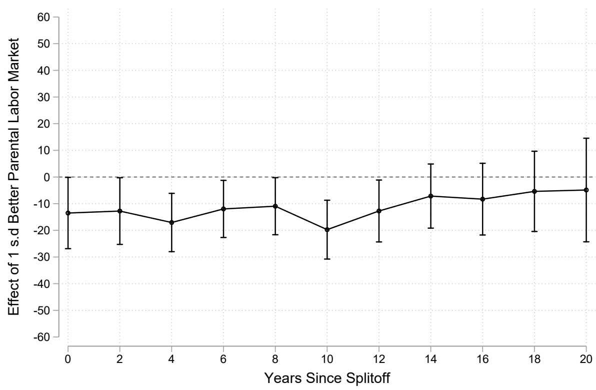
4.3.3 Home Equity

The effect of parental labor demand growth on children's home equity is plotted in Figure 8. I find essentially no effect here, which is surprising. It implies that homeownership is a pretty common phenomenon, and does not depend so much on your parents doing well. It could also be that children of successful parents buy homes that are more expensive, and I look at this in Figure 9. However, this does not seem to be the case either.

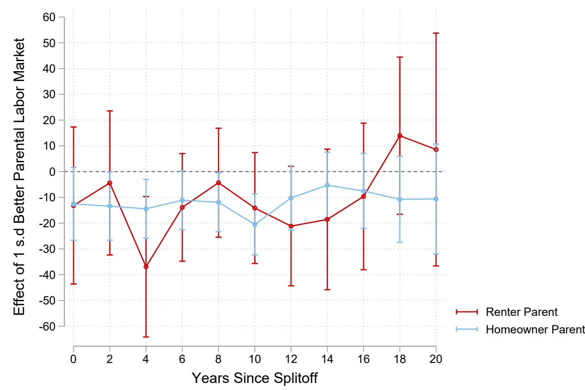
However, recall that all these regressions account for area fixed effects, which soak in a lot of the knock on effects of local markets on measures like home values. This is especially true because children tend to stick close to where their parents live (Zabek (2017)).

4.3.4 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 10 and Figure 11 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.

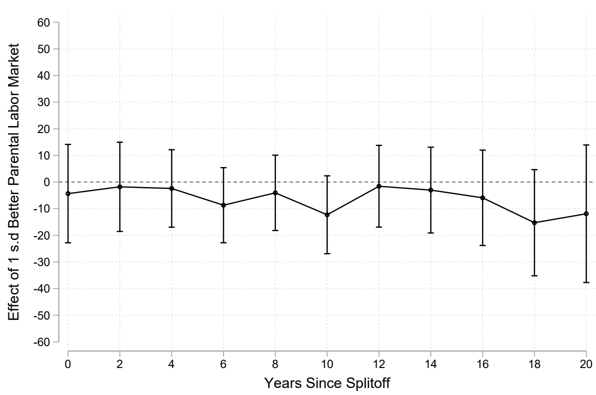


(a) All Parents

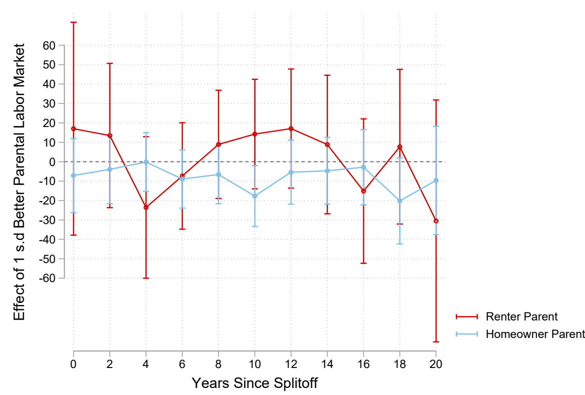


(b) By Parental Homeownership

Figure 8: Effect of Parental Labor Markets on Home Equity

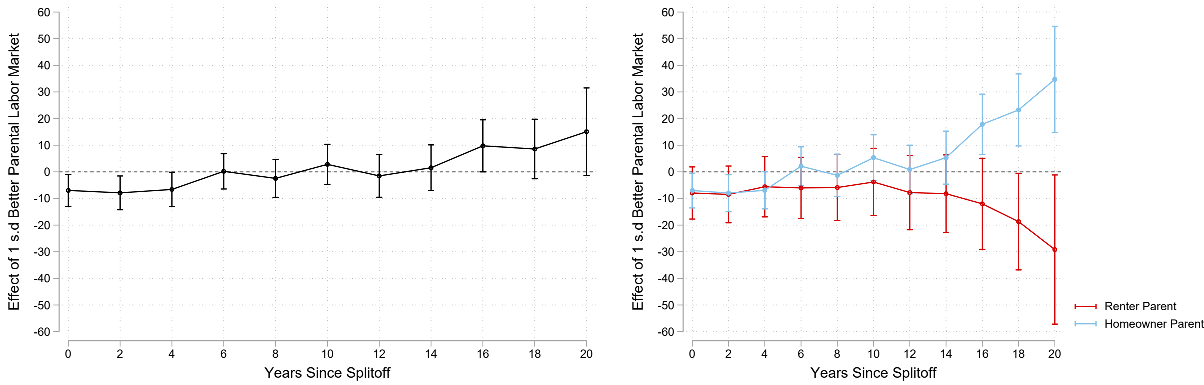


(a) All Parents



(b) By Parental Homeownership

Figure 9: Effect of Parental Labor Market Growth on Child's Home Value



(a) All Parents

(b) By Parental Homeownership

Figure 10: Effect of Parental Labor Markets on Child's Assets (without Home)

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. Alternatively, they could just be earning more and, therefore, saving more in absolute terms as well. These explanations are investigated in more detail in the next section.

4.4 Intermediating Outcomes

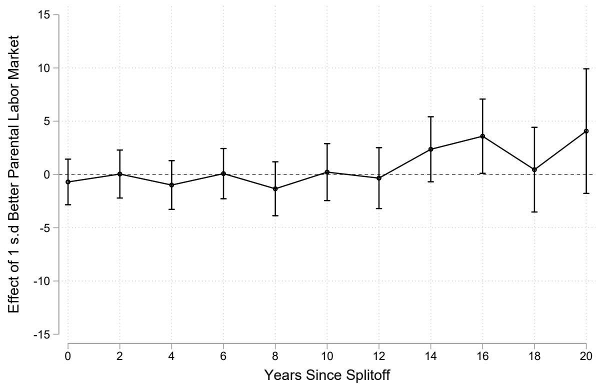
Now, I turn towards investigating outcomes that might mediate the wealth accumulation of splitoff households. I consider income, homeownership, and inheritances as possible channels.

4.4.1 Income

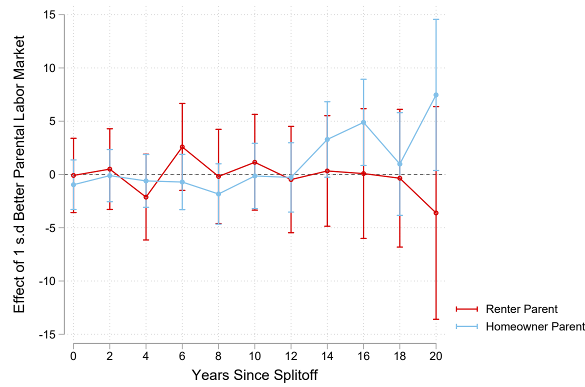
Good parental labor markets have no effect on the labor income of the child. This is somewhat surprising given the literature on the effect of parental wealth on a child's education. However, recall that all regressions control for parental area fixed effects, which means that we are comparing a child who splitoff at the peak of the IT boom in San Francisco, vs. one who split off in the IT bust. If children tend to stay near their parents, i.e., in the same area, then it might be that there is no discernable effect on their labor earnings because it is being absorbed by the area fixed effect, especially early in their careers.

4.4.2 Inheritance

The effects of parental labor markets on inheritance are plotted in Figure 13. These results show that children inherit almost $10,000 more for a 1 s.d. better parental labor market.

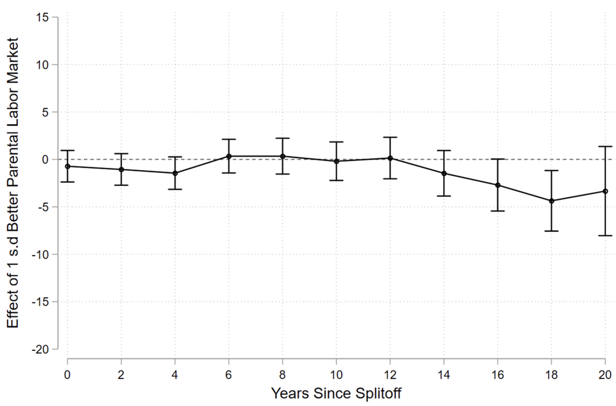


(a) All Parents

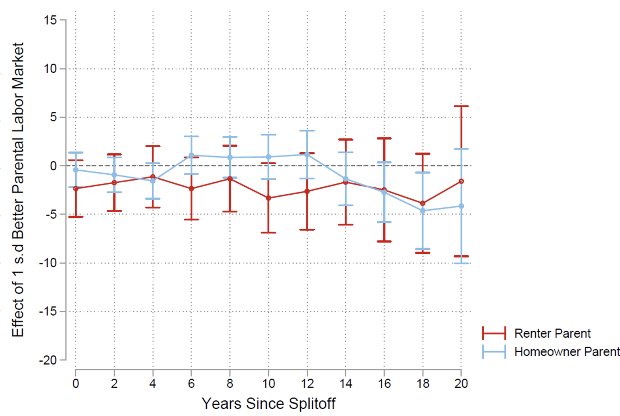


(b) By Parental Homeownership

Figure 11: Effect of Parental Labor Markets on Child's Debt (without Mortgage)

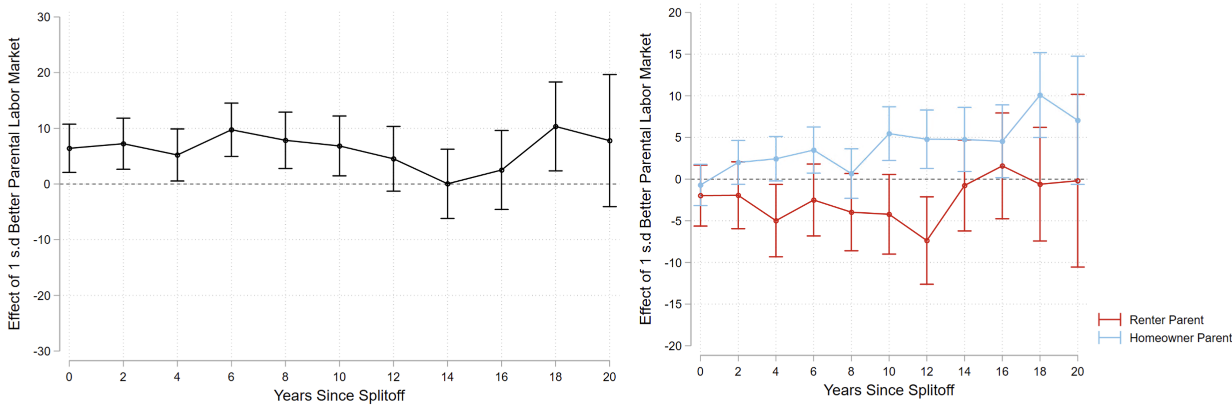


(a) All Parents



(b) By Parental Homeownership

Figure 12: Effect of Parental Labor Market Growth on Child's Labor Income



(a) All Parents **(b)** By Parental Homeownership

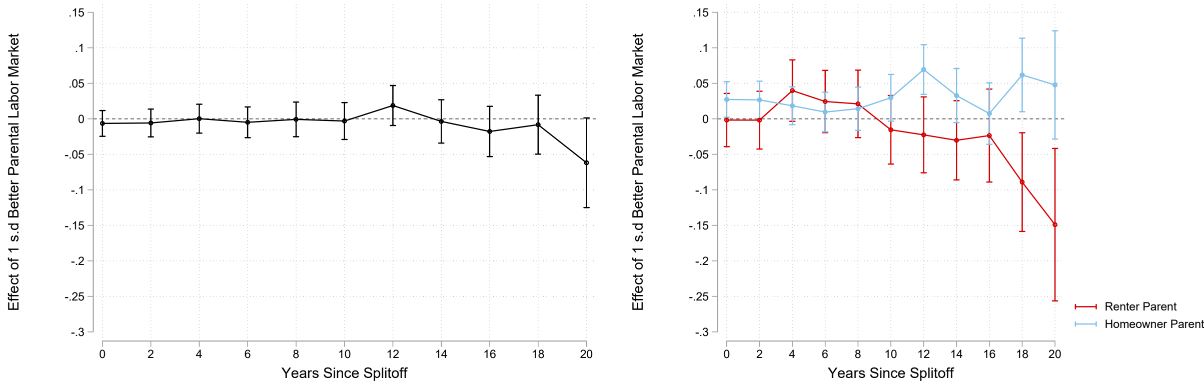
Figure 13: Effect of Parental Labor Market Growth on Child's Inheritance

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, although their response isn't statistically different from renter parents in the latter periods. This is likely because of the inherent noise in the data, and also because not many children receive a positive inheritance in any period.

4.4.3 Homeownership

Finally, it could also be that children of parents who had better labor markets enter into homeownership sooner. There is some evidence for this, but following the pattern of other results, is only true for the children of homeowner parents. This makes sense in the light of the inheritance/gift results, because parents often help children pay the downpayment for homes (Brandsaas, 2021). From 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.



(a) All Parents

(b) By Parental Homeownership

Figure 14: Effect of Parental Labor Market Growth on Child's Homeownership

4.5 Summary

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

1. One standard deviation (1 s.d.) better labor markets for parents increases their child's net worth by almost $30,000. This increase in wealth comes entirely from non-housing assets that the child owns, and there is no effect on the child's home equity. However, there is a positive effect on homeownership.

2. 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.

3. One standard deviation (1 s.d.) better labor markets for parents has no effect on their children's labor income. The main channel of wealth transmission seems to be direct inheritances or gifts received by children, which are about $10,000 more for the children of homeowner parents. They are also more likely to become homeowners after around 10-12 years from split off.

Overall, there is 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. As different areas grow at different rates across the United States, this has implications for wealth inequality. However, it is hard to quantify these implications purely from the empirics since there are many channels at play: one has to consider the effects of local labor and housing markets, of homeownership, of intergenerational transfers, and the fact that households can be mobile. 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.

To begin quantifying the relative importance of these mechanisms for wealth inequality across the United States, I rely on a parsimonious model, which is described next.

5 Local Markets and Wealth Inequality in a Parsimonious Model

I begin by studying local labor and housing markets within a stylized framework. This 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. A major simplifying assumption I make is that there is no transition between productivity types, i.e., a household cannot "change" its productivity. At the end of the period, the household leaves bequests to kids that can include a home (if they own one).

I calibrate the model to the 1999 economy, and call this the "initial" equilibrium. The main quantitative exercise is to feed productivity increases in local areas across deciles between 1999 and 2019 into the model and calculate a "final" equilibrium. 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 different "final" equilibria.

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 kid and dies.

Each household is born with a productivity "type" $z \in \{1, 2, ..., 10\}$. This rules out income risk. This can be thought of as an extreme "caste" system, where a household cannot move across income deciles. However, each income decile is allowed to have a different wage in each area. Further, I also make the assumption that the population in each income decile is 10.

5.1.2 Timing

A household of a particular 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

Each area has its own labor and housing markets, which set wages at each decile 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

Dynasties in each area can choose to be renters or homeowners. They supply labor inelastically. Their wages depend on their "type", which is predetermined, known, and can be one of ten levels $z \in \{1, 2, ..., 10\}$. 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 to the kid, 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 dynasties, 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[10], which means that as wages increase, dynasties want to increase bequests disproportionately more. Effectively, it means that richer dynasties save more, and consequently their kids benefit more from an increase in local labor demand.

5.2.2 Homeowners

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

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

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

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

where p_h is the price of housing, and δ^H is the depreciation rate of housing stock, and κ_z is the utility bump that households get from being homeowners. This can also 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 dynasties 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 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 by 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 Dynasties 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 $\xi_H = 1$.

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.

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.

Summary Table 3 provides a summary of the parameters I use in the calibration. Appendix D describes the data sources I use in the model in greater detail.

Figure 15 shows the the exact matching of the FHFA price index in the initial equilibrium. Figure 16 shows the matching for local employment, and Figure 17 provides the same for homeownership rates across income deciles.

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 3: Summary of Parameters

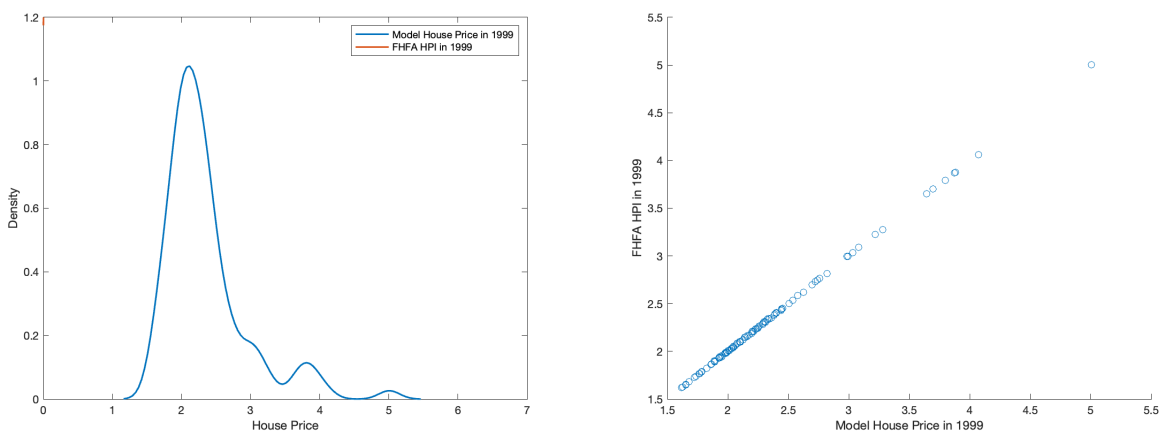


Figure 15: Calibration of House Prices in Initial Equilibrium

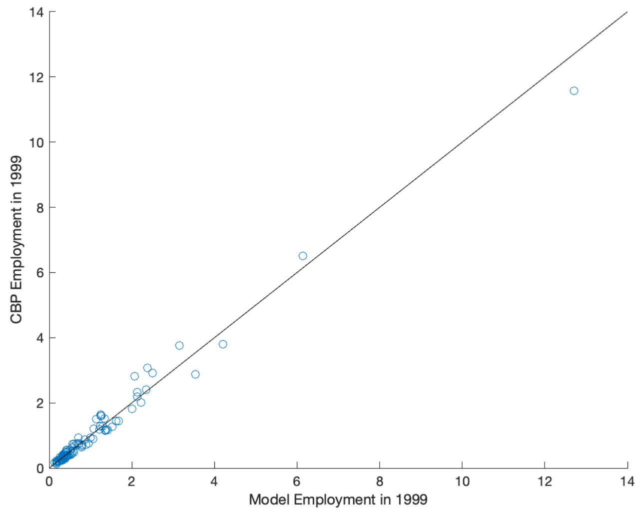


Figure 16: Calibration of Employment in Initial Equilibrium

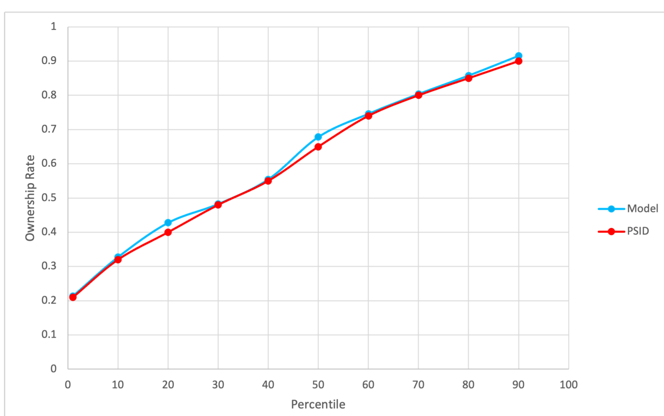


Figure 17: Calibration of Homeownership in Initial Equilibrium

5.9 Simulation

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

To analyze the importance of the role of local markets, I perform four quantification exercises in the model. First, I examine the role of the dispersion in local labor market growth. In other words, what if every local market in the country grew at the same rate? To do this exercise, I calculate the average growth in productivities between 1999 and 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 18 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.

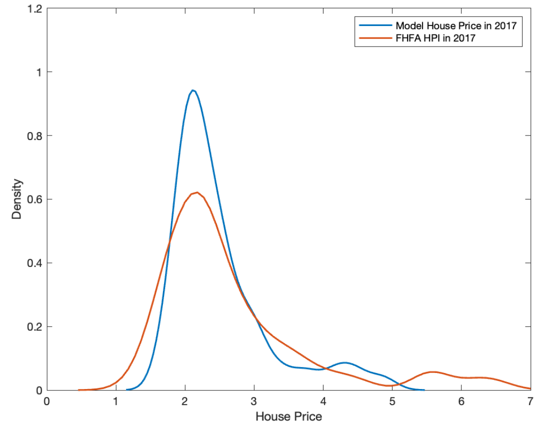


Figure 18: Comparing Model-Generated House Price Distribution to FHFA HPI in 2017

Figure 19 compares the two model-generated distributions of house prices in 1999 and 2017. It should be noted that the 1999 distribution is exactly calibrated to match the data (as was seen in Figure 15).

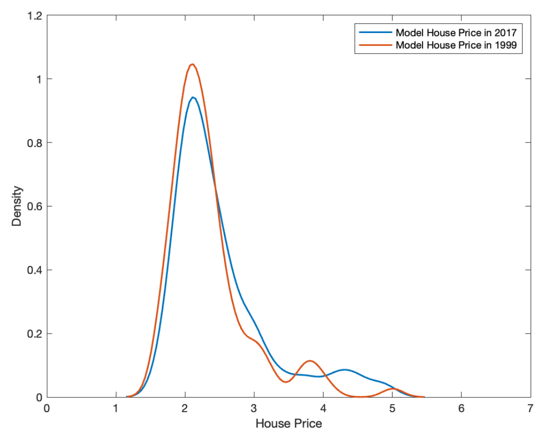


Figure 19: Comparing Model-Generated House Price Distribution in 1999 and 2017

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.

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

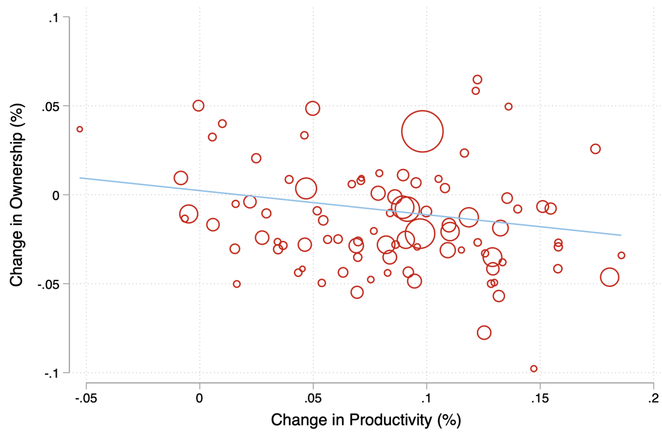


Figure 20: Ownership and Homeownership in the Model

5.10.3 Wealth Inequality in the Model

Figure 21 plots the initial and final distributions of wealth in the model for both owners and renters. Note that for owners, their wealth includes both housing and non-housing wealth – housing wealth is just the value of their home, i.e., $p_h h$, and non-housing wealth is their investment in the risk free asset, a. For renters, their wealth is non-housing wealth by definition.

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

Gini coefficients are presented in Table 4. 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

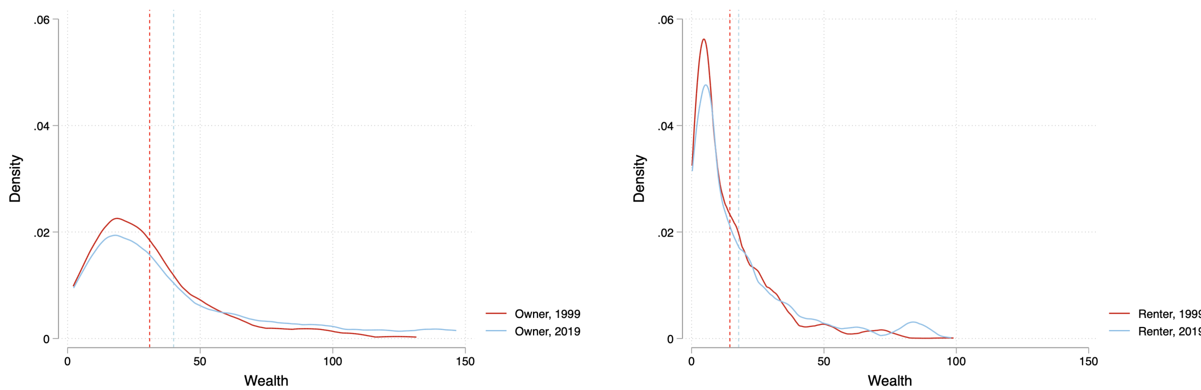


Figure 21: Wealth Distributions of Owners and Renters

period. These patterns are roughly borne out by the model as well. The wealth Gini for owners in the model is 0.40 in 1999, and increases to 0.45 in 2019, an increase of 0.05 units. The corresponding numbers for renters are 0.51 in 1999 and 0.55 in 2019. Overall, the model produces an increase in the wealth Gini of 0.05 points from 0.46 to 0.51. This increase is roughly $0.05/0.07 = 71\%$ of the increase observed in the data.

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

Perhaps a more intuitive way to understand the level of inequality is the 90/50 ratio. This is simply the ratio of the 90th percentile of wealth to the 50th percentile. These can be found in Table 5. 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.

	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 4: 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 5: 90/50 Ratio in Model and PSID 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 6: Effect of a Change in Labor Demand on Wealth by Tenancy in Model

Table 6 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 7: 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 8: 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 7 and Table 8 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 2, 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 9.

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

Table 9: 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 10: 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 10), 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 11 (changes in Gini coefficients) and Table 12 (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 11).

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

Table 11: Increase in Gini Coefficients 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

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

Table 12: Increase in 90/50 Ratio in Model With Perfectly Elastic Housing Markets

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

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

Table 13: Increase in Gini Coefficients in Model Without Geographic Mobility

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

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

Table 14: Increase in 90/50 Ratio in Model Without Geographic 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

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 for the children of parents who had one standard deviation better labor markets in the ten years prior to the child splitting off, net worth is higher by almost $30,000, 20 years after the split-off, although this is driven by the children of homeowner parents. Further, the increase in wealth comes from the non-housing part of the wealth portfolio of the child, and is driven by assets, not debt. I also find that these households are more likely to be homeowners, although they do not own more expensive homes or earn higher labor income. I find that inheritances and gifts made to children plays an important role in the transfer of wealth between generations.

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.

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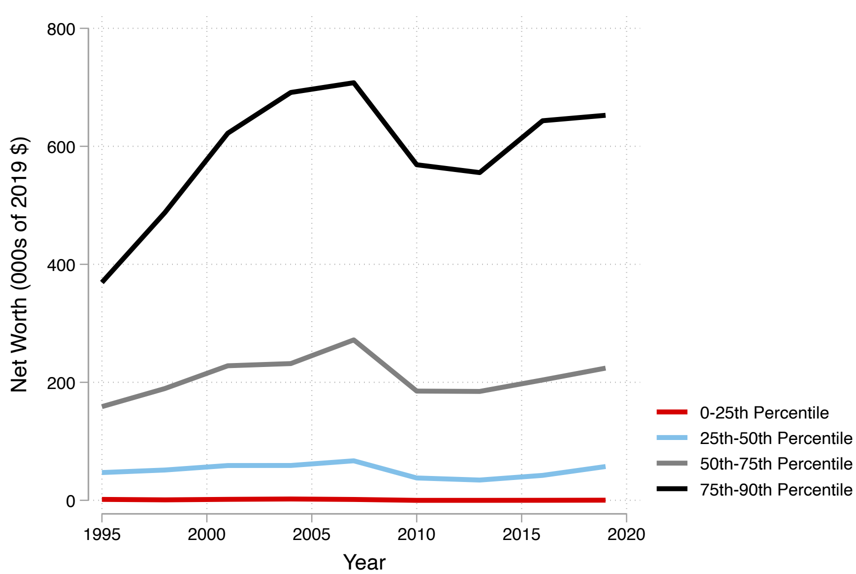
A Wealth Inequality amongst the Bottom 90%

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



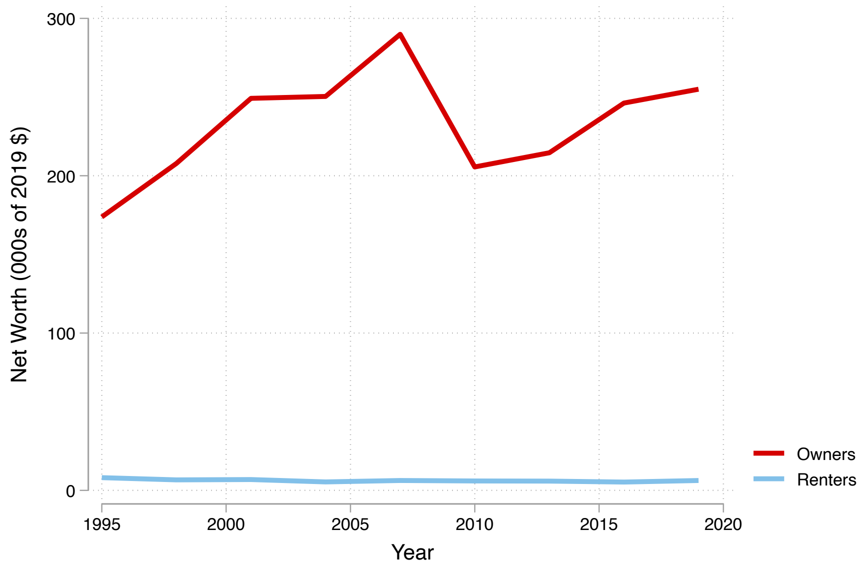
This figure plots the evolution of median net worth between 1995 and 2019. The numbers are calculated from the Survey of Consumer Finances (SCF). Median net worth is plotted according to four percentile groups: 0-25th percentile, 25th-50th percentile, 50th-75th percentile, and 75th-90th percentile. The 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 Data: Descriptive Statistics

C 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:

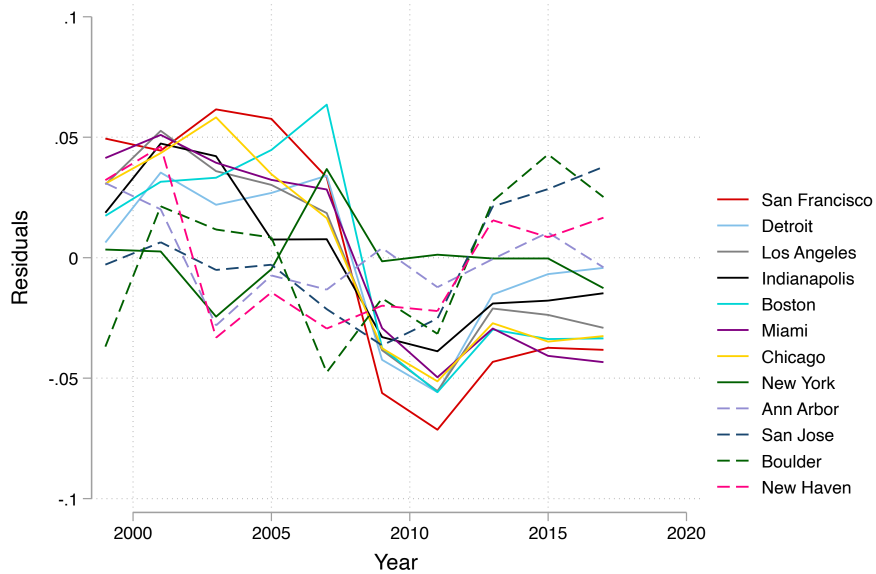


Figure A.3

$$\Delta\theta_{j,T} = \beta_0 + \beta_1\mu_T + \beta_2\lambda_j + \epsilon_{j,T} \tag{8}$$

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.3. The residuals represent the relative performance of an area over time, so that a positive value means that an area outperformed its average, while a negative one means that labor demand growth was slower (or even negative) than average. The graph suggests that most areas did relatively well in the earlier periods, with only Boulder, CO showing poor growth between 1989 and 1999 (which is the 1999 coefficient). Most areas also show a downward shift around the time of the Great Recession, followed by varied levels of recovery. In general, these cities can be divided into following three broad patterns in their trends.

First, we notice that most big areas follow a pattern where they do relatively well in earlier periods, followed by a big downward spike at the Great Recession, and then a slow recovery (Figure A.4). 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.6), 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.5).

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.

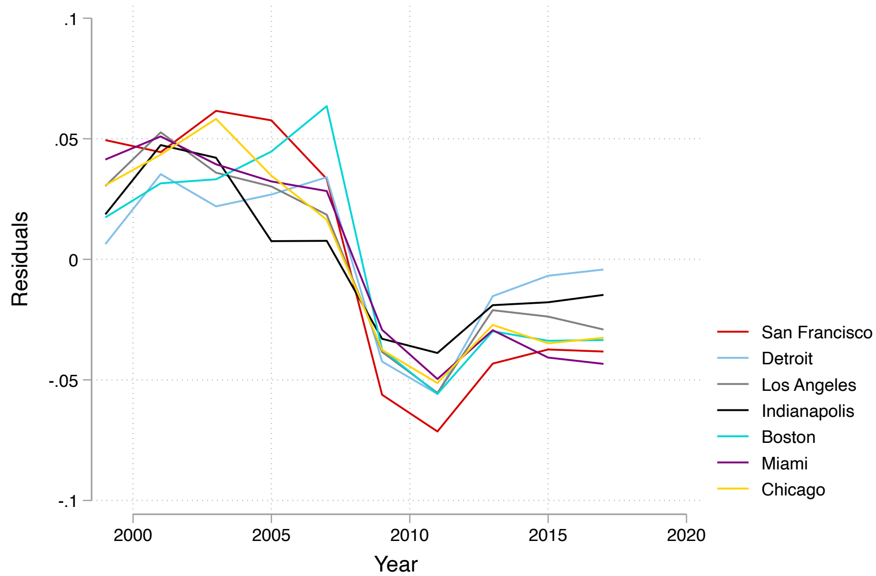


Figure A.4

Figure A.5

Figure A.6

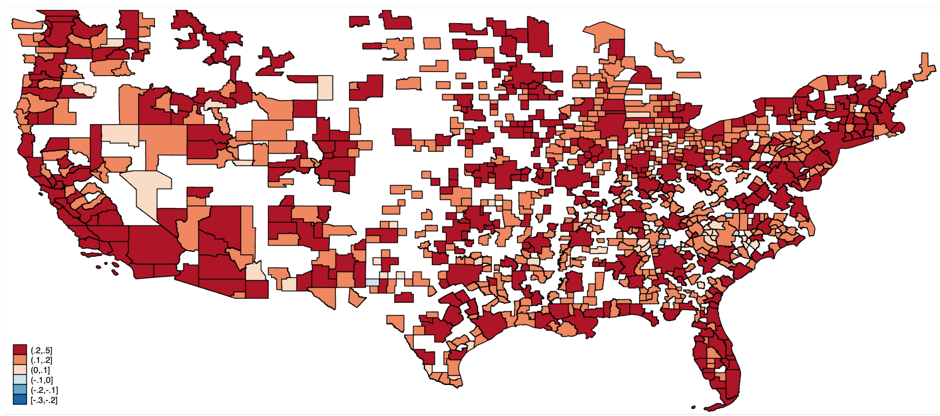


Figure A.7: Spatial Distribution of Labor Demand Growth Between 1989 and 1999

These patterns also reflect the spatial distribution of labor demand growth itself. Figures A.7, **??**, and A.9 present the spatial distribution of labor market growth between 1989 and 1999, between 1999 and 2009, and between 2007 and 2017 respectively. Between 1989 and 1999, most areas experienced strong growth in their labor markets. However, this slow down between 1999 and 2009, mostly due to the Great Recession. In fact, many areas in this period, particularly in the Midwest, experienced negative labor demand growth. Finally, labor demand growth between 2007 and 2017 captures both the effects of the Great Recession and the recovery. Most areas have recovered by the end of this period (although not all, most notably in the so called "Rust Belt").

To get a sense of why the frequency might matter, I plot the spatial distribution of labor demand growth calculated over a shorter period (Figure A.11) vs. a longer one (Figure A.10). 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

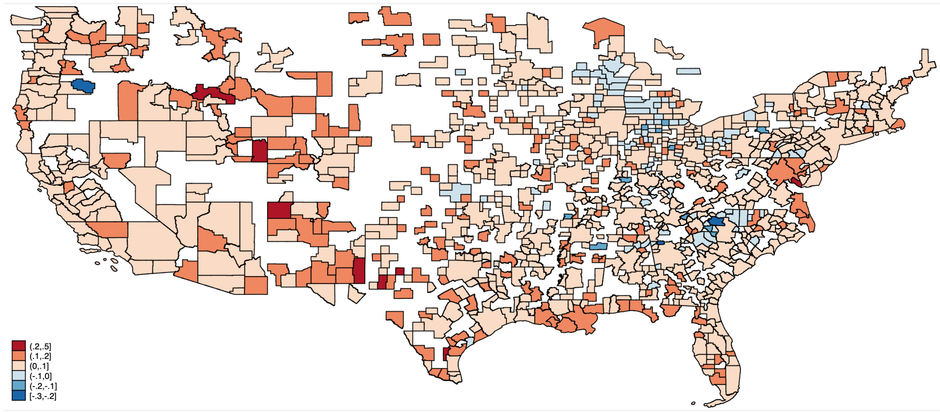


Figure A.8: Spatial Distribution of Labor Demand Growth Between 2001 and 2011

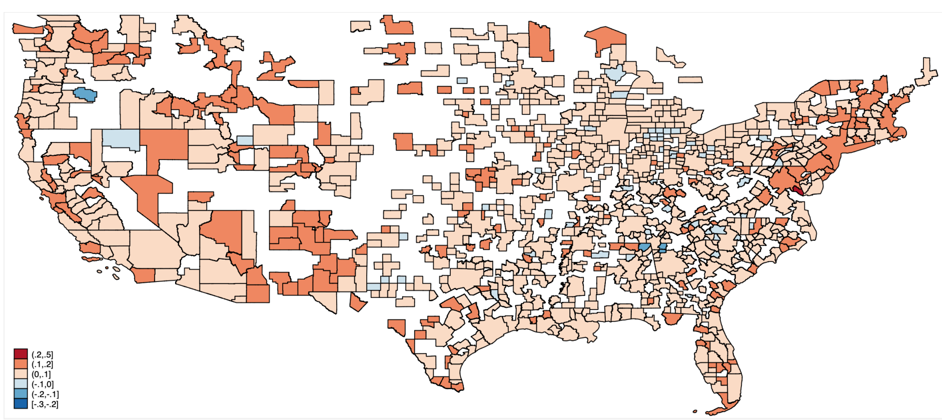


Figure A.9: Spatial Distribution of Labor Demand Growth Between 2007 and 2017

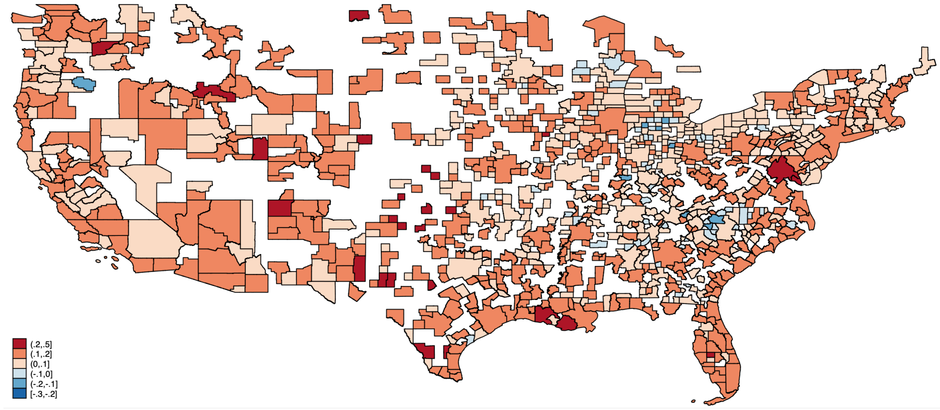


Figure A.10: Spatial Distribution of Labor Demand Growth Between 1999 and 2009

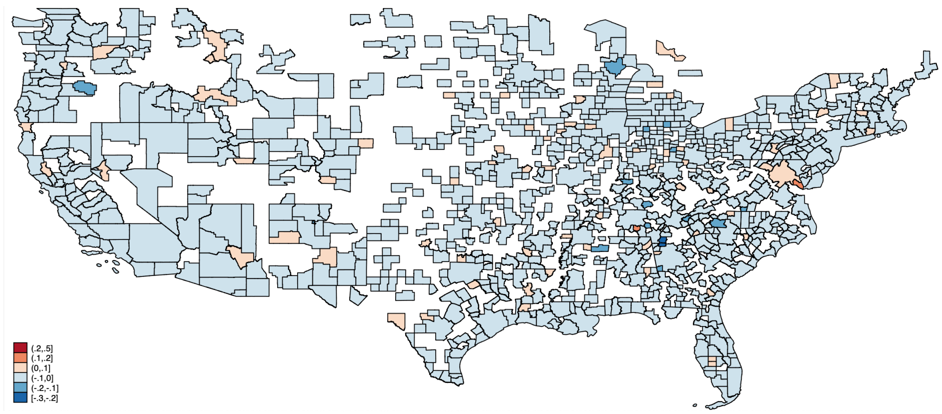


Figure A.11: Spatial Distribution of Labor Demand Growth Between 2007 and 2009

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.

D Other Data Sources Used for Model

D.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.

D.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.