Micro-Level Impact of Initial Public Offerings on Bay Area Housing Inflation

Mina Nezam-Mafi
Senior Honors Thesis
Department of Economics
University of California, Berkeley
April 30, 2021

Abstract

The San Francisco Bay Area suffers from a highly inflated housing market, with home values increasing five times faster than the national rate. While the impact of Silicon Valley's technology boom on the Bay Area's housing crisis is widely recognized, few have attempted to quantify the direct, micro-level impact of initial public offerings (IPO) on regional home prices. In this study, I examine 711 emerging growth IPOs in the Bay Area during the 20-year period of 1996 through 2015. I find that IPO offer size in the Bay Area has had a statistically significant impact on home values within the same zip code as well as those 5, 10, and 20 miles away from the company's headquarters. Additionally, I find that the effect of IPO offer size decreases as firm-home proximity increases and that IPOs influence home values in both the short and long term. I incorporate a number of additional data specifications to ensure the robustness of my results. Furthermore, I offer possible explanations for the results, discuss policy implications, and present extensions for future research.

Acknowledgements

I would like to express my deepest gratitude to my advisor, Enrico Moretti, who coached me through writing my thesis and challenged me to ponder the unknowns of my topic. I thoroughly enjoyed meeting with him because of his vast knowledge of and enthusiasm for urban economics. Without his guidance or expertise, this thesis would not have been possible.

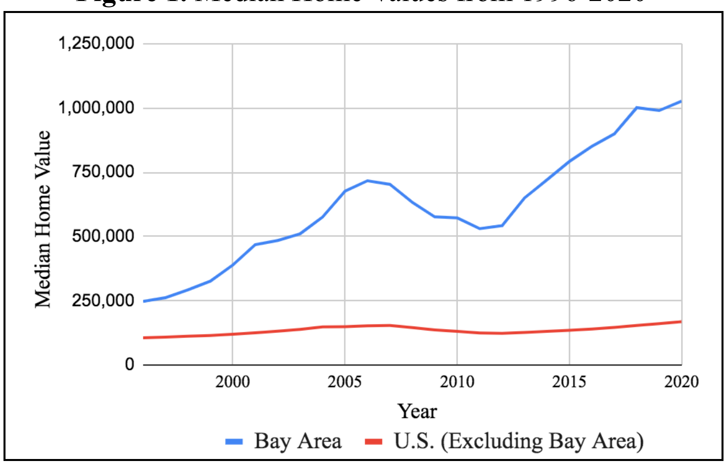
TABLE OF CONTENTS

1. **Introduction** **3**
2. **Literature Review** **6**
    - 2.1. History of Bay Area Housing Market **6**
    - 2.2. Relationship between Silicon Valley Technology Boom and Income Inequality **7**
    - 2.3. Relationship between IPOs and Housing Inflation **9**
3. **Data** **14**
    - 3.1. Home Value Data **14**
    - 3.2. IPO Data **16**
    - 3.3. Combined Dataset **17**
4. **Model** **19**
5. **Results** **23**
    - 5.1. Regression Output **23**
    - 5.2. Home Values and IPO Offer Size **26**
    - 5.3. Home Values and Firm Age at Time of IPO **28**
    - 5.4. Home Values and Firm Industry **28**
    - 5.5. Home Values and Lagged IPO Offer Size **29**
6. **Robustness Tests** **30**
    - 6.1. Home Values Estimation Error **30**
    - 6.2. Zip Code Fixed Effects Error **31**
7. **Discussion** **32**
8. **Conclusion** **34**
9. **Appendix** **36**
10. **References** **38**

1. INTRODUCTION

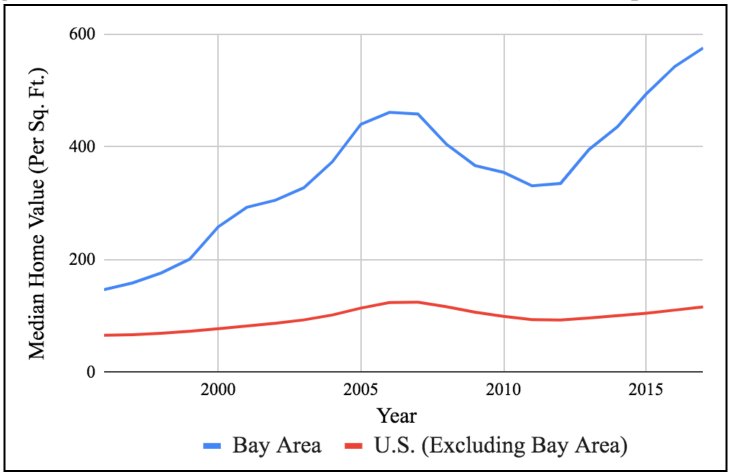
Having grown up in Menlo Park, I have always been astounded by the rapidly rising home values in the San Francisco Bay Area. In January 1996, the median home value in the Bay Area was $247,997; by December 2020, home values had appreciated by 334% to $1,076,920, making purchasing a home as a low- or middle-income household nearly impossible (see Figure 1]).[1] This appreciation is significant compared to the rest of the United States, which only experienced a 65% appreciation in home values during the same time period.[2] Since the dot-com boom of the late 1990's, Silicon Valley has evolved into the global epicenter of innovation and is home to some of the world's largest technology companies as well as thousands of startups. Although the influx of capital from Silicon Valley's prosperity has likely influenced the region's rising home values, few academics have attempted to quantify the direct, micro-level impact of initial public offerings (IPO) on the region's housing inflation.

Figure 1. Median Home Values from 1996-2020



[1] ZHVI, Zillow Research
[2] ZHVI, Zillow Research

Figure 2. Median Home Values from 1996-2017 (Per Square Foot)



An IPO allows the firm's original shareholders to publicly trade a fraction of their stake in the company that they could previously only trade in private markets. These original shareholders typically include the firm's founders, angel investors, venture capitalists, and employees that hold stock options. The correlation between IPOs and rising home values rests on the assumption that original shareholders choose to live near the company's headquarters. There is a plethora of research supporting the idea that founders and employees prefer to live near their offices in order to minimize commute time.[3] Furthermore, with the Bay Area accounting for 44% of total U.S. venture capital spending in 2019, it is reasonable to assume that the majority of those that invest in Bay Area-based companies also reside within the nearby metropolitan area.[4]

With the assumption of shareholder-headquarter proximity established, there are many hypotheses as to why IPOs contribute to an acceleration of growth in housing prices. First, an unexpected increase in a firm's market value may cause a wealth shock for original shareholders which may subsequently trigger a housing demand spike.[5] Even an expectation of a wealth shock in the future (i.e. the date of the IPO filing but before shares are issued) may trigger a change in housing demand. Second, shareholder assets become far more liquid when a company goes

[3] Carlson, 2011
[4] Jones Lang LaSalle, 2020
[5] Hartman-Glaser et al., 2020

public; this change in liquidity may lead to a change in housing demand as well. If shareholders live in a metropolitan area with a static housing supply, this increase in housing demand causes home values to rise. From 2012 to 2017, the Bay Area added nearly 373,000 new jobs, but only issued 58,000 permits to build new houses.[6] Due to very little growth in the housing supply that fails to offset job growth in the region, a demand shock to the Bay Area housing market would undoubtedly lead to an increase in housing prices.

In this paper, I examine Bay Area IPOs during the 20-year period from 1996 through 2015. I investigate changes in median home values on the date of the IPO filing and use lagged variables to capture the date that the shares are issued (i.e. listed), the expiration date of the lockup period (i.e. when shareholders are able to sell their stock), and changes in home values up to 5 years after the IPO is filed, thereby capturing both the short-term and long-term impact of IPOs on home values. In order to discern the scope of IPO influence, I look at housing prices located in the same zip code as the company's headquarters, as well those within a 5, 10, and 20 mile radius from the headquarters. In my empirical analysis, I find that IPO offer size has had a statistically significant impact on home values, with the influence decreasing as the distance between the homes and company headquarters increases. Additionally, IPO offer size not only has a short-term impact on home values; lagged variables reveal a long-term impact as well, although the results vary based on proximity. I subject my model to numerous robustness checks in order to ensure its validity. Furthermore, I discuss policy implications of these results and explore further extensions of this research. Ultimately, this paper plays a role in bridging the literature gap between urban and financial economics in the Bay Area, while consequently revealing the critical impact that Silicon Valley's prosperity has had on the real estate landscape of the region.

[6] Bloomberg, 2017

2. LITERATURE REVIEW

2.1. History of Bay Area Housing Market

Housing inflation in the Bay Area is not a novel phenomenon, and its roots can be traced back to the early 20th century. In 1916, Berkeley was the first city in America to adopt single-family zoning laws for its Elmwood neighborhood, with the aim of preserving the nature, parks, and quality of life of the residents living in the neighborhood.[7] Single-family zoning ensures that land is designated for single-family residential units, in turn prohibiting the construction of "apartment buildings, duplexes, townhouses, mobile home parks, and two-family attached dwellings."[8] These regulations do more than restrict the housing supply; they particularly hinder the construction of affordable housing that low-income families make use of, typically leasing or purchasing multi-family residences. Today, local governments have imposed exclusionary zoning policies such as single-family zoning across the majority of residential land in the Bay Area, forcing the housing supply in the region to remain fairly static. Professor Saxenian of UC Berkeley's School of Information revealed that in 1980, there were over 670,000 jobs in Santa Clara County; however, restrictive land use policies only allowed for the construction of 480,000 housing units in the county.[9] As a result, the average home price was already double the national average by 1980.[10] More recently, the Journal of Economic Perspectives disclosed that the imposition of new "binding land-use restrictions" in San Francisco between 1991 and 2016 had a stifling effect on the development of new housing and led to a 109% increase in home prices during the time period.[11] Therefore, it is clear that

[7] Menendian, 2020
[8] Menendian, 2020
[9] Saxenian, 1983
[10] Saxenian, 1983
[11] Glaeser and Gyourko, 2018

exclusionary zoning laws in the Bay Area have dramatically hindered growth in the housing supply and allowed housing prices to skyrocket.

Dr. Stephen Barton, Director of the Berkeley Rent Stabilization Board, conducted research on other potential causes of the Bay Area's housing inflation. In his 2011 study, Barton finds that higher rents in the Bay Area are not associated with higher quality housing when compared to the Bay Area housing landscape of the 1960s.[12] Rather than concentrating on exclusionary zoning laws, Barton attributes the constricted residential availability of the Bay Area to the surplus availability of high-quality infrastructure, freeways, companies, universities, and parks.[13] Barton contends that it is this array of amenities that draws people to live in the Bay Area, fueling housing demand. While there is a lot to offer, the supply is limited. Furthermore, the Bay Area's housing supply is restricted by its own geography including hills, coastlines, and steep slopes. Barton believes these geographical barriers make new housing harder to come by and existing housing consequently more expensive in the Bay Area.[14]

2.2. Relationship between Silicon Valley Technology Boom and Income Inequality

Despite tremendous economic growth, income inequality has rapidly increased in Silicon Valley since the dot-com era. Today, the Bay Area has the largest income inequality in California. According to KQED, Bay Area wage earners in the 90th percentile earned $384,000 on average in 2020, while those in the bottom 10th percentile made $32,000.[15]

Studies have revealed a number of different factors fueling income inequality in the Bay Area, all of which have been exacerbated by the technology boom during recent decades. In a 1993 effort to reduce CEO pay, the Clinton administration allowed companies to deduct

[12] Barton, 2011
[13] Barton, 2011
[14] Barton, 2011
[15] Hellerstein, 2020

executive pay above $1 million from their taxable income if it was linked to company performance, such as through stock options.[16] Contrary to the policy's intent, executive compensation skyrocketed, particularly in the Bay Area during the 21st century when many high-technology companies went public. When a company goes public, the firm's original shareholders are able to publicly trade a portion of their income. However, the average worker holds far fewer stock options than executive workers, so the economic gains of this policy have disproportionately benefited the highest-income bracket, triggering income inequality. According to Pew Research, the top 100 highest-paid CEOs in the Bay Area made 2,776% more than the average worker in San Francisco.[17]

The Bay Area's income inequality has been further exacerbated by stagnant low- and middle-income wages. According to the Public Policy Institute of California, incomes for families in the 90th percentile have increased by 60% since 1980, while incomes for those in the 10th percentile have only increased by 20%.[18] There are numerous reasons why low- and middle-income wages have experienced very little growth, but one of particular interest in the Bay Area is the lack of competition in the job market. During the Obama administration, it was revealed that technology companies like Facebook and Google had signed no-poaching agreements to prevent workers from receiving job offers from competitors.[19] Because these agreements reduced alternative job opportunities for employees, Bay Area technology companies developed monopsonistic power (i.e, bargaining power over their workers) allowing them to suppress wages below the perfectly competitive level. This lack of bargaining power has been further exacerbated by the rise of the gig economy. Gig workers are independent contractors that

[16] Reich, 2015
[17] Srikant and Cooper, 2020
[18] Hellerstein, 2020
[19] Krueger and Posner, 2018

enter temporary agreements with corporations. They are a low-cost alternative to hiring employees, since they are not granted health insurance, retirement plans, or workers' compensation coverage. Silicon Valley companies have not only hired gig workers to replace blue-collar jobs such as janitors, but also as “the people who test operating systems for bugs, review social media posts that may violate guidelines, and screen thousands of job applications.”[20] Because low- and middle-income workers now face the threat of being replaced by contract workers, they are forced to accept lower wages, allowing income inequality to widen.

2.3. Relationship between IPOs and Housing Inflation

“Local Economic Spillover Effects of Stock Market”

Although scarce, there have been a few studies that consider the impact of IPOs on changes in home prices. The first is “Local Economic Spillover Effects of Stock Market” by Butler et al. which looks at the impact of IPOs on real estate, labor markets, migration and other sociological factors.[21] The researchers considered 2,400 IPOs across the U.S. from 1998 to 2015, excluding those during the dot-com peak (1999 and 2000).[22] The study concludes that IPOs are associated with a statistically significant rise in local home prices. Two years after the IPO, the price of “expensive” houses (i.e. homes within the 65th to 95th percentile range) within 2 miles of an IPO headquarters had increased 0.7% more than other homes in the surrounding region.[23] Surprisingly, they found that IPOs had no statistically significant effect on the prices of inexpensive homes (i.e. homes within the 5th to 35th percentile range). Consistent with the theory that home value growth is driven by proximity to IPOs, the authors found that home values rose most in houses near company headquarters and decreased with distance.

[20] Irwin, 2017
[21] Butler et al., 2018
[22] Butler et al., 2018
[23] Butler et al., 2018

This study is significant because it not only validates the hypothesis that IPOs impact home prices, but it also introduces very important variables to consider in my research – namely, the fact that home types (i.e. expensive versus inexpensive homes) and distance from headquarters play a role in housing price surges. Unlike this national study, my research focuses specifically on the Bay Area, where IPOs are commonplace and wealth has gradually accumulated. Because housing supply is stagnant in the Bay Area, I estimate that IPOs will have a more profound effect on housing prices than what was found in this study for the country at large. While my study does not distinguish between expensive and cheap homes at the individual level, I look at the median home value in each zip code in order to find the influence of IPOs on the average home. Because median home values in the Bay Area are much higher than the national average, they will likely be impacted by the economic spillover effects of IPOs.

"Post-IPO, Home Values Grew Faster in Areas Home to Lots of Facebook Employees"

Zillow – the supplier of the primary home values dataset utilized in my research – conducted a case study on the impact of Facebook's IPO in May 2012 on home values in surrounding communities. Facebook is located in Menlo Park and had the fourth largest IPO in U.S. history, with a peak market capitalization of over $104 billion.[24] Rather than looking at zip codes, Zillow used census tracts, which roughly equate to neighborhoods, as their unit of measurement. Using data from the U.S. Census Bureau, the researcher found the 10 tracts that were most likely to have the most Facebook employees living there in 2012. The study estimated that between 2012 and 2013, home values in tracts with the Facebook employees grew 20.9% while surrounding tracks only grew by about 16.8%, showing a clear correlation between IPOs and increases in home value containing shareholders.[25]

[24] Rudden, 2021
[25] Tucker, 2019

Facebook is one of the most renowned technology companies and had one of the largest IPOs in history; as a result, the impact of Facebook's IPO on housing prices likely does not reflect that of a smaller company in the area. By considering all IPOs in the Bay Area between 1996 and 2015, my study removes much of the noise and circumstantial evidence present in the Facebook case study. Regardless, the Zillow case study is beneficial to understanding the Bay Area population. Assuming that Facebook employees' homebuying preferences are representative of other residents of the area, this study demonstrates that Bay Area residents may increase their housing demand in response to the wealth shock or change in liquidity associated with an IPO.

"Cash to Spend: IPO Wealth and House Prices"

The study that relates most to my research is "Cash to Spend: IPO Wealth and House Prices," published in 2020 by Hartman-Glaser et al. The authors explore the impact of changes in wealth and liquidity due to IPOs on local housing prices by examining 725 IPOs in California from 1993 through 2017.[26] The authors take a spatial difference-in-differences approach to look at home prices within a 1, 5, and 10 mile radius of each company's headquarters that had an IPO.[27] The researchers examine prices of home transactions following three dates: the date the company filed for the IPO, the IPO date, and the end of the lockup period. They found that after the IPO filing date, average home prices within 10 miles of headquarters rose by 1% more than surrounding home prices.[28] On the IPO date, the average home prices rose an additional 0.8%.[29] Surprisingly, the researchers found that there was no additional rise in home prices following the lockup expired.

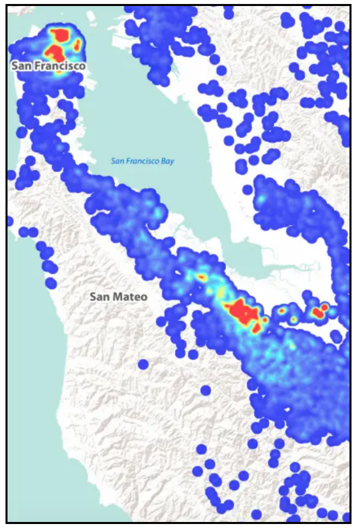
[26] Hartman-Glaser et al., 2020
[27] Hartman-Glaser et al., 2020
[28] Hartman-Glaser et al., 2020
[29] Hartman-Glaser et al., 2020

Although my paper has some similarities to Hartman-Glaser et al., there are a few key differences. First, the authors utilize the Zillow Transaction and Assessment Dataset (ZTRAX) which looks at the prices that houses are sold at each month. In contrast, my research utilizes the Zillow Home Value Index (ZHVI), which estimates home values each month. ZHVI is a stronger index than ZTRAX for understanding changes in the housing market because ZHVI includes almost all homes in the U.S. – from brand new houses to houses that have been off the market for decades – whereas ZTRAX only includes homes that have sold, which is about 2% of homes in a given year.[30] Additionally, ZHVI is more complete than ZTRAX because it considers much more than just the sell price, which may be influenced by negotiations and current events. In contrast, ZHVI's home value estimate takes into consideration factors such as the quality of the neighborhood and home attributes. With more data and more factors considered, ZHVI allows this study to achieve a better sense of an IPOs impact on housing prices than that of Hartman-Glaser et al.

Another key factor that distinguishes this research from that of Hartman-Glaser et al. is the control. Hartman-Glaser et al. uses the East Bay as a control in their difference-in-difference analysis, treating San Francisco as a natural commuting barrier.[31] This is a weak methodology because the East Bay has many commuters to both San Francisco and the Peninsula, since housing prices are so prohibitively expensive. Figure 3 below illustrates where Google employees lived in 2015:

[30] Zillow Research, 2019
[31] Hartman-Glaser et al., 2020

Figure 3. Heat Map of Where Google Employees Lived in 2015



Source: *Business Insider* (2015)

Although the majority of Google workers live around the Mountain View headquarters as well as in San Francisco, there is also a huge percentage that commute from the East Bay. As a result, it is reasonable to assume that some original shareholders likely reside in the East Bay when their companies IPO, leading to an underestimation of the impact of IPOs on housing inflation. Furthermore, there are numerous IPOs in the East Bay itself; between 1996 and 2015, there were 94 IPOs in Alameda County, 18 IPOs in Contra Costa County, and 1 IPO in Solano County. As a result, in this research I expanded the treatment group to consist of all nine Bay Area counties including Alameda, Contra Costa, Solano County in the East Bay, making the East Bay an ineligible control group. Rather, I approached the difference-and-difference analysis by using the Bay Area zip codes themselves as controls rather than using an entirely new housing market. I compared pre-IPO and post-IPO home values in each zip code in order to distinguish whether IPOs had an impact on housing inflation.

Finally, Hartman-Glaser et al. focuses solely on the short-term impact of IPOs on housing inflation. In contrast, I use IPO filing date as a starting point and apply lagged variables to the model in order to capture the effects of the IPO date, end of the lockup period, and up to five years after the IPO filing date on home values. Therefore, my research deviates from that of Hartman-Glaser et al. by examining both the short and long term effects of IPOs on housing.

3. DATA

3.1. Home Values Data

In order to examine changes in home values, I use the Zillow Home Value Index (ZHVI) Per Square Foot, a dataset composed of home values divided by square footage across the United States, parsed by month and zip code. Zillow constructs ZHVI using Zestimates, an estimate of home value generated through machine learning and a variety of data sources including public data (such as tax data), user-generated data (such as photographs), and real estate data (such as home sales data) while taking into account home attributes and geographic location. There are Zestimates for nearly 100 million homes in 90,000 regions in the United States.[32] I only selected home values that fell into the nine counties that make up the Bay Area: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties.

The dataset begins in January 1996 and contains monthly home value estimates for each zip code through December 2020. Although my analysis only covers IPOs that were filed between January 1996 through December 2015, I utilize the entire dataset through 2020 in order to capture both the short-term and long-term effect of IPOs on home values. Furthermore, while ZHVI is parsed by month, I eliminate this granularity and look at home values in each zip code per year in order to remove the noise that is associated with monthly changes in home values.

Although ZHVI contains *median* home values in each zip code per year (rather than the individual home values), the characteristic of square footage of the home is controlled for in the construction of the dataset, making differently sized homes comparable. However, by using

[32] Zillow Research, 2019

aggregate data with no other housing characteristics to control for (such as number of bedrooms or year of construction), it is important to recognize that there may be sample selection bias. Selection bias arises when the selection of data in a statistical analysis is chosen in such a way that randomization is not achieved, thus making the sample unrepresentative of the population intended to be analyzed. The formula to find selection bias is $\tau = E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0]$, where $E[Y_i \mid D_i = 1]$ is the observed outcomes for the treated group and $E[Y_i \mid D_i = 0]$ is the observed outcomes for the untreated group. This equation can be expanded to:

$$\begin{aligned}
\tau &= E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] \\
&= E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0] \\
&= E[Y_{1i} - Y_{0i} \mid D_i = 1] + E[Y_{0i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0]
\end{aligned}$$

where $E[Y_{1i} - Y_{0i} \mid D_i = 1]$ is the average treatment effect on the treated group and $E[Y_{0i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0]$ is the selection bias.[33] If selection into the treatment is not random and is associated with potential outcomes, then the bias term does not equal zero. Since Zestimates are based in large part on housing transactions in the ZHVI dataset, there may be selection bias. If a home has not been on the market for decades, it is less likely to be included in ZHVI due to lack of transaction history than a home that has been sold recently. As a result, houses that have not been sold recently are likely to be under-represented. Therefore, if certain types of homes are more likely to be sold following an IPO – for example, if newly constructed homes are more likely to be sold following an IPO than older homes – then newly constructed homes would be over-represented in the ZHVI dataset, making this a non-random selection of data. The only way that selection bias would not exist would be if the houses that were sold following an IPO were completely random, which is unlikely.

[33] Lambert, 2014

Figure 4. Summary Statistics of Home Values Data

	Obs.	Mean	Std. Dev.	Min.	Max.
Median Home Value Per Sq. Ft.	5,289	388.4054	212.4619	79	1,735
Note: For more specific home value summary statistics stratified by year, see Figure 13 in Appendix.					

3.2. IPO Data

The next dataset used is "Firm Database of Emerging Growth Initial Public Offerings (IPOs) from 1990 through 2015" by Martin Kenney and Donald Patton at the University of California, Davis. I chose this dataset over other published IPO datasets because it includes variables regarding the size of the IPO (e.g. Offer Size, Company Founding Date) as well as detailed information on the address of the company's headquarters (e.g. Zip Code). This dataset includes all emerging growth IPOs on American stock exchanges from 1990 through 2015, which consists of 4,420 IPOs. I filtered the dataset to consist of IPOs that occured in the nine Bay Area counties between 1996 and 2015 (inclusive). The authors define emerging growth companies as de novo firms, or firms that are not based on older firms (i.e. not a spinoff or subsidiary operation).[34] This definition differs from the definition of emerging growth used in the 2012 Jumpstart Our Business Startups (JOBS) Act, which defines emerging growth companies to be any company with annual revenue of less than $1 billion.[35] I subscribe to Kenney and Patton's definition of emerging growth, which is not based on revenue at the time of the IPO.

While Kenney and Patton's IPO dataset provides the date of the IPO (i.e. the date that the shares are issued), I wanted to build a model using the date that the IPO is filed, since expectations of a wealth shock could trigger increased housing demand. Therefore, I turn to

[34] Kenney and Patton, 2017
[35] Kenney and Patton, 2017

another dataset – the Securities Data Company (SDC) Platinum database – in order to obtain the IPO filing date as well as the firm's industry. I combine the SDC dataset with Kenney and Patton's dataset, merging the two on the ticker symbol (i.e. the abbreviation used to identify stocks on public exchanges). In order to convert industry from categorical data to numerical data, I took the four most common industries that had IPOs in the Bay Area (i.e. Pers/Bus/Rep, Manufacturing, Radio/TV/Telecom, & Retail) and converted them into dummy variables.

Figure 5. Summary Statistics of IPO Data

	Obs.	Mean	Std. Dev.	Min.	Max.
IPO Offer Size	711	109,000,000	610,000,000	4,000,000	16,000,000,000
Firm Age at IPO	711	6.990155	5.347493	0	50

Note:

Industry - Pers/Bus/Rep: 336 (47.3%)
Industry - Manufacturing: 299 (42.1%)
Industry - Radio/TV/Telecom: 16 (2.3%)
Industry - Retail: 14 (2.0%)

3.3. Combined Dataset

After constructing the home values dataset and the IPO dataset, I merged the two together by zip code and year so that each row represented a new zip code and year combination for all zip codes in the Bay Area and for all years between 1996 and 2020 (inclusive). I combined this master dataset with a free dataset downloaded from SimpleMaps.com containing the latitude and longitude for all zip codes in the United States. After appending latitude and longitude, I used the Libpysal package in Python to find the arc distance of zip codes located 5, 10, and 20 miles away from the zip code for each IPO's headquarters. Because I introduced latitudes and longitudes in the dataset, arc distance was the appropriate metric to calculate distance between zip codes, with the arc referring to the natural arc of the Earth in miles.[36] After getting zip codes within 5, 10, and 20 miles from each row of the dataset, I aggregated IPO offer size in those zip codes to find the sum of offer sizes in the surrounding areas. I then dropped the latitude and longitude columns, since they would no longer serve purpose in the empirical analysis.

Figure 6. List of Variables in Final Dataset

Variable	**Description**
Zip Code & Date	Every unique combination of zip codes in the Bay Area (243 zip codes) and years (between 1996 and 2020, inclusive).
Median Home Value Per Sq. Ft.	Median home value divided by square footage for every unique combination of *Zip Code* and *Date*.
Offer Size (within zip)	Size of the IPO offer in dollars calculated by multiplying the initial share price by the number of shares offered. *Offer size (within zip)* refers to the aggregate sum of offer sizes for all IPOs that occurred during the *Date* listed above and at a company's headquarters located within the same *Zip Cod*e listed above.
Offer Size (within 5mi)	*Offer size (within 5mi)* refers to the aggregate sum of offer sizes for all IPOs that occurred during the *Date* listed above and at a company's headquarters located within 5 miles of the *Zip Cod*e listed above.
Offer Size (within 10mi)	*Offer size (within 10mi)* refers to the aggregate sum of offer sizes for all IPOs that occurred during the *Date* listed above and at a company's headquarters located within 10 miles of the *Zip Cod*e listed above.
Offer Size (within 20mi)	*Offer size (within 20mi)* refers to the aggregate sum of offer sizes for all IPOs that occurred during the *Date* listed above and at a company's headquarters located within 20 miles of the *Zip Cod*e listed above.
Age at IPO	The year of the IPO issue date subtracted by the year that the firm was founded.
Industry: Pers/Bus/Rep	Dummy variable referring to whether or not the company that IPO'd was in the *Pers/Bus/Rep* (personal/business/representative) industries.
Industry: Manufacturing	Dummy variable referring to whether or not the company that IPO'd was in the *Manufacturing* industry.
Industry: Radio/TV/Telecom	Dummy variable referring to whether or not the company that IPO'd was in the *Radio/TV/Telecom* industries.
Industry: Retail	Dummy variable referring to whether or not the company that IPO'd was in the *Retail* industry.

[36] Pysal Developers

4. MODEL

I built multiple regression models in order to evaluate the impact of IPOs on home values. Home values are log transformed in order to impose linearity between the dependent variable and the regressors. Model 1 is the most simplified version of the model and can be expressed as follows:

$$log(home\ value_{yz}) = \beta_0 + \beta_1 OS_{yz} + \varepsilon_{yz}$$

In this equation, OS_{yz} refers to IPO offer size, with y representing each year between 1996 and 2020 (inclusive) and z representing each zip code in the Bay Area. The coefficients can be interpreted as measuring the percentage change in prices caused by unit changes in IPO characteristics. Specifically, a unit change in IPO offer size corresponds to a $100 * \beta_1\%$ change in $log(home\ value)$. Model 1 suffers from substantial omitted variable bias because uniform changes in both year and zip code are not controlled for. As a result, this model will likely have a low R^2, since there are many variables that influence the dependent variable which are not accounted for. Furthermore, failing to control for omitted variables that are positively correlated with both home values and IPO offer size may lead to an overestimation of the predicted effect of β_1.

In Model 2, I diminish one source of omitted variable bias by incorporating year fixed effects. Year fixed effects control for factors common to the entire Bay Area that change yearly. For example, year fixed effects control for changes in the U.S. inflation rate each year, an important variable that affects the entire Bay Area housing market in a uniform manner. Model 2 can be expressed as:

$$log(home\ value_{yz}) = \beta_0 + \beta_1 OS_{yz} + FE_y + \varepsilon_{yz}$$

In this equation, FE_y represents a vector of year fixed effect dummy variables. Because fixed effects are composed of dummy variables, then one dummy variable can be predicted using all other dummy variables, leading to multicollinearity; this is known as the dummy variable trap. In order to avoid the dummy variable trap, Stata automatically drops one dummy variable when using fixed effects. With year fixed effects now accounted for in Model 2, β_1 becomes more accurate as standard errors decrease and R^2 increases. Although Model 2 reduces omitted variable bias by including year fixed effects, it does not eliminate it completely because the model still does not account for fixed effects related to zip code.

In Model 3, omitted variable bias is substantially reduced through the inclusion of zip code fixed effects, which control for permanent variables affecting home prices in a zip code over time. For example, if one zip code has higher home values because it has lower crime rates and better schools, zip code fixed effects controls for these factors, making this zip code comparable to another zip code with higher crime and lower-quality schools. Model 3 is expressed as:

$$log(home\ value_{yz}) \ = \ \beta_0 + \beta_1 OS_{yz} + FE_y + FE_z + \varepsilon_{yz}$$

In this equation, FE_z is a vector of zip code fixed effect dummy variables. Again, Stata drops one dummy variable in order to avoid multicollinearity and the dummy variable trap. By incorporating zip code fixed effects, β_1 will decrease because the influence of IPO offer size is no longer overestimated. Furthermore, standard errors will further decrease and R^2 will increase in order to reflect the inclusion of more variables that influence home values.

Model 4 introduces and controls for IPO characteristics beyond offer size. Specifically, the model accounts for Firm Age at IPO and Industry, the latter of which is broken up into dummy variables for the four industries that had IPOs most frequently in the Bay Area:

Pers/Bus/Rep, Manufacturing, Radio/TV/Telecom, and Retail (defined in Figure 6). Model 4 is expressed as:

$$log(home\ value_{yz}) = \beta_0 + \beta_1 OS_{yz} + FE_y + FE_z + \beta_2 C_{yz} + \varepsilon_{yz}$$

In this equation, C_{yz} is a combined variable referring to the IPO characteristics mentioned above (i.e. Firm Age at IPO and Industry dummies). There are many possible hypotheses that are tested by introducing new IPO-related control variables to Model 4. For example, older firms may cause a larger wealth shock to original shareholders when they go public, potentially leading to greater changes in home values. Another hypothesis is that technology firms raise home values more than manufacturing firms when they IPO. If these characteristics prove to be statistically significant, then some bias will be reduced by adding them to the model.

Model 5 incorporates lagged offer size variables into the regression. Lagged offer size is valuable because it may take multiple years for an IPO to influence housing demand and become fully reflected in home values. As a result, it is important to examine both the short and long term effects of IPOs on home values, which can be done using lagged variables. Model 5 includes five years of lagged variables. Therefore, if an IPO is filed in 1996, the model will reflect the IPO's effects on home values from 1996 to 2001, providing greater scope through which to assess the effects of IPOs on housing prices. Model 5 can be expressed thusly:

$$log(home\ value_{yz}) = \beta_0 + \beta_1 OS_{yz} + FE_y + FE_z + \beta_2 C_{yz} + \beta_3 LOS_{yz} + \varepsilon_{yz}$$

In this equation, LOS_{yz} refers to the five years of lagged IPO offer sizes in each year and zip code. If lagged variables prove to be statistically significant, then some omitted variable bias will be reduced by adding them to the model. However, there is also the risk of multicollinearity if IPO attributes prove to be correlated to each other, which would reduce the precision of the estimates. A correlation coefficient of at least 0.7 indicates the presence of multicollinearity; as seen in Figure 5 below, there are no correlation coefficients that surpass that benchmark.

Figure 5. Correlation Matrix for Independent Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) IPO Offer Size	1.000										
(2) Firm Age at IPO	0.172	1.000									
(3) Industry: Pers/Bus/Rep	0.220	0.463	1.000								
(4) Industry: Manufacturing	0.100	0.565	-0.030	1.000							
(5) Industry: Radio/TV/Telecom	0.026	0.129	-0.007	-0.007	1.000						
(6) Industry: Retail	0.021	0.203	-0.006	-0.006	-0.002	1.000					
(7) Offer Size L1	0.027	0.048	0.051	0.052	0.000	0.002	1.000				
(8) Offer Size L2	0.047	0.086	0.032	0.090	-0.001	0.018	0.027	1.000			
(9) Offer Size L3	0.011	0.029	0.024	0.036	0.001	-0.000	0.047	0.027	1.000		
(10) Offer Size L4	0.014	0.034	0.028	0.036	-0.003	0.010	0.011	0.047	0.027	1.000	
(11) Offer Size L5	0.007	0.032	0.020	0.022	-0.003	-0.000	0.014	0.011	0.047	0.027	1.000

I replicate the five models listed above four different times for the different spatial distances considered: home values within the same zip code as company headquarters as well as home values 5, 10, and 20 miles away. Because this study explores whether proximity to the headquarters of a company going public via IPO influences home values, I hypothesize that there is an inverse relationship between distance and influence; that is, IPOs should have a decreasing effect on home values as distance between the homes and company headquarters increases.

5. RESULTS

5.1. Regression Output

Figure 6. IPO Attributes on Bay Area Home Values (Within Zip Code) with Fixed Effects

	(1) logHV	(2) logHV	(3) logHV	(4) logHV	(5) logHV
IPO Offer Size	.06*	.096***	.015**	.016**	.016**
	(.032)	(.023)	(.006)	(.007)	(.007)
Firm Age at IPO				0	0
				(.001)	(.001)
Industry: Manufacturing				-.005	-.005
				(.013)	(.013)
Industry: Pers/Bus/Rep				-.004	-.005
				(.012)	(.012)
Industry: Radio/TV/Telecom				-.012	-.013
				(.037)	(.037)
Industry: Retail				-.046	-.046
				(.043)	(.043)
Offer Size L1					.013**
					(.006)
Offer Size L2					.01
					(.006)
Offer Size L3					.006
					(.006)
Offer Size L4					.007
					(.006)
Offer Size L5					.005
					(.006)
Year Fixed Effects?	-	X	X	X	X
Zip Code Fixed Effects?	-	-	X	X	X
Observations	5289	5289	5289	5289	5284
R-squared	.001	.003	.932	.932	.932

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Figure 7. IPO Attributes on Bay Area Home Values (Within 5 miles) with Fixed Effects

	(1) logHV	(2) logHV	(3) logHV	(4) logHV	(5) logHV
IPO Offer Size	.059*** (.008)	.095*** (.006)	.011*** (.002)	.011*** (.002)	.008*** (.002)
Firm Age at IPO				0 (.001)	0 (.001)
Industry: Manufacturing				-.01 (.013)	-.009 (.013)
Industry: Pers/Bus/Rep				-.008 (.012)	-.011 (.012)
Industry: Radio/TV/Telecom				-.017 (.037)	-.019 (.037)
Industry: Retail				-.05 (.043)	-.05 (.043)
Offer Size L1					.007*** (.002)
Offer Size L2					-.002 (.003)
Offer Size L3					0 (.003)
Offer Size L4					.005** (.002)
Offer Size L5					.006*** (.002)
Year Fixed Effects?	-	X	X	X	X
Zip Code Fixed Effects?	-	-	X	X	X
Observations	5289	5289	5289	5289	5284
R-squared	.011	.047	.933	.933	.933

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Figure 8. IPO Attributes on Bay Area Home Values (Within 10 Miles) with Fixed Effects

	(1) logHV	(2) logHV	(3) logHV	(4) logHV	(5) logHV
IPO Offer Size	.023*** (.005)	.061*** (.004)	.006*** (.001)	.006*** (.001)	.004*** (.001)
Firm Age at IPO				0 (.001)	0 (.001)
Industry: Manufacturing				-.008 (.013)	-.007 (.013)
Industry: Pers/Bus/Rep				-.006 (.012)	-.007 (.012)
Industry: Radio/TV/Telecom				-.018 (.037)	-.02 (.037)
Industry: Retail				-.048 (.043)	-.044 (.043)
Offer Size L1					.001 (.001)
Offer Size L2					.003* (.001)
Offer Size L3					.001 (.001)
Offer Size L4					0 (.001)
Offer Size L5					.004*** (.001)
Year Fixed Effects?	-	X	X	X	X
Zip Code Fixed Effects?	-	-	X	X	X
Observations	5289	5289	5289	5289	5284
R-squared	.005	.496	.964	.964	.964

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Figure 9. IPO Attributes on Bay Area Home Values (Within 20 Miles) with Fixed Effects

	(1) logHV	(2) logHV	(3) logHV	(4) logHV	(5) logHV
IPO Offer Size	0	.038***	.005***	.005***	.005***
	(.002)	(.002)	(.001)	(.001)	(.001)
Firm Age at IPO				0	0
				(.001)	(.001)
Industry: Manufacturing				-.007	-.007
				(.013)	(.013)
Industry: Pers/Bus/Rep				-.006	-.006
				(.012)	(.012)
Industry: Radio/TV/Telecom				-.019	-.019
				(.037)	(.037)
Industry: Retail				-.047	-.047
				(.043)	(.043)
Offer Size L1					0
					(.001)
Offer Size L2					0
					(.001)
Offer Size L3					.001
					(.001)
Offer Size L4					-.001
					(.001)
Offer Size L5					0
					(.001)
Year Fixed Effects?	-	X	X	X	X
Zip Code Fixed Effects?	-	-	X	X	X
Observations	5289	5289	5289	5289	5284
R-squared	0	.493	.964	.964	.964

Standard errors are in parentheses
*** $p<.01$, ** $p<.05$, * $p<.1$

5.2. Home Values and IPO Offer Size

As seen in the regression outputs above, IPO offer size has a statistically significant positive effect on home values. In Model 1, a $1 increase in IPO offer size is associated with a 6% increase in home values within the same zip code of the company's headquarters, a 5.9% increase in home values within 5 miles, and a 2.3% increase in home values within 10 miles when compared to home values before the IPO. For homes within 20 miles of the company's headquarters, a one unit increase in IPO offer size has a statistically insignificant effect on home values. Clearly, the impact of IPO offer size on home values is significant and decreases as distance from the headquarters of the IPO increases. However, as previously discussed, there are a number of omitted variables in Model 1 because both year and zip code fixed effects have not yet been integrated. This is reflected in the low R^2 values for Model 1.

Because of the omitted variable bias in Models 1 and 2 and the lack of IPO characteristics, it is more valuable to analyze the coefficients of IPO offer size in Model 4, where fixed effects and controls are included and coefficients have stabilized. In Model 4, the coefficient for IPO offer size decreases as more localized fixed effects are added. This indicates that the model is controlling for additional omitted variables positively correlated with both IPO offer size and home value. In Model 4, IPO offer size remains statistically significant. A $1 increase in IPO offer size with both year and zip code fixed effects is associated with a 1.6% increase in home values within the same zip code, a 1.1% increase in home values within 5 miles, a 0.6% increase in home values within 10 miles, and a 0.5% increase in home values within 20 miles. The coefficient within the same zip code as the company with the IPO is significant at a p-value of 0.05 while the coefficients within 5, 10, and 20 miles are significant at a p-value of 0.01, showing that these variables have strong statistical significance. If these coefficients are applied to the 2020 Bay Area average home value of $1,076,920, then a $1 increase in IPO offer size implies a home value premium of $17,231 within the same zip code, $11,846 within 5 miles, $6,462 within 10 miles, and $5,385 within 20 miles. As hypothesized, the impact of IPO offer size on home values decreases as distance between homes and company headquarters increases. When examining the standard errors, there do not seem to be any large spikes as year or zip code fixed effects are added. This indicates that there is sufficient variation in IPO offer sizes over time and across zip codes.

Intuitively, the positive relationship between IPO offer size and home values makes sense. If the IPO offer size is larger, the IPO is more likely to raise more money and generate greater profits, thus creating larger wealth shocks and more potential liquidity for original shareholders. This in turn triggers a larger increase in housing demand, which causes home values to rise more than no IPO or a smaller IPO offer size would have caused.

5.3. Home Values and Firm Age at Time of IPO

In Models 4 and 5, the firm's age at the time of the IPO was added to the regression in order to decipher whether it would influence home values. All models revealed the same results; the firm's age at the time of the IPO has no statistically significant impact on home values, with a p-value consistently larger than 0.1. When the firm's age was squared and cubed, the variable still proved to be insignificant. Therefore, we can infer that while IPOs have had a positive effect on home values in the Bay Area, firm age at the time of the IPO is not the factor driving rising home values.

5.4. Home Values and Firm Industry

In Model 4 and Model 5, firm industries were included to understand whether IPOs in certain industries were associated with larger changes in home values than others. All models revealed that industry has no statistically significant impact on home values. Therefore, an IPO's industry is not the driving force increasing home values. One reason why the firm's industry may be insignificant in this model is because the industries drawn from the SDC dataset are too broad. For example, the category Pers/Bus/Rep (defined in Figure 6) – which accounts for nearly half of all IPOs in the Bay Area – fails to differentiate between industries such as technology and healthcare. A potential extension of this research would be to use a dataset with more specific industries in order to test whether there is a correlation between the industry of a firm that IPOs and nearby home values.

5.5. Home Values and Lagged IPO Offer Size

In order to capture the long term effect of IPOs on home values, I included five years of lagged variables for IPO offer size in Model 5. Based on the regression outputs, lagged variables yielded inconsistent results depending on the distance examined. For homes within the same zip code as the company, a one year lag of IPO offer size (while controlling for year and zip code effects) positively affected home values by 1.3%, demonstrating that IPOs not only raised home values within the same year but also one year after. No other lagged variables were statistically significant for homes within the same zip code as the company headquarters. For homes within 5 miles of the company, a $1 increase in the one year lag of IPO offer size increased home values by 0.7%. Meanwhile, a $1 increase in the IPO offer size four years after the IPO increased home values by 0.5%, and a $1 increase in the five year lag increased home values by 0.6%. For homes within 10 miles of the company, the five year lag increased home values by 0.4%. For homes within 20 miles of the company, there were no statistically significant impacts from lagged IPO offer size on home values.

Although the statistical significance of lagged variables is not uniformly distributed, it is clear from the model that IPO offer size affects home values not just within the same year that the IPO is filed but also in the long-run. Furthermore, as company-home proximity increases, the influence of lagged offer size decreases, showing the same inverse relationship that was seen with home values and unlagged IPO offer size (see Section 5.2).

6. ROBUSTNESS TESTS

6.1. Home Values Estimation Error

An important consideration in my analysis is that I utilize estimates of home values rather than actual home transactions. Accordingly, there is likely some error between the estimates and actual market values. According to Zillow, "most Zestimates are 'within 10 percent of the selling price of the home.'"[37] As a result, I returned to the original dataset and assigned every row to a random number between 0 and 20. Depending on the random number assigned, I then multiplied the home value per square foot by a value between 0.9 and 1.1, corresponding to the +/– 10% margin of error. I then redid the Model 4 regression for home values within the same zip code as the company's headquarters, as well as those within 5 miles, 10 miles, and 20 miles of the headquarters.

As seen in Model 5, randomly assigning a 10% margin of error results in a few small differences in coefficients from the original model. For homes within the same zip code, the coefficient for offer size reduces slightly (.016 to .015) and decreases in statistical significance ($p<.05$ to $p<.1$). Therefore, for homes within the same zip code as the company which IPO'd, offer size is less predictive of home values. For homes within 10 miles of company headquarters, the coefficient for offer size slightly increases (.006 to .007) with no change in statistical significance. Standard errors do not change significantly when the margin of error is added. Because adjusting for the 10% margin of error does not significantly change results, the robustness of the original regression is substantiated.

[37] Fontinelle, 2019

Figure 10. IPO Attributes on Bay Area Home Values (+/– 10% Margin of Error) with Fixed Effects

	(1) logBay	(2) logBay	(3) logBay	(4) logBay
Offer Size (within zip)	.015* (.008)			
Offer Size (within 5mi)		.011*** (.002)		
Offer Size (within 10mi)			.007*** (.001)	
Offer Size (within 20mi)				.005*** (.001)
Firm Age at IPO	0 (.001)	0 (.001)	0 (.001)	0 (.001)
Industry: Manufacturing	-.009 (.015)	-.014 (.015)	-.014 (.015)	-.011 (.015)
Industry: Pers/Bus/Rep	-.006 (.014)	-.011 (.014)	-.01 (.014)	-.009 (.014)
Industry: Radio/TV/Telecom	-.029 (.042)	-.034 (.042)	-.037 (.042)	-.036 (.042)
Industry: Retail	-.051 (.05)	-.055 (.049)	-.055 (.049)	-.053 (.049)
Year Fixed Effects?	X	X	X	X
Zip Code Fixed Effects?	X	X	X	X
Observations	5289	5289	5289	5289
R-squared	.953	.953	.953	.953

Standard errors are in parentheses
**** $p<.01$, ** $p<.05$, * $p<.1$*

6.2. Zip Code Fixed Effects Error

Throughout this study, I make the assumption that utilizing zip code fixed effects controls for omitted variables that are permanent in each zip code and correlated with home values, such as crime level and school quality. There is abundant research demonstrating the effect of school quality on home values, including the prominent 1999 study "Do Better Schools Matter? Parental Valuation of Elementary Education" which revealed that elementary school quality significantly influences housing demand and therefore housing prices.[38] In order to test the assumption that fixed effects successfully control for omitted variables, I appended the column Average School Rating to the original dataset. For Average School Rating, I calculated the average rating for public elementary, middle, and high schools (district and charter) within each zip code using data from the website GreatSchools.org. For zip codes with no public schools, I used the average rating of schools within the school district.

After attempting to run Model 4 again with the column Average School Rating as an added control, Stata omitted Average School Rating from the regression due to collinearity, stating the error "Average School Rating is probably collinear with the fixed effects." Because Average School Rating did not result in a coefficient, this robustness test successfully demonstrates that zip code fixed effects control for localized omitted variables that influence home values, such as school quality.

7. DISCUSSION

There are many policy implications of this research. Despite tremendous economic growth in recent decades, Bay Area residents have been disproportionately impacted by the prosperity of Silicon Valley. Home values have surged dramatically in the Bay Area, and as demonstrated in this analysis, IPOs have played a significant role in increasing home values. This has triggered a massive domino effect of geographical dislocation and homelessness with very little government intervention to combat it, as the prosperity of the Bay Area's highest earners has concealed the suffering of its lowest. Intervention by local and state officials is essential to ensuring that residents can sustain a dignified quality of life with basic health and protection. Potential policies include eliminating single-family zoning laws that restrict the

[38] Black, 1999

construction of apartments and other multi-family housing units, and increasing the housing budget to finance the development of permanently affordable rental housing in the Bay Area.

While public policy initiatives targeting the housing crisis are urgent, regional and national trends suggest that Silicon Valley's prosperity may not last forever. A Silicon Valley exodus may be underway, as startups and technology companies weigh the benefits of living in the hub of entrepreneurship against the high costs of property and living. Major firms such as Charles Schwab, HP Enterprise, Oracle, and Tesla have announced plans to abandon their Silicon Valley headquarters and move to lower-cost areas such as Texas, which provides the benefits of lower taxes, a more affordable cost of living for employees, and lower costs to conduct business – all of which are driven primarily by lower property costs.[39]

Furthermore, there has been a nationwide decline in the number of IPOs over the last several decades. Between 1980 and 1999, 372 U.S. companies went public on average each year (on NASDAQ and NYSE); in the 21st century, however, the annual average has been 174 IPOs – a decrease of over 114%.[40] In the Bay Area specifically, there were 78 IPOs in 1996 and only 24 IPOs in 2015, a dropoff of 225% across the time frame studied in this paper.[41] Many alternative sources of capital have emerged to offset the decline of IPOs, such as venture capital and private equity. Furthermore, many companies have opted for alternative methods to become publicly traded, such as through special-purpose acquisition companies or direct listings. As a result, even if Silicon Valley remains the epicenter of entrepreneurship, IPO volume will likely continue to decline and contribute less to the region's housing market inflation.

Finally, although IPOs and Silicon Valley's economic prosperity have triggered large spikes in home values that have disproportionately hurt low-income families, low-income

[39] Loizos, 2020
[40] Gao et al., 2012
[41] Kenney and Patton, 2017

families also benefit from living in this innovation hub. As Enrico Moretti states in the book *The New Economy of Jobs,* for every new job created in the Bay Area's innovative industries, five new jobs are created in the region, three of which go to workers without a college degree.[42] At the end of 2019, the unemployment rate in the Bay Area was 2.3% – half the unemployment rate in the rest of California – showing the employment benefits to living in an economically prosperous region.[43] Additionally, although low- and middle-income households have not experienced huge increases in wages, Silicon Valley's job market still offers higher wages for low-income workers than other parts of California.[44] As a result, in order to benefit the low- and middle-income workers that suffer most from rising home values, policies should focus on increasing affordable housing without restricting economic prosperity in the Bay Area.

8. CONCLUSION

In this paper, I explored the relationship between IPOs and rising home values in the Bay Area. Using multiple regression models, I found that IPOs have a statistically significant impact on Bay Area home values located within the same zip code as well as within 5, 10, and 20 miles from headquarters. I also found that the impact of IPO offer size decreases as the distances of the homes to company's headquarters increases. Furthermore, I discovered that lagged offer sizes have a statistically significant impact on home values, demonstrating that IPOs influence home values in both the short- and long-term. I subjected my results to a number of checks in order to ensure that key assumptions made regarding estimated home values and localized fixed effects were sound and did not undermine the robustness of my model.

[42] Moretti, 2013
[43] SocketSite, 2021
[44] Reidenbach, 2016

There are many potential extensions of this research. First, rather than using zip code-level aggregate data, this experiment should be applied to a dataset containing individual home values in order to control for housing characteristics beyond square footage and remove sample selection bias. This would allow researchers to evaluate whether certain types of houses gain more value after IPOs than others, which would be useful information for policymakers and homeowners alike. Second, by combining the change in home values following IPOs found in this research with local IPO volume trends, researchers can forecast future home prices in the Bay Area, which would be beneficial to both real estate investors as well as policymakers looking to curb inflation in the Bay Area housing market. Third, in order to better understand whether the industry of the company that IPO'd plays a role in raising home values, this study should be re-run using a dataset with more discrete industry assignments. Finally, in order to examine external validity and create comparisons for the Bay Area, this study should be replicated in different markets with high IPO volumes. For example, this research could be replicated internationally in Shanghai, China, which is projected to become the world's largest IPO market.[45] Very few researchers have looked at the effects of IPOs on home values, so establishing best practices and consensus estimates through replication will help to legitimize these studies for future use in public policy and decision-making.

[45] He, 2020

9. APPENDIX

Figure 11. Number of Emerging Growth IPOs in Bay Area Per County (1996-2015)

County	# of IPOs
Santa Clara	336
San Mateo	174
Alameda	94
San Francisco	72
Contra Costa	18
Marin	9
Sonoma	7
Solano	1
Napa	0

Figure 12. Number of Emerging Growth IPOs in Bay Area Per Year (1996-2015)

Year	# of IPOs
1996	78
1997	44
1998	44
1999	153
2000	136
2001	15
2002	9
2003	9
2004	28
2005	12
2006	16
2007	24
2008	2
2009	3

2010	12
2011	20
2012	24
2013	24
2014	34
2015	24

Figure 13. Summary Statistics of Home Values Data (Stratified by Year)

		Obs.	Mean	Std. Dev.	Min.	Max.
Median Home Value Per Sq. Ft.	**1996**	228	158.5658	51.48465	79	337
	1997	237	172.6203	62.71836	79	438
	1998	240	196.7458	76.51164	81	471
	1999	240	218.625	84.25142	91	511
	2000	240	283.3792	116.4382	110	661
	2001	240	317.925	121.4062	126	741
	2002	240	330.9833	120.0046	141	799
	2003	240	350.7417	116.5716	167	805
	2004	240	402.4958	126.4539	190	941
	2005	240	470.1458	130.8605	236	1039
	2006	240	489.6375	133.377	252	1060
	2007	240	486.375	147.4422	218	1045
	2008	240	437.2458	165.7093	170	1038
	2009	240	381.3	156.2504	119	964
	2010	243	371.7819	159.732	112	931
	2011	243	353.3045	163.185	104	950
	2012	243	367.3704	182.4189	96	1032
	2013	243	441.535	211.9404	123	1156
	2014	243	492.6708	233.5185	163	1281
	2015	243	562.8477	277.1128	175	1529

10. REFERENCES

"Bay Area Employment Drops, Labor Force Down 123K." *SocketSite,* 22 Jan. 2021, https://socketsite.com/archives/2021/01/bay-area-employment-drops-unemployment-rate-ticks-up.html

Barton, Stephen E. "Land Rent and Housing Policy: A Case Study of the San Francisco Bay Area Rental Housing Market." *The American Journal of Economics and Sociology,* vol. 70, no. 4, 2011, pp. 845–873., https://doi.org/10.1111/j.1536-7150.2011.00796.x.

Black, Sandra E. "Do Better Schools Matter? Parental Valuation of Elementary Education." *The Quarterly Journal of Economics,* vol. 114, no. 2, pp. 577-599, 1 May 1999, https://doi.org/10.1162/003355399556070.

Butler, Alexander W., et al. "Local Economic Spillover Effects of Stock Market Listings." *Social Science Research Network*, 5 Dec. 2018, ssrn.com/abstract=2695464.

Carlson, Nicholas. "Zuckerberg Buys A $7 Million Home Near Facebook's New Campus." *Business Insider,* 5 May 2011, https://www.businessinsider.com/zuckerberg-buys-a-7-million-home-near-facebooks-new-campus-2011-5.

Clark, Patrick. "Why Can't They Build Homes Where the Jobs Are?" *Bloomberg,* 23 June 2017, www.bloomberg.com/news/articles/2017-06-23/why-can-t-they-build-more-homes-where-the-jobs-are.

Fontinelle, Amy. "Zillow Estimates: Not As Accurate As You Think." *Investopedia,* 25 June 2019, https://www.investopedia.com/articles/personal-finance/111115/zillow-estimates-not-accurate-you-think.asp#:~:text=According%20to%20Zillow%2C%20most%20Zestimates,the%20Zestimate%20will%20be%20off

Gao, Xiaohui, et al. "Where Have All the IPOs Gone?" *U.S. Securities and Exchange Commission*, 3 Apr. 2012, www.sec.gov/info/smallbus/acsec/acsec-backgroundmaterials-090712-ritter-article.pdf.

Glaeser, Edward, and Joseph Gyourko. "The Economic Implications of Housing Supply." *Journal of Economic Perspectives*, vol. 32, no. 1, 2018, pp. 3–30., doi:10.1257/jep.32.1.3.

Hartman-Glaser, Barney, et al. "Cash to Spend: IPO Wealth and House Prices." *Social Science Research Network*, 30 Nov. 2018, ssrn.com/abstract=3329651.

He, Laura. "Shanghai Could Be the World's Biggest IPO Market This Year. Holding the Title

Will be Tough.” *CNN Business,* 21 Oct. 2020, https://www.cnn.com/2020/10/31/investing/china-markets-ipo-intl-hnk/index.html.

Hellerstein, Erica. “It's Official: Bay Area Has Highest Income Inequality in California.” *KQED*, 31 Jan. 2020, www.kqed.org/news/11799308/bay-area-has-highest-income-inequality-in-california#:~:text=It%27s%20official%3A%20The%20gap%20between,anywhere%20else%20in%20the%20state.&text=Bay%20Area%20residents%20in%20the,in%20the%20bottom%2010th%20percentile.

Ingram, David. “Tech IPOs Threaten to Add Fuel to America's Hottest Housing Market.” *NBC News,* NBCUniversal News Group, 22 Dec. 2018, www.nbcnews.com/tech/tech-news/tech-ipos-threaten-add-fuel-america-s-hottest-housing-market-n950136.

Irwin, Neil. “To Understand Rising Inequality, Consider the Janitors at Two Top Companies, Then and Now.” *The New York Times.* 3 Sep. 2017. https://www.nytimes.com/2017/09/03/upshot/to-understand-rising-inequality-consider-the-janitors-at-two-top-companies-then-and-now.html

Kenney, Martin and Donald Patton. 2017. Firm Database of Emerging Growth Initial Public Offerings (IPOs) from 1990 through 2015.

Krueger, Alan, and Eric Posner. “Corporate America is Suppressing Wages for Many Workers.” *The New York Times,* 28 Feb. 2018. https://www.nytimes.com/2018/02/28/opinion/corporate-america-suppressing-wages.html

Lambert, Ben. “Random Assignment - Removes Selection Bias.” *Youtube,* 2 Feb. 2014, Accessed 25 Apr. 2021. https://www.youtube.com/watch?v=pE6zYPjFh4A

“Libpysal.cg.KDTree.” *Libpysal: Python Spatial Analysis Library Core,* Pysal Developers, pysal.org/libpysal/generated/libpysal.cg.KDTree.html.

Loizos, Connie. “Oracle Is Headed to Texas Now, Too.” *TechCrunch,* 11 Dec. 2020, techcrunch.com/2020/12/11/oracle-is-headed-to-texas-now-too/.

Menendian, Stephen, et al. “Single-Family Zoning in the San Francisco Bay Area.” *Othering & Belonging Institute at UC Berkeley,* 7 Oct. 2020, https://belonging.berkeley.edu/single-family-zoning-san-francisco-bay-area.

Moretti, Enrico. *The New Geography of Jobs*. Mariner Books, 2013.

Pender, Kathleen. "Finally, Some Insight on the Impact of IPOs on Home Prices." *San Francisco Chronicle,* 5 Feb. 2019, www.sfchronicle.com/business/networth/article/Finally-some-evidence-on-the-impact-of-IPOs-on-13589281.php.

Reich, Robert. *Saving Capitalism: For the Many, Not the Few.* Alfred A. Knopf, 2015.

Reidenbach, Luke. "Inequality and Economic Security in Silicon Valley." *California Budget & Policy Center,* 25 May 2016, calbudgetcenter.org/resources/inequality-economic -security-silicon-valley/.

Rudden, Jennifer. "Largest IPOs in the United States as of January 2021." *Statista*, 25 Jan. 2021, www.statista.com/statistics/226152/largest-ipos-in-the-united-states-by-issue-volume/#:~:text=Totaling%2021.77%20billion%20U.S.%20dollars,energy%20company%20based%20in%20Italy.

Saxenian, AnnaLee. "The Urban Contradictions of Silicon Valley: Regional Growth and the Restructuring of the Semiconductor Industry." *International Journal of Urban and Regional Research*, vol. 7, no. 2, June 1983, pp. 237–262, https://doi.org/10.1111/j.1468-2427.1983.tb00592.x.

Srikant, Ahalya, and Julia Cooper. "Bay Area CEOs See Big Raises, Pay Gaps and Few Women Among the 100 Highest-Paid." *San Francisco Business Times,* 19 June 2020, www.bizjournals.com/sanfrancisco/news/2020/06/19/bay-area-highest-paid-ceos-2019.html.

"The Impact of the Tech Boom on Housing." *The United States Census Bureau,* 18 Aug. 2020, www.census.gov/library/stories/2019/04/impact-of-tech-boom-on-housing.html.

"The San Francisco Bay Area Accounted for 44 Percent of Total Venture Capital Spending in 2019." *Jones Lang LaSalle*, 28 Jan. 2020, www.us.jll.com/en/views/snapshots/san-francisco-snapshot-1-28-20-jll#:~:text=Contact-,The%20San%20Francisco%20Bay%20Area%20accounted%20for%2044%20percent,venture%20capital%20spending%20in%202019.

Tucker, Jeff. "Post-IPO, Home Values Grew Faster in Areas Home to Lots of Facebook Employees." *Zillow,* 4 Feb. 2019, www.zillow.com/research/facebook-ipo-home-values -22940/.

Weller, Chris. "This Heat Map Shows Where Google Employees Live in the Bay Area." *Business Insider,* 29, Jun. 2015, https://www.businessinsider.com/this-heat-map-shows-a-

Fundamental-problem-of-working-at-google-2015-6

"Zillow Home Value Index (ZHVI)." *Zillow Research,* Zillow, www.zillow.com/research/data/.

Zillow Research, 2019. *Zillow Home Value Index Methodology, 2019 Revision: What's Changed & Why*, 18 Dec. 2019,www.zillow.com/research/zhvi-methodology-2019-highlights -26221/.