High-technology IPOs and Neighborhood Inequality*

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Abstract

How does going public by high-technology firms affect local neighborhoods? The paper finds that those IPOs result in economic growth, but greater inequality and gentrification among incumbent residents in both short and long run. I document positive wage effect on both high-skilled and low-skilled workers but displacement effect on low-skilled workers only. With rising housing price and rent, there is also a growing number of homeless people in the local neighbourhoods. Finally, I construct a spatial equilibrium model to quantify the change in workers' utility and estimate that an average IPO can increase the productivity of surrounding high-skilled workers by 20%.

JEL classification: R11, R13, G14

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1 Introduction

Since the 1980s, the prominent welfare gap between workers with different skills is in the spotlight for its policy implications. In OECD countries, college graduates earn 61% more than high school graduates in the U.K., and even in the most egalitarian country, Denmark, the wage gap is still 22% (OECD, 2007). In the paper, I propose that equity markets and high-technology firms play a vital role in local neighborhood inequality, by linking high-technology IPOs with the welfare of residents near headquarters. Although a high-technology can foster local economic prosperity and productivity, its negative effect on inequality is less understood by the public. Through its spillover effect, it generates substantial and long-lasting impacts, such as enlarging the wage and employment gap between high-skilled and low-skilled workers and causing gentrification in local neighborhoods, which leads to a housing market boom and an increase in homelessness rates. By incorporating welfare measures into a structural model, I show that high-technology IPOs result in a welfare increase for high-skilled workers at the expense of low-skilled workers. To understand the mechanism, I study patent outputs generated in nearby neighborhoods and document that the positive labor demand shock on high-skilled workers primarily arises from a productivity increase due to knowledge spillover. Using the same structural model, I estimate that high-skilled workers in a neighborhood exposed to an average high-technology IPO experience a productivity increase of roughly 20%.

In the past two decades, the rapid growth of high-technology firms has sparked a revolution in business and society. These firms have been supported by the U.S. government for their important role in stimulating economic growth and innovation. According to Rushe (2018), U.S. local governments have subsidized high-technology firms with over $9.3 billion between 2013-2018, in exchange for local development and job creation. This amount has been rapidly increasing over the years. However, surprisingly little attention has been paid to studying the influence of high-technology firms on the welfare of incumbent residents.

Moreover, high-technology IPOs are active in financial markets, and they now constitute about 50% of all IPOs, as shown in Figure (1). Although the total number of IPOs has a cyclical pattern, the share of high-technology IPOs is relatively stable. However, these IPOs are mostly from I.T., pharmaceutical, and financial service firms, which primarily recruit college graduates, comprising only 37% of the total population. These features have implications for the skill wage premium, relative labor supply between high-skilled and low-skilled workers, and the inequality and gentrification of local neighborhoods. As Morck et al. (1990) suggested, the equity market is not a sideshow of the real economy, and a high-technology IPO is likely to affect the local labor and housing markets and the productivity of local peer firms. Since it serves as a skill-biased shock in favor of the productivity of high-skilled workers, it creates welfare differentials between local workers.

To build more intuition, one may consider the example of Facebook IPO illustrated in Butler et al. (2019). The tech giant, headquartered in Palo Alto, held its NASDAQ debut on May 18, 2012. Following the large IPO, thousands of Facebook employees became millionaires. The influence on local economy is multiple and far-reaching. First, those employees can leave Facebook and establish their startups, which also recruit high-skilled workers from the local labor market (Babina et al. (2017), Babina and Howell (2019)). Second, other high-technology firms nearby Facebook can also benefit from the agglomeration effect of knowledge transfer. Due to larger portion of high-skilled workers in their employees, the aggregate productivity of high-skilled workers in the local area increases (Marshall (1890), Matray (2021)).

Therefore, we would see an increase in wage for high-skilled workers in Palo Alto. Meanwhile, the demand for local services, in which low-skilled workers mainly operate, also increases because of the income effect of high-skilled workers. In turn, the increase in wage of low-skilled workers may be a secondary effect of Facebook IPO. On the other hand, real wage and welfare changes are more complicated, for Facebook IPO also heats up the local housing market and raises the price of local goods through consumption (Mian et al., 2013), leading to an increase in living costs. As a result, the real wage, especially for low-skilled workers, can decline, leading to complexity in analyzing welfare. Finally, because marginal high-skilled workers and low-skilled workers will re-optimize their choice of home and work locations in response to the shock, we would see positive sorting of high-skilled workers in contrast to negative sorting of low-skilled workers into Palo Alto.

In this paper, I formalize the conjecture above by combining results from reduced form evidence and structural estimation. To this end, I firstly define high-technology firms according to NAICS codes that constitute high-technology industries by U.S. National Science Foundation (NSF) (National Science Foundation, 2020), and crosswalk them to SIC codes. To segregate skill groups, I refer workers with at least four-year college educational attainment as high-skilled workers, and other workers as low-skilled workers. Admittedly, education levels and skills are not equivalent, but it is still the best single proxy especially when other measures like work experience or field of study are not available.

In the reduced form analysis, I estimate the effects of high-technology IPOs on wages and employment by skill groups, as well as on housing market outcomes, by comparing neighborhoods nearby the headquarters of IPO firms and those farther away, while controlling for observed and unobserved confounders in several ways. In all specifications, wages rise disproportionately in favor of high-skilled workers, while the employment of low-skilled workers drops. At the same time, the positive effect on the housing market is significant and persistent. These results suggest that the benefits of high-technology IPOs transfer into the welfare of high-skilled workers, but low-skilled workers are hurt, as the spillover effect on living costs overwhelms the increase in low-skilled wages. Since both the treatment and control groups consist of numerous residents, any significant effect on the group level should be interpreted mainly as a spillover effect. While a firm may increase its payroll and employment after going public (Borisov et al., 2021), any economically significant aggregated change in social welfare is unlikely to be solely driven by one single firm.

To understand the mechanism driving such pronounced inequality, I focus on high-skilled workers and peer firms to study the intensive and extensive margin of high-technology IPOs. The reduced-form analysis shows that productivity of high-skilled workers increases nearby IPO headquarters, as measured by patent outputs. However, I do not observe any change in the number of high-technology establishments in the treatment area. Therefore, the demand shift in high-skilled labor is predominantly driven by productivity growth rather than firm entry or expansion.

Next, I briefly discuss two threats to identification. First, the decision and timing of going public may be predictable to the public, as the IPO process can span over an extended period and is surrounded by numerous rumors in the real world. If local residents or firms expect a forthcoming high-technology IPO to affect themselves, they may adjust household decisions before the real event. For instance, potential home buyers may prefer to purchase real estate earlier to exploit price advantages before appreciation caused by nearby IPOs. In such a case, I would underestimate the effect by simply comparing the changes before and after IPOs. To address this concern, I employ dynamic difference-in-differences and use estimation for years before IPO as falsification tests. In the end, I can alleviate the concern since there is no pre-trend in any specification."

Another concern is the possibility of macroeconomic shocks occurring simultaneously with IPOs, which could potentially confound the treatment effect estimate. To address this concern, I propose several assurances. Firstly, since the IPO cases follow staggered adoption, a single one-time confounding shock should be less of a concern. Secondly, I control for various fixed effects, including firm-by-year effect, county-by-year effect, and census tract or ZIP code effect to absorb unobserved dynamics. Additionally, I construct a counterfactual for IPOs using the closest withdrawn IPO issuer and bin neighborhoods by their distance to the withdrawn issuer. Provided that the withdrawn issuer is similar to the successful issuer and the outcome of IPOs is orthogonal to the local economy, a specification with the distance bin fixed effect would address the concern for endogeneity. Alternatively, I also estimate the propensity score for census tracts based on a rich pool of predictors, and then divide them into bins to allow for different trends in different bins as a substitute identification strategy. Finally, the results obtained using these alternative strategies are highly similar.

The standard difference-in-differences estimation provides an answer to the question of how much each welfare measure changes because of the IPO shock, but it does not fully explain how workers of different skills benefit from IPOs in nearby areas. Examining welfare measures in isolation would distort conclusion because higher living costs can offset the benefit from wage increases. To complement the reduced form estimation, I propose a discrete choice spatial equilibrium model to identify workers' utility changes and strength of spillover effect. Using the random utility model proposed by Berry (1994) and Berry et al. (1995) with data on the origin-destination commuting flow of workers, I can directly estimate the utility changes without knowing about individual specific choices. Consistent with the reduced form results, high-skilled workers experience positive utility changes, but low-skilled workers experience negative ones. This implies that the burden of higher living costs on low-skilled workers overwhelms their wage increase and forces marginal workers to leave their residences for more affordable neighborhoods. Taking one step further, I design the IPO shock as productivity changes of high-skilled workers, and model it as a function of distance from local neighborhood to IPO firms. Finally, I apply shift-share instrumental variables on skill wages to account for endogenity stemmed from unobserved amenity changes. The estimated structural parameters in the model show that the spillover effect on productivity is economically and geographically extensive: A representative IPO would typically raise the productivity of high-skilled workers in the same ZIP code by 21.7% after five years.

The research does have limitations. A caveat is that the comparison between neighborhoods with different distances to firm headquarters only captures the relative effect of high-technology IPOs. Like other literature using the spatial approach, the paper cannot identify the absolute treatment effect relative to no shock, but uses the effect on neighborhoods that are less affected as the benchmark. The issue is documented by literature. In the presence of general equilibrium adjustments, all participants in all labor markets will adjust and arrive at a new equilibrium, so there is no perfect control group to find. Moreover, even though workers are very immobile, policies and shocks can have ripple effect as local labor markets are overlapped (Manning and Petrongolo, 2017). Consequently, measuring the total effect is impossible as one can never separate labor markets perfectly.

A related point to the relative treatment effect is that the paper cannot incorporate all aspects of the impacts brought by IPOs on people's lives, such as convenience and new products. To see this, in the structural model, workers' utility is defined narrowly as a function of real wage and (unobserved) amenity changes. An astute reader would aware that the definition fails to capture many other potential impacts of IPOs. For instance, the Google Cloud, which came shortly after the Google IPO, remarkably streamlined collaboration and reduced communication costs in business, thus bolstering the productivity of workers. However, this positive effect is left out of the analysis. Hence, focusing solely on real wages may lead to an underestimation of the contribution of high-technology IPOs to economic growth and social welfare. Nevertheless, the analysis of inequality remains robust, as long as workers living across the nation have equal access to the service.

This paper lies on the intersection of literature on equity market and local labor market. The question about how IPO firms and institutional investors benefit or lose financially from going public draws extensive research.[1] Among the articles, Maksimovic et al. (2022) is the one most closely related, as they find IPO firms respond more to investment opportunities and have higher produc-

[1] Surveys on this topic include Ritter and Welch (2002), Ljungqvist (2008) and Jenkinson and Jones (2009).

tivity. Accordingly, my paper extends their findings by complementing the effect on residents, who are outsiders to IPO firms. It shows that the welfare implication for incumbent residents is not negligible, contributing to the existing literature by pointing out that a largely underrepresented group is also an important stakeholder of IPOs.

Moreover, the work also links the two seemingly disjoint fields by proving that equity market can directly affect the inequality of local neighborhoods through the channel of firms. Literature usually stand on one side only. In corporate finance, researchers study the welfare gap by treating people as investors in equity market or employees in firms.(Li et al. (2021), Pan et al. (2022)).[2] On the other hand, labor economists often study inequality and local productivity based on endogenous changes in local characteristics (Guerrieri et al., 2013), direct investment by firms (Greenstone et al. (2010),Qian and Tan (2021)) or place-based policies by government (Kline and Moretti (2014), Tian and Xu (2022)), but are silent on the role of equity market. Recently, two papers have made an effort to bridge the gap between IPO and the local economy (Butler et al. (2019), Cornaggia et al. (2019)). Nonetheless, they find competing results, and since they treat workers are homogeneous, the rising inequity is shadowed by overall economic changes. This paper differs from these two papers in its main focus and policy implications. Finally, a limitation for the previous papers on the topic has been discussed: changes in welfare remain indeterminate when studying wage and living costs separately. However, this paper overcomes this challenge by combining welfare measures structurally.

More broadly, the paper contributes to a strand of literature on the spillover effect generated by geographically proximate firms, such as firm bankruptcy (Bernstein et al., 2019) and investment (Dougal et al., 2015). A small subset of papers focus on positive externality of innovation and its transfer across firms (Bloom et al. (2013), Arqué-Castells and Spulber (2022), Matray (2021)). Following the conclusion, encouraging and subsidizing firms for innovation should always be beneficial. Nevertheless, this paper shifts the attention from peer firms to local residents, and is more conservative on policy implication, since it uncovers a non-negligible exacerbating inequality beneath economic growth.

The rest of the paper proceeds as follows. Section 2 describes data construction and presents

[2]Though a similar transmission is also possible through income effect by equity market participants, it is indirect and much less clear.

summary statistics and Section 3 discusses the empirical strategy for identifying the spillover effect of high-technology IPOs on local neighborhoods and its estimation results. Section 4 brings welfare outcomes into a structural model and estimates the differential effect on workers' utility. Section 5 presents robustness check on reduced-form results and evidence of heterogeneity treatment effect. Finally, Section 6 concludes.

2 Data

In the section, I describe main data sources used by the analysis. The study heavily relies on demographic and business variables at the census tract or ZIP code level, as well as IPO data from financial database. To conduct structural estimation, I incorporate commuting patterns of workers between ZIP codes to measure changes in utility.

2.1 High Technology IPOs and Establishments

To collect completed IPO events from 2003 to 2017, I rely on two financial databases, Audit Analytics and Thomson, which provided additional information such as IPO proceedings and the most current address of firm headquarters. As it is possible for firms to relocate their headquarters, I manually checked the 10-K files to adjust the business address to the location when the IPO occurs.[3] Next, I utilize the Google Geocoding service to convert addresses to geographical coordinates and map them to ZIP codes and tracts used by the 2010 Census.

To identify high-technology firms, I refer to the list of NAICS codes considered as high technology by the U.S. National Science Foundation (NSF)[4] and crosswalk them to 1987 SIC codes. High-technology firms are defined as those with SIC codes listed above, and I manually verify that their business activities primarily involve high-skilled workers. Furthermore, I obtain firm assets and revenue from Compustat. To ensure a high-quality sample and focus on influential IPOs , I exclude ABS & REIT and further restrict to firms with IPO share price no less than \$5 and assets larger than \$100 million by the year-end of IPO.

After conducting the necessary filtering, I identify a total of 396 high-technology IPOs that

[3] I do not use headquarters location information from the databases, because they record the current headquarters location and backfill to all previous years.

[4] The list is available at https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.htm

occurred during the sample period. This number is consistent with the figures reported by Bernstein (2015) and on Jay Ritter's website[5]. Of these, 31 firms relocated their headquarters at some point. However, with the exception of five firms, the distance between the new and old headquarters is less than 20 miles for the remaining twenty-six firms, so relocating the headquarters is less of a concern. Additionally, I manually verify the address and use the location of the firm's headquarters in the year of IPO as the center of the treatment areas.

Figure (2) illustrates the geographic distribution of high-technology firm headquarters, while Table (1) and Table (2) summarize the distribution of firms by geography and industry. The majority of high-technology firms are concentrated in wealthy and densely-populated communities along the west and east coasts, as well as in some large cities in the middle of the country. The top three cities favored by high-technology IPO firms are New York (17), Houston (13), and Austin (11), while the top three counties are Middlesex, MA (24), Santa Clara, CA (20), and San Mateo, CA (18), and the top three states are CA (93), TX (46), and MA (29). In terms of industry distribution, the most common SIC code is 7370 - Services-Computer Programming, Data Processing, Etc (68), followed by 2836 - Biological Products (37) and 7372 - Services-Prepackaged Software (29). Figure (3) displays the number of high-technology IPOs that occurred each year, which shows a cyclical pattern that is similar to that of overall IPOs. Although 2014 had the highest number of high-technology IPO cases (54), only seven high-technology firms went public in 2008.

Table (4) Panel A summarizes the IPO information and financial position of the firms in the sample. Overall, high-technology firms in the sample are similar to other public firms. However, IPO proceeds and total assets are highly skewed, as some tech giants such as Facebook and Google launched large IPOs. To account for the heterogeneity of firms, Case-Year fixed effects are included in the later analysis.

The sample of withdrawn IPOs is also comprised of high-technology firms and is obtained from Thomson/Refinitiv using the same procedures outlined in the previous section. During the same sample period, 118 cases of withdrawn IPOs are identified. For each census tract in the sample, the distance to the nearest withdrawn IPO firm headquarters is calculated, and then split into five bins within each actual IPO.

An IPO Zone is defined as the collection of neighborhoods within 30 miles of a firm headquarters.

[5] The data is available at https://site.warrington.ufl.edu/ritter/ipo-data/

IPO Zones are time-invariant and can geographically overlap with each other. Since each IPO firm uniquely maps to an IPO Zone, these two terms may be used interchangeably in the paper.

Lastly, the number of high-technology establishments by ZIP codes is collected from NSF to investigate whether IPOs induce establishment growth. The data are grouped into bins by employment, such as establishments with less than one hundred employees.

2.2 Local Neighborhoods Characteristics

For reduced form analysis, a neighborhood refers to a census tract, an aggregated area of census blocks used in the U.S. census. Compared with other small geographical areas like ZIP codes, Census tracts have relatively stable boundaries and provide rich data for accurate estimation. Data consist of 70,004 census tracts across the U.S., harmonized to 2010 Census to account for boundary changes between two waves of censuses. In contrast, for structural estimation, data are summarized on the ZIP code level to reduce computational difficulty.

Data on wage and employment by skill groups, as well as demographic characteristics such as age and race, are gathered from the ACS 5-year Data, all available in the Integrated Public Use Microdata Series (IPUMS). (Manson et al., 2021).[6] I treat characteristics in 2006-2010 ACS Data as of data in 2008 and so on. A small number of observations contain missing values. They are firstly interpolated by the weighted average of values in their 5 miles nearby tracts, with the population as the weight. For imputing the remaining missing values, I compute the average growth rate and multiply it with lagged values for imputation. For wages, they are adjusted to 2010 dollars by the GDP deflator.[7] Numerical variables are winsorized at 1% and 99% level. Table (3) presents the definition of variables and Table (4) provides descriptive statistics on the census tract level.

Figure (4) visualizes the time trend of wages by skill groups. Although nominal wages rise steadily, deflated wages are stable over time. Notably, a vast and persistent wage gap of around 20,000 dollars exists between high-skilled and low-skilled workers. Understanding the factors that drive this skill wage premium is crucial for policymakers seeking to promote economic equity.

Another important measure is the number of homeless people. I use the 2007 - 2017 data from Annual Homeless Assessment Report (AHAR) by U.S. Department of Housing and Urban

[6] In Section 4, I also use data of 5% sample of the population from the 1990 Census for constructing the shift-share IV. The data structure is highly similar to the ACS data, except for the geographic level. I will discuss the data later.

[7] Alternatively, I also use CPI as a deflator, and the results are very similar.

Development (HUD) and map the data to census tracts by the crosswalk provided by Glynn et al. (2021). Although the AHAR data do not include information on the skill level of homeless people, the vast majority should be extremely low-skilled workers. Therefore, the measure is an important indicator of the welfare of low-skilled workers.

To examine housing markets, I collect data on median rents from IPUMS and complement it with House Price Index (HPI) from the Federal Housing Finance Agency (FHFA). The FHFA HPI is a weighted, repeat-sales index that measures the movement of single-family house prices. This index allows me to separate the effect on household consumption from the overall changes in the housing market.

Figure (5) describes pairwise correlation between census characteristics. Neighborhoods with higher payroll tend to have more college graduates, higher living cost and lower poverty rate. In contrast, correlation between welfare measures and demographic characteristics like age and race is much smaller in magnitude.

Table (4) Panel B summarizes the outcomes and demographic characteristics of census tracts. Inequality across neighborhoods is significant. For example, the median wage of high-skilled workers living in the richest neighborhood is ten times the median wage of those living in the poorest neighborhoods. Moreover, while some neighborhoods achieve a poverty rate of less than 1 percent, there are neighborhoods where more than half of the residents live in poverty.

n propensity score estimation, a rich pool of predictors is constructed based on the 2000 ACS Census, which was collected prior to all IPOs in the sample. As census tracts are small geographical areas, an IPO occurring in one census tract can be related not only to the tract itself, but also to characteristics of nearby census tracts. Therefore, for each census tract, three concentric rings with radii of 5 miles, 10 miles, and 15 miles are drawn, and all variables are calculated for each ring.

2.3 Productivity Measures for High-skilled Workers

Productivity is difficult to measure without imposing any functional form of production function, as the inputs and outputs on either the individual or high-technology establishment level are not observable. Additionally, there is a risk of selection bias in the study, as individual characteristics and migration are unobservable. If high-skilled workers sort into the neighborhoods nearby IPOs and thus increase firm outputs, the effect on productivity tends to be underestimated.

To mitigate the concern, I collect patent outputs generated by all public high-technology firms from Kogan et al. (2017)[8]. The dataset also includes economic values adjusted to 2010 dollars, as measured by the authors. The economic values of patents can reveal the quality of patents. The original paper documents further details about the methodology for constructing the dataset.

2.4 Commuting Pattern of Workers

In the structural model, workers are free to choose where they live and work to maximize their utility without cost of migration. To capture the interactions between different areas, I use the LEHD Origin-Destination Employment Statistics (LODES) datasets that contain information on the number of workers in home-work commuting flows between two census blocks. These data are collected between 2002 and 2015 in most U.S. states (U.S. Census Bureau, 2022). The accompanying RAC and WAC datasets divide workers by income and industry. As noted, to reduce the computational burden, I aggregate the data to the ZIP code level instead of the census tract level.

To calculate the number of high-skilled and low-skilled workers commuting from one ZIP code to another, I combine LODES with the 2009 National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2022), which provides information on a sample of travelers, such as purpose of the trip and educational attainment of travelers. Similar to Qian and Tan (2021), I use a LASSO model to predict the share of high-skilled workers in commuting flow between each pair of ZIP codes and describe the methodology later.

3 Identification Strategy

3.1 Construct counterfactuals by Withdrawn Issuers

"By controlling for distance, I can compare neighborhoods close to IPO firm headquarters and those far away to estimate the treatment effect. However, one may worry that the decision and timing of an IPO are correlated with unobserved local characteristics, which in turn may affect the welfare outcomes. The correlation is the main threat to the identification strategy.

Unlike manufacturing firms, high-technology firms depend less on the local economy, as their

[8] I would like to thank the authors for making the dataset publicly available. The original data used in the paper is from 1996 to 2010, but it has been extended to 2020, covering the entire sample period of high-technology IPOs

inputs and outputs are tradable across the country or even the world. To further alleviate this concern, I control for the distance to the closest neighborhood with a withdrawn high-technology issuer and divide neighborhoods into bins based on the distance. Next, I compare census tracts with similar proximity to the closest withdrawn issuer but different proximity to IPO headquarters to reduce confounding effects."

The first underlying assumption is that withdrawn IPOs are good counterfactuals of actual IPOs. In Busaba et al. (2001), they investigate a sample of U.S. IPOs and find that withdrawing issuers are very similar in size and profitability to issuers completing their IPOs. I also confirm that industry distribution across the two types of issuers has no significant difference. Therefore, we can think withdrawn issuers approximate successful issuers in financial position and business operation.

Second, for valid identification, more importantly, though the filing of an IPO can potentially correlate with unobserved local characteristics, the outcome of IPO cannot be driven by those characteristics. While, for manufacturing firms, their business cycle may be affected by local demand or supply shocks, it is unlikely the case for high-technology firms, as they produce worldwide tradable goods and services and mainly rely on human capital instead of physical inputs. To further address the concern, I compare observed local characteristics and summarise them in Table (5). Although there can still be unobserved characteristics, descriptive statistics show that two types of issuers reside in almost identical local economies, which provides further assurance for the quality of counterfactuals.

Figure (6) (a) and (b) illustrates the above identification strategy, using the IPO event by Open Solutions Inc as illustration. The company specializes in complex information system design and information technology project management. It is headquartered in Hartford, CT and raised approximately 85 million dollars by going public in 2003. In graph (a), the red point in the center identifies the location of headquarters of the IPO firm. The shaded area consists of census tracts within 15 miles, and blank area is tracts within 15-30 miles. They constitute the treatment and control group respectively. In graph (b), the dark yellow point in the left bottom indicates headquarter of the closest withdrawn issuer, China Bull Management Inc. The high technology company withdrew its S-1 Form on 11/17/2011. Tracts colored dark blue within the shaded area and tracts colored light blue in the blank area belong to the distance bin, as they share a similar distance to the withdrawn issuer. The main identification strategy compares the outcomes of the dark blue area with the light blue area by using distance bins as a fixed effect.

Another alternative identification strategy involves using the two-month NASDAQ market return before IPO as an instrument. The strategy is pioneered by Bernstein (2015) and used by Cornaggia et al. (2019) in a similar setting to this paper. However, the flaws of the instrument have been well discussed in Butler et al. (2019).[9] In addition to their discussion, using the IV entails aggregating outcomes from the census tract level to the IPO Zone level, as the mapping from the market return to the IPO firm is one-to-one. This change would not only result in a different interpretation of the results, but also significantly reduce the sample size.

In order to validate the identification strategy, I construct a set of alternative counterfactuals by estimating a propensity score model with a rich pool of candidates, and identify highly similar effect of high-technology IPOs. More details about the propensity score model and the strategy come in Section 5.

3.2 Treatment Effect of High-Technology IPOs

In this section, I employ a difference-in-differences approach to estimate the treatment effect of high-technology IPOs on tract-level neighborhood outcomes. For each IPO case, the treatment group consists of census tracts located within 15 miles of the firm's headquarters, while the control group includes tracts with a distance of more than 15 miles but less than 30 miles. I collapse all observations by cases into a single panel, allowing a census tract to belong to multiple IPO zones and possibly serve as the treatment group for one IPO case and the control group for another. In Section (5), I also conduct a case-by-case estimation for effect, following Greenstone et al. (2010). Overall, the results are fundamentally similar.

The baseline specification is as follows:

$$Y_{it} = \alpha + \beta Treat_{ik} \times \mathbf{1}\{t > t_0^k\} + \theta Treat_{ik} + \mathbf{X}_{\mathbf{it}}^{\intercal}\mathbf{\Pi} + \delta_i + \gamma_{ct} + \eta_{kht} + \epsilon_{ikt} \tag{1}$$

[9]In the paper, they find the IV is weak by the extremely low R^2 found in the first stage. Besides the two-month market return, I independently verify that the IV is weak in predicting the success of IPOs. Alternatively, using one-month and three-month returns yields similar undesired results. Another issue is that market returns can correlate with other equity market transactions, such as mergers and acquisitions. These activities also turn out to affect the local economy. Thus, the IV would fail the exclusion restriction.

Y_{it} are welfare outcomes related to census tract i in year t, including wage and employment by skill groups and housing market outcomes. $Treat_{ik}$ is an indicator for tract i belongs to treatment group of IPO case k, and $\mathbf{1}\{t > t_0^k\}$ denotes the dummy for year t is after the year of IPO by firm k. The term $Treat_{ik}$ accounts for the level difference between the treatment group and control group, thus allowing us to consistently estimate β, which is the DID estimator and identifies the average effect of high-technology IPOs. $\mathbf{X}_{it}^{\intercal}$ denotes optional time-variant covariates for census tracts. I control for various fixed effects: firstly, the tract fixed effect δ_i absorbs time-invariant characteristics of each census tract, such as geography and climate. Alternatively, one can modify it as interacted with IPO case so that the interacted fixed effect further absorbs the dummy $Treat_{ik}$. Second, γ_{ct} is the county-year fixed effect, controlling for unobserved dynamic confounders on the county level, such as amenity measures and regulations. Finally, by treatment status and IPO cases, I divide census tracts into five bins based on their predicted propensity score, denoted by $h = 1, .., 5$. Therefore, the final ingredient is the firm-score-year fixed effect η_{kht} which not only absorbs time-variant firm-level characteristics, such as financial positions and investments, but also controls for heterogeneity related to IPO across neighborhoods. After controlling for all fixed effects, the comparison is between tracts in the treatment group and their counterparts with similar propensity scores, given the IPO case k. Standard errors are clustered on the level of firms to adjust for potential correlation treated by the same IPO event.

Table (14) shows the result. For columns (3) (4) (7) and (8), the case-tract fixed effect replaces the tract fixed effect, and columns (2) (4) (6) and (8) add covariates in additional to fixed effects. Note that the panel is collapsed from repeated observation level, so each of census tract can relate with more than one high-technology IPO because of overlapped IPO Zones. The interacted fixed effect absorbs the dummy for treatment and account for possible heterogeneous treatment effect by different IPO cases on the same neighborhood. As neighbourhood characteristics are only measured by tracts and years[10], the two specifications would yield the same results if the treatment effect is homogeneous and stable over the years. Any disparity in coefficient estimates would mirror potentially heterogeneous and dynamic effects, and I explore the features later in this section and in Section (5).

[10]However, for the same reason, assuming different level of outcomes for the same census tract when it belongs to another IPO Zone does not reflect the reality. The side effect of interacted fixed effect is removing excessive variation.

For most outcomes, the point estimate of effect remains stable after including further controls. In determining robustness, Oster (2019) suggests that the importance of unobservables is jointly determined by point estimates and R^2. I compute the bounds and they are well above 1 in all specifications.[11] Moreover, R^2 is large enough, so it is unlikely that further unobserved characteristics could drive down the results.

For labor markets, while IPOs raise wage of both high-skilled and low-skilled workers, they also enlarge the skill wage premium significantly. By taking wages in the logarithm, one can interpret the coefficient as changes in percentage. On average, a high-technology IPO would increase wage of high-skilled workers by 1.16% and wage of low-skilled workers by 0.52%. Correspondingly, it would raise skill wage premium by 0.73%. Since both treatment group and control group consist of many residents, the aggregate economic impact is prominent given the magnitude.

On the other hand, I find a decrease in employment nearby IPO firm headquarters, especially for low-skilled workers by -1.36%. In contrast, although there is some evidence of job displacement for high-skilled workers, the magnitude is much smaller, and the effect is insignificant when no covariate is considered[12]. As a result, high-technology IPOs enlarge wage premium and relative labor supply simultaneously. The finding is consistent with the supply-demand framework developed by Welch (1973) and Katz and Murphy (1992) and empirical finding of increasing returns to skills in Acemoglu and Autor (2011). This indicates that high-technology IPOs can have a effect on inequality on local neighborhoods.

The displacement of workers can result from migration or unemployment. The first possibility is driven by higher living costs, fueled by high-skilled workers' consumption. Marginal low-skilled workers would leave their original place in order to re-optimize utility. Meanwhile, job destruction may occur in other sectors like manufacturing because of rising price of local goods. As low-skilled workers are concentrated in those sectors, they are hurt and more likely being unemployed because of reduced labor demands.

Since I control for the local unemployment rate in the regression, the coefficient should be

[11] The bound δ is approximated by $\beta^* \approx \tilde{\beta} - \delta \times (\mathrm{o}\,\beta - \tilde{\beta}) \times (R^{max} - \tilde{R})/(\tilde{R} - \mathrm{o}\,R)$ where o denotes specification without covariates, and ˜ denotes specification with covariates. R is the shorthand of R^2. I set R^{max} to 1, which is the most conservative. δ is calculated by assuming $\beta^* = 0$, which implies no treatment effect. The criterion $\delta = 1$ means that unobservables are as important as observables in driving estimation results.

[12] Note that not all high-skilled workers are employed by technology related industries, so they may not experience higher wage but only higher living cost. Therefore, some marginal high-skilled workers also migrate out. Due to unavailability of occupational data, I cannot identify the composition changes in occupations within the skill group

interpreted as the migration effect. It confirms the finding in Cornaggia et al. (2019), though the authors do not make a distinction on skills. Thus, I add the literature by showing that the displacement effect on employment almost accrues changes in relative supply. Moreover, similar to this paper, I independently regress the unemployment rate on the treatment, and the coefficients are insignificant for both high-skilled and low-skilled workers.

Another important measure for the welfare of low-skilled individuals is the change in the number of homeless people in a neighborhood. Homelessness is a major issue in the United States and is closely related to the structural changes in society. Many homeless people suffer from unemployment or low-paying jobs and lack affordable housing, resulting in personal hardship and physical or mental illness. Over time, the growth of homelessness also diminishes the appeal of cities and can lead to potential social unrest.

According to HUD data, there were more than 500,000 homeless people in America by the end of 2017. Typically, homeless individuals are unemployed, so their characteristics may differ from the group of low-skilled workers. However, most of them are extremely low-skilled (educated), making them vulnerable to the impact of nearby high-technology IPOs, especially if such events cause rental prices to rise.

I use the longitudinal HUD data on the number of homeless people by Continuum of Care (CoC). CoC is a survey entity and also the most granular geographic unit in the HUD data. To construct the panel on the census tract level, I adopt the crosswalk by Glynn et al. (2021). A CoC is usually mapped to multiple census tracts, so census tracts are weighted by their total population. Given homeless people are mostly people in poverty, I also use the number of people in poverty as weights. As the HUD data only start from 2007, so I restrict the beginning year of the sample of IPOs to 2007 as well. Moreover, I focus on the census tracts with at least one homeless person over the sample period to exploit data variation, and report the estimated results in Table (7) separately.

Consistent with the displacement effect on low-skilled workers, it also becomes evident that high-technology IPOs increase the number of homeless people significantly. Comparing with controlled neighborhoods, the treatment group has fewer homeless people, as shown by the coefficient of $Treat$. However, following a high-technology IPO the number of homeless people in logarithm roughly increases by 0.006. Even though we do not observe the demographic characteristics or home ownership status of these homeless people, the majority should be previous renter living in the same area. They may become unemployed following the IPO, or they were already unemployed prior to the shock. In which case, it is very likely that the continuously rising rent is an important driving force of higher homeless rate.

Being homeless is miserable, and harms the physical and mental health greatly. Numerous studies report the prevalence of health issues among homeless population, and such effect usually haunts over the entire life cycle. Thus, even based on the evidence alone, it is far from obvious that high-technology IPOs are positive or at least neutral to everyone in the local neighbourhoods.

Next, high-technology IPOs have a prominent positive effect on house net worth and rents. House Price Index excludes commercial land uses, so I can separate household consumption from firm investment. In line with Mian et al. (2013) and Butler et al. (2019), IPOs heat up the local housing markets through both firm and household consumption channels. Higher housing values also indicate higher living costs in the area because of their strong correlation, so the change in the real wage is not apparent. In parallel, one cannot infer the change in welfare from estimating outcomes separately, which is the limitation of reduced form results.

Besides the baseline difference-in-differences, to incorporate the dynamic effect of high-technology IPOs and test for confounders by people's expectation, I adapt equation (1) to the dynamic difference-in-differences by estimating the exact specification.

$$Y_{it} = \alpha + \sum_{\substack{s \neq -1 \\ s=-3}}^{6} \beta_s Treat_{ik} \times \mathbf{1}\{t - t_0^k = s\} + \mathbf{X}_{it}^{\intercal}\mathbf{\Pi} + \delta_i + \gamma_{ct} + \eta_{kht} + \epsilon_{iks} \tag{2}$$

All notations follow the baseline regression (1), except for s denotes the relative period from the year of IPO. I normalize the effect in the year before IPO to zero. Here, β_s measures the effect in period s relative to period -1, and periods $s < 0$ are falsification test for pre-trend. In the regression tables, I denote s as *Period*.

Figure (7)-(8) plot the estimate over times. It also includes the simultaneous 95% confidence intervals (Montiel Olea and Plagborg-Møller, 2019). Advocated by Freyaldenhoven et al. (2019), the simultaneous confidence intervals are designed to contain the true path over time and therefore more useful for detecting pre-trend and identifying post-treatment effects.

The signs of the post-IPO coefficients align with the static DID estimates. There is a notable positive treatment effect on high-skilled wages and a negative effect on low-skilled employment. One can see that the treatment effects are long-lasting, with no reversal of effects, as evidence from the local economy continues to absorb the influence of IPOs even after ten years. In contrast, the reduction in high-skilled employment is small and reverses after five years since the IPOs. In the long term, the benefits resulting from higher wages and local amenities for high-skilled workers outweigh the burden of increased living costs. Finally, the pre-IPO estimates support the common trend assumption of DID, as the confidence intervals contain zero. The common trend also rules out potential anticipation effects of IPOs, reinforcing that the changes in outcomes are solely due to the actual IPO events.

Table (8) provides coefficient estimation results. The coefficient measures the average effect of high-technology IPOs in the given period relative to period -1. As before, critical values and confidence intervals are simultaneous instead of pointwise. Similar to the discussion, coefficients for years prior to the year of IPO are not significantly different from zero. However, we see strong effects after IPOs on all outcome variables except for low-skilled wage. Moreover, the effect accumulates over time, as the magnitude of coefficients is monotonically increasing. Taking high-skilled wage as an example, one can see the effect mounts to 0.72% log points in six years from 0.5% log points over the first three years. In comparison, the decrease in low-skilled employment is about -0.68% log points initially, but dampens to -1.02% log points afterward.

The dynamic treatment effect has policy implications that are equally important as the average treatment effect. While the average treatment effect on labor and housing outcomes reveals that exacerbating inequality may be a concern for policymakers, the deepening magnitude of effects further indicates that such policies should target long-term outcomes rather than on a temporary basis. Typically, related policies involve improving the quality or quantity of labor/housing supply, such as job training programs or the construction of affordable housing. Other policies, like rent control, may be effective for short-term outcomes but can be unsustainable or have side effects over a longer period, thus affecting the prosperity of the local economy.

Before introducing a structural model to quantify welfare changes, I focus on the transmission mechanism of the IPO effect on wage and employment for high-skilled workers. In equilibrium, wages are paid based on productivity levels, and employment is jointly determined by labor demand and supply. With referring to relevant terminology, the change in labor productivity and wage reflects the intensive margin of the IPO treatment effect, while the extensive margin refers to the number of high-skilled workers and high-technology firms in local neighborhoods. I will demonstrate that the intensive margin dominates and leads to higher wages, while labor demand, proxied by the number of high-technology firms, remains stable over the period.

3.3 Mechanism: Knowledge Spillover and Productivity Growth

To begin with, I define the intensive margin as the productivity of high-skilled workers in local neighborhoods surrounding high-technology IPOs. Using patent data at the high-technology firm level, I obtain the geographical locations of these firm headquarters and then crosswalk them to census tracts. I then restrict the samples to census tracts with at least one patent during the sample periods. Since knowledge transfer and spillover are more common within the same industry, I firstly consider patents in the same first-digit SIC industry as the IPO firm for each IPO case, and then study the patents generated by firms in other industries.

The former identification strategy is still adaptable, so I run specification (1) to test the intensive margin on high-skilled labor. Given that many census tracts generate no patent in some years, I augment the specification with an indicator for whether the dependent variable equals to zero. Results are in Table (9).

On average, firms nearby high-technology IPOs generate more industry-specific patents, both in terms of quantity and quality. [13] However, we do not find evidence for the spillover effect across industry. Hence, the productivity spillover across workers with different skills is a second-order effect, and the fact explains my finding in welfare inequality.

The estimation on patent growth echoes with findings in Matray (2021). These results are also consistent with the literature on agglomeration economy, which emphasizes the significance of knowledge spillover between workers. Consequently, if high-skilled productivity increases more than low-skilled productivity, the wage differential will also become larger. Hence, the intensive margin serves as an explanation for the underlying channel for the gentrification effect of high-technology

[13] Regression with fixed effects cannot deal with the many-zero issue in dependent variables. For the reason, I complement the standard difference-in-differences with a Tobit Model and still cluster standard errors on the IPO Zone level. the Tobit Model yields a much larger treatment effect as taking observations with zero patent into account better. However, the Tobit Model does not include fixed effects, due to the well-known incidental parameter problem in Neyman and Scott (1948). An upward bias is possible if firms generate more intellectual property in later years. Nevertheless, there is strong evidence for productivity increase overall, though the point estimate may not be reliable. Results for Tobit Model are available upon request.

IPOs.

To perform a more detailed analysis, I also run the specification with full set of covariates and fixed effects on two sub-samples: census tracts with original high productivity on patent outputs and those with low productivity. Definition of two sub-samples is based on the average number of patent outputs in year 2000, which is prior to all high-technology IPO events. As shown above, high-technology IPOs only boost patent growth in the same industry, so I also restrict to patents in the same industry as the IPO firm. The coefficient estimates are plotted in Figure (A3). Interestingly, the result shows that a high-technology IPO improve high-skill productivity only for census tracts whose are unproductive in high-skill outputs originally. Albeit worsening inequality, the IPO shocks may accelerate the convergence in productivity within high-skilled workers, which leaves more space for further research.

It may be a concern that explanations other than productivity increase exist, as growth in patent quality and quantity may also relate to a larger labor supply or an increase in the number of high-technology establishments. In the previous section, I showed that high-skilled employment remains stable after high-technology IPOs. In this section, I will discuss the identification and estimation of the number of high-technology establishments around IPO headquarters.

As Babina et al. (2017) points out, employees may leave for start-ups following the going public of their former employer. In addition to start-ups, established high-technology firms may also enter local neighborhoods to enjoy the benefits of agglomeration. If these new establishments emerge after IPOs and tend to pay higher wages for employees for competition (most likely by established firms) or heavily invest in innovation (most likely by start-ups), then the driving force of wage and patents is more likely a demand shock rather than productivity. Nonetheless, my analysis does not find any evidence for such a strong extensive margin in terms of the number of high-technology establishments.

Hence, I run specification (1) using the number of high-technology establishments recorded by NSF as dependent variables. I perform the analysis at the ZIP code level instead of the census tract level, as the smallest data granularity is ZIP code. Crosswalk from ZIP codes to census tracts is fuzzy, as a ZIP code typically includes several census tracts. On the other hand, the identification strategy by controlling for distance is adoptable, and ZIP-code level covariates from IPUMS are available. For these reasons, I use observations at the ZIP code level and display the results in

Table (10).

In the table, I first show results for all high-technology establishments and then restrict to establishments with fewer than one hundred employees, given that newly created establishments and start-ups should have fewer employees. Without adding covariates, the treatment effect is positively significant, but with relatively low t-statistics. Moreover, the magnitude is moderate. After controlling for covariates, the coefficients are not significantly different from zero. Conditional on high-technology IPOs having minimal or no effect on establishment growth, we may conclude that the demand shock on high-skilled labor is less of a concern for the identification of productivity growth. Consistent with the results, high-skilled employment is stable before and after IPOs. Taken together, the extensive margin of high-technology IPOs is small for high-skilled labor, and the intensive margin should play the dominant role.

Though it becomes clear that high-technology IPOs stimulate productivity growth primarily through agglomeration and knowledge spillover, the magnitude of the effect on productivity remains less clear. As productivity cannot be measured directly, I impose a functional form on the production function and labor market using a structural model in the next section and quantify the magnitude.

4 Estimating Changes of Welfare

In this section, I offer a framework to bring welfare measures together to quantify the change in workers' utility by high-technology IPO events. The setup shares the features of Rosen (1979) and Roback (1982) with heterogeneous workers, while the estimating procedure follows Berry et al. (1995), Diamond (2016) and Qian and Tan (2021). In the model, workers differ in skill levels but face the same local housing market. Each worker chooses the location of residence and workplace, and supplies one unit of labor inelastically. The model allows me to estimate the change in mean utility by aggregate level worker data.

4.1 Model Setup

4.1.1 Firm Production and Local Labor Demand

Consider an economy with finite number of independent neighborhoods, indexed by j. Each neighborhood has a homogeneous representative firm producing a single output with a mixture of high-skilled and low-skilled labor. Assume firms have CES production function

$$Y_{jt} = [(A^H_{jt}H_{jt})^\rho + (A^L_{jt}L_{jt})^\rho]^{\frac{1}{\rho}} \tag{3}$$

where H_{jt} and L_{jt} denotes amount of high-skilled and low-skilled labor in neighborhood j in time t, respectively. A^H_{jt} and A^L_{jt} are time-specific local productivity shifters. Define

$$\sigma = \frac{1}{1-\rho} \tag{4}$$

as the elasticity of substitution between high-skilled and low-skilled workers.

In a competitive labor market, skill wages are paid on their marginal products. Therefore,

$$W^H_{jt} = \frac{\partial Y_{jt}}{\partial H_{jt}} = (A^H_{jt})^{\frac{\sigma-1}{\sigma}} \left[(A^L_{jt})^{\frac{\sigma-1}{\sigma}} \left(\frac{H_{jt}}{L_{jt}} \right)^{-\frac{\sigma-1}{\sigma}} + (A^H_{jt})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} \tag{5}$$

$$W^L_{jt} = \frac{\partial Y_{jt}}{\partial L_{jt}} = (A^L_{jt})^{\frac{\sigma-1}{\sigma}} \left[(A^L_{jt})^{\frac{\sigma-1}{\sigma}} + (A^H_{jt})^{\frac{\sigma-1}{\sigma}} \left(\frac{H_{jt}}{L_{jt}} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} \tag{6}$$

Denote $w^s_{jt} = log\left(W^s_{jt}\right), s \in \{H, L\}$. Next, the logarithm of wage gap is

$$w^{diff}_{jt} := w^H_{jt} - w^L_{jt} = \frac{\sigma-1}{\sigma} log\left(\frac{A^H_{jt}}{A^L_{jt}}\right) - \frac{1}{\sigma} log\left(\frac{H_{jt}}{L_{jt}}\right) \tag{7}$$

Now consider a firm in a neighborhood going public in time t, and the event would influence adjunct neighborhoods through its spillover effect on productivity, as shown in the reduced form. To incorporate the scenario, I model the evolution of local productivity shifters as a decreasing function of the distance to the IPO firm. For simplicity, I assume that the shock only affects the productivity of high-skilled workers, so low-skilled workers shall be used as a benchmark. To this end, I parameterize the productivity shifters as

$$A^H_{jt} = cA^H_{j,t-1}exp(\lambda_0 + \lambda_1 d_{j\leftarrow IPO}) \tag{8}$$

$$A^L_{jt} = cA^L_{j,t-1} \tag{9}$$

c is some constant. The function $exp(\lambda_0 + \lambda_1 d_{j\leftarrow IPO})$ serves as a multiplier and measures the spillover effect on neighborhood j as a function of distance. $d_{j\leftarrow IPO}$ denotes the geographical distance from j to the location of IPO issuer. I expect $\lambda_0 > 0$ and $\lambda_1 < 0$, for closer neighborhoods absorb larger positive spillover effect, and λ_0 and λ_1 measures the total effect and the decay rate respectively.

Plugging A^H_{jt} and A^L_{jt} and into equation (7) and then taking the first difference, I can have the change in wage gap as

$$\Delta w^{diff}_{jt} = \frac{\sigma - 1}{\sigma}(\lambda_0 + \lambda_1 d_{j\leftarrow IPO}) - \frac{1}{\sigma}\Delta log\left(\frac{H_{jt}}{L_{jt}}\right) \tag{10}$$

For the case $\sigma > 1$ (high-skilled and low-skilled labor are substitutes), the first part on the right hand side accounts for IPO spillover effect, and should be positive as the IPO is in favor of high-skilled workers. The second part measures the relative changes in local labor supply, and is inversely related to the wage gap. The reduced form results show that both Δw_{jt} and $\Delta log\left(\frac{H_{jt}}{L_{jt}}\right)$ increase over time, so this must imply that rising in productivity differential overwhelms rising in relative labor supply. In the equation above, the structural estimators of interest are $(\sigma, \lambda_0, \lambda_1)$

4.1.2 Workers' Utility and Local Labor Supply

Now I model the utility function of workers and derive the labor supply curve. The utility function is primarily a function of residential and workplace location, and it will determine the local labor supply and thus can be used for welfare analysis in equilibrium. workers enjoy utility gain from wages, which depends on workplace location, and dis-utility from rents, which depend on residential location. Moreover, commuting cost and amenities also enter the utility function linearly. For heterogeneity, I let high-skilled and low-skilled workers have different preference over such characteristics and estimate the parameters in the next section.

To begin with, still consider the same finite number of neighborhoods as before. Each worker

w, with skill level $s \in \{H, L\}$ chooses residential location i and work location j to maximize utility. The worker consumes both local goods and tradable goods. In time t, his/her (indirect) utility is given by

$$V^s_{ijwt} = w^s_{jt} - \theta^s r_{it} - \gamma^s \tau_{ij} + a^s_{ijt} + \zeta^s \epsilon_{ijwt} \tag{11}$$

[14]

w^s_{jt} denotes the log wage for people working in neighborhood j at time t by their skill groups. r_{it} is the log of spending on housing. As mentioned, I assume that high-skilled and low-skilled workers face the same housing market. In equilibrium, the annualized spending on housing is the same across homeowners and renters. θ^s is the spending share of income on local goods. τ_{ij} measures the commuting cost from home location i to work location j, and the elasticity can vary by skills. a^s_{ijt} is the endogenous amenity measures differing by skills. Besides real wages, workers' utility depends on local amenities directly, and different types of workers can have heterogeneous tastes with respect to amenities. Finally, I assume that the error term ϵ_{ijwt} follows the Type-1 Extreme Value (T1EV) distribution, scaled by preference of location ζ_s. High-technology IPOs are modeled as exogenous and unexpected to local workers. The assumption has been justified by analysis in the last section. Therefore, workers can and only can re-optimize utility by choosing (i, j) after the IPO event.

We can divide the above equation by ζ^s and denote $\beta^s := \frac{1}{\zeta^s}$, so get the transformed mean utility δ^s_{ijt} equal to

$$\delta^s_{ijt} = \beta^s(w^s_{jt} - \theta^s r_{it} - \gamma^s \tau_{ij} + a^s_{ijt}) \tag{12}$$

It is the average utility across workers living in i and working in j. The setting enables me to

[14]The utility function is transformed from Cobb-Douglas utility assuming bounding budget constraint. In specific, worker w maximizes utility by choosing his spending on local good M_{wt} and nationally tradable good C_{wt} subject to the payroll W^s_{jt} in workplace. Moreover, he enjoys gain from amenities and incurs a commuting cost from home to work as a function of distance. His utility is

$$\max_{M,C} \quad log(M^{\theta^s}_{wt}) + log(C^{1-\theta^s}_{wt}) + a^s_{ijt} + \zeta^s \epsilon_{ijwt}$$

subject to

$$R_{it} M_{wt} + P_t C_{wt} + exp(\gamma^s \tau_{ij}) \leq W^s_{jt}$$

I take the national good as numeraire so $P_t = 1$.

focus on the shift of mean utility, without knowing the idiosyncratic taste of workers. With T1EV distribution of error, the model is the conditional logit model in McFadden (1973). Therefore, in each skill group, the share of people choosing the combination (i, j) is the average probability that (i, j) maximizes utility of workers. Therefore,

$$\hat{\pi}^H_{ijt}(\delta) := \frac{H_{ijt}}{\sum_{i'}\sum_{j'} H_{i'j't}} = \frac{exp(\delta^H_{ijt})}{\sum_{i'}\sum_{j'} exp(\delta^H_{i'j't})} \tag{13}$$

$$\hat{\pi}^L_{ijt}(\delta) := \frac{L_{ijt}}{\sum_{i'}\sum_{j'} L_{i'j't}} = \frac{exp(\delta^L_{ijt})}{\sum_{i'}\sum_{j'} exp(\delta^L_{i'j't})} \tag{14}$$

Estimation consists of two steps following the standard practice. The first step is to treat δ^s_{ijt} as parameters to estimate, and the effect of high-technology IPO on welfare is the difference in δ^s_{ijt} before and after the events. In equilibrium, the predicted share of workers choosing (i, j) equalizes the actual share of workers. Equation (13)(14) are contraction mapping from the vector of mean utility to the share of workers by skill group (Berry et al., 1995). I can solve for mean utility numerically by non-linear least square, as long as observing π^s_{ijt}. Supplied with some starting values of δ^s_{ijt}, the model can solve for optimized mean utilities that minimize

$$\sum_i \sum_j (\hat{\pi}^s_{ijt} - \pi^s_{ijt})^2 \tag{15}$$

The second interest is the utility response to changes in wages and rents, characterized by β_s and $\beta_s\theta_s$ respectively. As in Diamond (2016), I parameterize amenity changes as a function of the (log) employment ratio of high-skilled and low-skilled workers as below:

$$\Delta a^s_{ijt} = \eta^s log\left(\frac{H_{it}}{L_{it}}\right) + \Delta\epsilon^{a,s}_{ijt} \tag{16}$$

By Plugging Δa^s_{ijt} in equation (12) and taking the first difference, one can decompose the mean utility into real wages and amenities

$$\Delta\delta^s_{ijt} = \beta^s(\Delta w^s_{jt} - \theta^s \Delta r_{it}) + \beta^s\eta^s\Delta log\left(\frac{H_{it}}{L_{it}}\right) + \beta^s\Delta\epsilon^{a,s}_{ijt} \quad , \qquad s \in \{H, L\} \tag{17}$$

The structural parameters of interest are $(\beta^H, \beta^L, \theta^H, \theta^L, \eta^H, \eta^L)$. I, the econometrician, observe workplace wage Δw^s_{jt}, rent Δr^s_{it}, employment ratio $\Delta log\left(\frac{H_{it}}{L_{it}}\right)$, but not the residual $\Delta\epsilon^{a,s}_{ijt}$. To separate variation in real wages that is exogenous to amenities, I adopt the shift-share IV on wages using 1990 as the base period. The instrument identifies shift in local demands, and thus correlates with contemporaneous changes in real wages. On the other hand, both the local industry composition in 1990 and national wage trends are orthogonal to current amenities changes, so the instrument satisfies the exclusion restriction. I will discuss the IV construction and application later.

4.1.3 Labor Market Equilibrium

In equilibrium, the labor demand in each neighborhood equalizes the number of workers choosing to work in the neighborhood, and all workers' utility are maximized. Taking together, we can express the spillover effect of high-technology IPOs as a function of all structural parameters above.

$$\begin{aligned}\underbrace{\Delta\delta^H_{ijt} - \Delta\delta^L_{ijt}}_{\text{double diff.}} = {} & \overbrace{\frac{\beta^H(\sigma-1)}{\sigma}(\lambda_0 + \lambda_1 d_{j\leftarrow IPO})}^{\text{high-skilled productivity}} - \underbrace{\frac{\beta^H}{\sigma}\Delta log\left(\frac{H_{jt}}{L_{jt}}\right)}_{\text{labor supply}} + \overbrace{(\beta^H - \beta^L)\Delta w^L_{jt}}^{\text{skill complementarities}} \\ & - \underbrace{(\beta^H\theta^H - \beta^L\theta^L)\Delta r_{it}}_{\text{rent}} + \underbrace{(\beta^H\eta^H - \beta^L\eta^L)\Delta log\left(\frac{H_{it}}{L_{it}}\right) + \Delta\epsilon^{a,H,L}_{ijt}}_{\text{amenities}}\end{aligned} \tag{18}$$

where

$$\Delta\epsilon^{a,H,L}_{ijt} := \Delta\epsilon^{a,H}_{ijt} - \Delta\epsilon^{a,L}_{ijt} \tag{19}$$

and the geographical distribution of workers is given by

$$H_{ijt} = \frac{exp(\delta^H_{ijt})}{\sum_{i'}\sum_{j'} exp(\delta^H_{i'j't})}\sum_{i'}\sum_{j'} H_{i'j't} \tag{20}$$

$$L_{ijt} = \frac{exp(\delta^L_{ijt})}{\sum_{i'}\sum_{j'} exp(\delta^L_{i'j't})}\sum_{i'}\sum_{j'} L_{i'j't} \tag{21}$$

The left hand side of equation (18) represents the net benefit of IPO on high-skilled workers using low-skilled workers as the reference group. Because σ is greater than 1, the welfare gap is positively related to high-skilled productivity and the IPO spillover effect. Next, it declines with the relative labor supply. The third term is derived as the residual term of relative wage, and the direction of skill complementarities depends on the sign of $\beta^H - \beta^L$. (β^H, β^L) can be interpreted as the (inverse) preference of location. If high-skilled workers have greater labor mobility, the difference would be positive, and then the residual term is also positive. Besides changes in relative wages (represented by the first three terms), the welfare differential is also exposed to rent and amenity changes, and the direction depends on the sign of the difference in structural parameters. To build more intuition, consider the simplest case that $\beta^H = \beta^L$, $\theta^H = \theta^L$ and $\eta^H = \eta^L$ where workers with different skills are homogeneous in their tastes to location, housing and amenities. The welfare effect simplifies as changes in productivity and local labor supply. Furthermore, for $\lambda_1 < 0$, the exposure to IPO shock is negatively related to distance.

Challenges for coefficient estimation arise from the fact that the residual term $\Delta\epsilon_{ijt}^{a,H,L}$ is unlikely exogenous to the utility differentials brought by IPOs. There are many channels for IPOs to influence local amenity. For example, the development of local neighborhoods can attract more business in the service sector, such as banks, restaurants and private schools. Secondly, firms can invest in local infrastructure for social responsibility and branding. In reduced form estimation, variation in amenities generated by the above channels are mainly absorbed in dynamic case and county fixed effects. In the structural part, I will use the shift-share IV as identification strategy.

4.1.4 Housing Market Equilibrium

Finally, I assume perfectly inelastic housing supply, and all residents are renters. The simplifying assumption enables me to focus on the labor market commuting decision. Also, a data limitation is I do not observe the commuting flow by renters and homeowners separately. With the above assumption, the equilibrium rent is equal to the total expenditure on housing divided by the total population living in the neighborhood, as

$$r_{it} = log\left(\frac{\sum_j(\theta^H W_{jt}^H H_{ijt} + \theta^L W_{jt}^L L_{ijt})}{\sum_j(H_{ijt} + L_{ijt})}\right) \tag{22}$$

4.2 Estimation

Estimation consists of several steps. First, I treat mean utilities of workers as parameters to estimate, and then recover them from commuting flows. By this step, I can also reveal the effect of IPOs as the changes in utility. Next, to estimate elasticity on real wage and amenities, I apply the shift-share IV defined later in the section. Finally, I can uncover the relationship between the spillover effect and geographical distance by identifying λ_0 and λ_1. More details for data imputation come in Appendix A.

To ease computational difficulty, I crosswalk data from census tract level to ZIP code level and still define the treatment group as ZIP codes within 0 - 15 miles to an IPO firm headquarter, and control group as within 15 - 30 miles. I use the subsample of high-technology IPOs during 2005-2010 to conduct estimation. The sample consists of 194 out of 396 high-technology IPOs in the previous analysis, and the estimation is run over each IPO event. Still for computational convenience, ZIP codes in the sample are restricted to those in IPO Zones.

The outlined model can be regarded as a two-period model for empirical estimation: lets period $t = 0$ is year [-3, -1] before the year of IPO, and period $t = 1$ is year [0, 5] after IPO. I take the average of commuting flow measures for each period. The change in mean utility is the difference in (log) utility between the two periods, and should be interpreted as percentage changes in untransformed utility.Given the actual share of workers commuting between each pair of neighbourhoods is observable, their mean utility can be recovered from equation (15) by contraction mapping, as well as the difference in mean utility between $t = 0$ and $t = 1$.

As in Table (11), I discover that a high-technology IPO increases the welfare of high-skilled workers but has the opposite effect on the low-skilled workers. On average, it is related to 0.26% increase in utility of high-skilled workers and 0.91% decrease in utility of low-skilled workers, if one takes the full sample of neighborhoods in IPO Zones (within 30 miles). If restricting the sample of neighborhoods to the treatment group (within 15 miles) only, then there is a larger positive effect on high-skilled workers, as knowledge transfer and productivity spillover are more concentrated in the closer neighborhoods and decline with distance. Overall, the changes are economically and statistically significant.

For visualization, I combine ZIP codes into ten bins $k = 1, ..., 10$. $k = 1$ representing ZIP codes that are within 0-3 miles, and $k = 2$ for 3-6 miles and so forth, and thus there should be 200 possible combinations of (i, j) for each IPO event[15]. I re-estimate the vector of mean utility on bins for each IPO event. Figure (9) displays the estimation result. On average, the change in the welfare of high-skilled workers is positive, while it is negative for low-skilled workers. Same as before, both utility changes are significant at the 1% level.

Next, I bring equation (17) to the data to estimate the structural estimators, and solve endogeneity by using shift-share IV. In Appendix A, I discuss the imputation of workplace wage and construction of the shift-share IV in detail.

Equation (17) is estimated by 2SLS. I calibrate $\theta^H = 0.63$ and $\theta^L = 0.68$ for share of incomes spending on local goods (Diamond, 2016). For robustness, I also use $\theta^H = \theta^L = 0.62$ (Moretti, 2013). The results are not sensitive to the choice of θ^s. In practice, I add IPO event fixed effect since there is one representative IPO firm in the model. The fixed effect absorbs firm heterogeneity, which is not captured by the model.

Finally, equation (18) enables estimating spillover effect parameters (λ_0, λ_1) empirically. Besides (θ^H, θ^L), I calibrate $\sigma = 1.4$ following Katz and Murphy (1992) and use the estimate of $(\beta^H, \beta^L, \eta^H, \eta^L)$. The identifying assumption is that the distance from workplace to IPO firms is orthogonal to amenity changes in the neighborhood.

I didn't discuss the commuting cost $-\gamma^s \tau_{ij}$ in worker's utility still the point, as it drops out when taking the first differenced utility. As part of the estimation, I can also estimate the semi-elasticity of commuting cost by a gravity equation. By taking logarithm for equation (13)(14) and substituting the mean utility by equation (12), I can yield the following reduced-form relationship:

$$log(\pi^s_{ij}) = \xi^s \tau^s_{ij} + \phi^s_{it} + \phi^s_{jt} + \epsilon^s_{ij} \tag{23}$$

the coefficient $\xi^s := \beta^s \gamma^s$ characterizes the semi-elasticity of workers' decision on commuting distance. ϕ^s_i and ϕ^s_j are skill-specific Home-Period and Work-Period fixed effect. I augment equation (23) by adding Case-by-Period fixed effect and clustering standard error at the IPO Zone level.

Although the above equation is estimated separately by skill groups, I yield $\xi^s \approx -0.09$ for both groups. Hence, the probability of commuting is negatively related to commuting distance, but the

[15]Note that the step is for visualization purpose only. In subsequent estimations, each ZIP code remains an independent neighborhood.

relationship does not vary much with the skill of workers. Corresponding results are in Table (12). With $\xi^H = \xi^L = -0.09$, I can calculate the commuting parameter (γ^H, γ^L) with estimated $(\hat{\beta}^H, \hat{\beta}^L)$.

Table (13) provides the estimation result of parameters. First, the shift-share IV returns a very strong first stage. Second, The values $\beta^H = 3.712$ versus $\beta^L = 3.428$ mean that high-skilled workers have slightly less heterogeneous preference on locations. It is consistent with the empirical finding on greater mobility of high-skilled workers than low-skilled workers. Importantly, I find that the spillover effect on productivity is far-reaching, given the low value of $\lambda_1 = 0.0008$.[16] Meanwhile, $\lambda_0 \approx 0.2$ implies that a representative IPO would raise the productivity of high-skilled workers in its local neighborhood by 21.7%. The magnitude is very close to the estimate of innovation spillover strength by Matray (2021), who estimates that the number of patents in an area has an elasticity of 0.2 on innovation activities by local listed firms.

"To shed more light on policy, I perform a counterfactual exercise by modifying the magnitude of the productivity shock λ_0. Other structural parameters are calibrated according to the values in Table (13). I assume the economy is in equilibrium at period 0, and hence use all observed demographic characteristics as inputs. In period 0, ten thousand workers are assigned to neighborhoods, which are collected into bins as before. In the simulation, I begin by recovering the productivity fundamentals $\{A_0^H, A_0^L\}$ in period 0 from equation (5) and (6), and amenity fundamentals a_0^H, a_0^L from equation (12).[17] Then, I model the evolution of productivity based on productivity shocks. The second step involves simulating the commuting flow in period 1. For this purpose, wages and rents are expressed as functions of $\{H_{ij1}, L_{ij1}\}$,, reflecting the mean utility of high-skilled and low-skilled workers for each pair (i, j). Consequently, equations (13) and (14) form a system of equations used to numerically solve for $\{H_{ij1}, L_{ij1}\}$.

Figures A4 provide simulation results for number of employments and residents, wages and rents with respect to the strength of productivity shock. All figures are expressed in ratio relative to no productivity shock. As the productivity shock increases, wages for both high-skilled and low-skilled workers rise due to productivity gains and the skill complementarity effect, respectively. Workers

[16] As the distance to IPO firms is truncated up to 30 miles, I cannot infer the boundary of spillover effect.

[17] To keep it simple, here I assume exogenous amenity, which implies that amenity fundamentals do not change in period 1. However, relaxing the assumption with equation 16 doe not change the effect of simulated productivity shock.

in locations near the IPO headquarters benefit more significantly. However, rents also increase with productivity, and neighborhoods close to the headquarters experience higher rents. Nevertheless, the overall effect on wages and rents is evenly distributed across neighborhoods, both near and far from the headquarters, as the decay of the productivity shock is relatively slow.

5 Robustness Check

This section revisits the reduced-form estimation to address potential concerns related to sample selection and identification. First, I apply alternative identification strategies to enhance credibility. Concerns in this area may stem from two factors: (1) the validity of using withdrawn high-technology issuers as counterfactuals and (2) the staggered adoption of IPOs. To address these concerns, I analyze the treatment assignment and substitute the counterfactual IPOs with a propensity score model, which includes a comprehensive set of covariates. The estimation supports the baseline findings. Additionally, I refine the sample of IPO events by excluding certain metropolitan areas where high-technology firms are concentrated. By evaluating the remaining IPO events, I confirm that the observed effects are not driven by labor and housing market trends in major cities or counties.

5.1 Validate Counterfactual by Propensity Score Model

To enhance the credibility of the findings, I validate the identification strategy by estimating a propensity score model, using events of going public in the sample as the response. In the model, I employ characteristics from the 2000 Census, as they were collected before all IPO events. To account for nearby census tracts, I calculate variables for each tract within 0-5, 5-10, and 10-15 mile ranges, and include rich interactions between these variables. Table B2 provides definitions for all variables in the model. The outcome is a binary variable that takes the value of one if there is an IPO event in the census tract. To avoid overfitting, I utilize the LASSO-Logit model, which minimizes

$$\sum_{i=1}^{N}(Y_i - \alpha - G(\mathbf{X}_\mathbf{i}^\intercal\beta))^2 + \lambda||\beta|| \tag{24}$$

where G(·) is the logistic function. The optimal λ is selected by ten-fold cross-validation. Next, I estimate the predicted propensity score for each census tract, and divide them into quintiles by treatment and control group. In this way, I can balance the panel by rich covariates.

Figure (6) (c) illustrates the identification strategy. The shaded and blank area are as before. For neighborhoods, the dark blue area and the light blue area share a similar propensity of holding a high-technology IPO, and thus belong to the same propensity score bin, while only the former is close to the real IPO issuer. Hence again, the difference in outcomes between the two groups attributes to the effect of going public.

The underlying assumption is that the location choice and timing of IPOs are independent of neighborhood characteristics, conditional on all observed variables in the propensity score model and all fixed effects added to the regressions. These fixed effects absorb dynamic changes at the county and IPO Zone levels. Although I cannot entirely rule out the influence of unobserved characteristics—a fundamental limitation of matching methods—the concern should be alleviated by the identification strategy provided by withdrawn IPOs. By combining the two strategies above, the results are expected to have high credibility.

I re-run regression (1) and substitute the distance fixed effect with the propensity score fixed effect. This approach allows me to compare tracts with similar local characteristics potentially correlated with IPOs, but only differ in whether they receive the actual IPO treatment. The estimation result is presented in Table (14). The effects remain significant after altering the identification strategy through fixed effects.

5.2 Validate Assignment of Treatment

Section 3 considers all high-technology IPO events, while some IPO Zones overlap with each other, especially for firms headquartered in metropolitan areas such as Boston, Houston and San Francisco. A direct problem for identification is that a census tract in the treatment group of an IPO event can also belong to the treatment or control group of another IPO. It then leads to a concern that different treatments can interfere with each other.[18] Unfortunately, like other issues in staggered DID, there is no perfect way to deal with it. Nevertheless, I provide two additional tests to alleviate

[18] Consider an artificial example where the whole area consists of two IPO events A and B, while A happens before B. If part of the treatment group of event A serves as the control group of event B, then a researcher who adopts DID may underestimate the treatment effect of event B due to contamination by prior event A.

the concern.

Firstly, I run a DID similar to the specification (1) for each IPO event. The purpose is to identify the case-specific treatment effect and compare it with the average treatment effect, same as in Greenstone et al. (2010). The case-by-case DID specification is

$$Y_{it}^k = \alpha^k + \beta^k Treat_i^k \times \mathbf{1}\{t > t_0^k\} + \mathbf{X}_{\mathbf{it}}^{\intercal\,k}\mathbf{\Pi}^k + \delta_i^k + \gamma_{ct}^k + \eta_h^k + \epsilon_{it}^k \tag{25}$$

The superscript k means that the regression is specific to the IPO case k. The only substantial change is that the propensity score fixed effect no longer interacts with IPO or year fixed effect. Since each IPO Zone contains a small portion of observations, interacted fixed effects would reduce excessive variation. The equation above compares the outcome of census tracts in the same county with similar propensity scores each year. Standard errors are clustered at the county-by-year level[19].

Figure (10) plots the treatment effect for various outcomes from low to high, including the 95% confidence interval. In line with the main result, the majority of IPO events have differential effects on wage and employment of workers with different skills, and a positive impact on housing value and rents.

However, the analysis still has limitations regarding identification, since a census tract that has been treated by an IPO can also serve as a control unit for another. Consequently, if the treatment group of IPO firm A constitutes the control group of IPO firm B, then the estimate for firm B would actually represent the treatment effect given by B minus the effect by A.

Therefore, the second robustness check considers only the first time that census tracts are treated by IPO events. Once a census tract falls within 15 miles of an IPO, the DID dummy variable takes the value of one from then on, and I do not consider subsequent treatments for this tract. In this approach, each tract can only be treated by one IPO event.

The Control group is census tracts that are never included in the 15-mile ring of IPOs, but are in the 30-mile ring of at least one IPO. Same as the treatment group, they belong to the IPO where for the first time they fall into its 30-mile ring. The specification is exactly the same as regression (1), and standard errors are still clustered at the IPO Zone level.

Table (16) presents similar results to Table (14). The downside is that the assignment places

[19] If clustering on the county level, then there are too few clusters in the regression.

higher weights on earlier IPOs, since they include more observations than later IPOs. For the same reason, the magnitude of coefficients is larger than the baseline estimation. Like other technology changes, high-technology IPOs can also exhibit decreasing marginal return. In the early 2000s, the U.S. had much less high-technology firms, but it has seen a prosperity in recent years. For the same one additional IPO, the effect is more considerable when local neighborhoods have less similar firms. Therefore, all other things equal, earlier high-technology IPOs should be more influential than their later companions.

5.3 Exclude Metropolitan Areas

High-technology firms typically prefer metropolitan areas as their locations, which in turn contribute to the development of large cities. For instance, Boston's city development is closely associated with the influx of biotechnology and pharmaceutical firms, and a similar pattern is observed in cities in California and Texas. Consequently, this raises two concerns for the research. First, the effect of high-technology IPOs may coincide with trends in big cities, which I cannot precisely control. Second, one might worry that the estimation is driven by IPOs in big cities, rather than being a general case across the nation.

These two issues can be addressed by excluding IPOs in (economically) large metropolitan areas. According to summary statistics, the top three cities with the highest number of high-technology IPOs are New York (17), Houston (13), and Austin (11), while the top three counties are Middlesex, MA (21), Santa Clara, CA (20), and San Mateo, CA (18). After excluding IPOs in these cities and counties, the sample size reduces from 396 to 292. However, the size remains large enough for valid inference.

Using a subset of data, I re-run regression (1) and obtain comparable results, as shown in Table (15). For skill wages and skill wage premium, the estimated treatment effects are slightly smaller. The consistency in wage results suggests that large cities benefit from increased labor productivity due to their geographical and demographic characteristics. On the other hand, the skill wage premium moderately enlarges, which may imply that the development of large cities plays some role in gentrification and inequality, but the effect of high-technology IPOs remains prominent. As for housing prices and rent, the effect also appears slightly smaller. Large cities are usually characterized by high property prices. Given that price and rent are in logarithm form, coefficients should be interpreted as the percentage increase/decrease in price and rent, which helps explain the magnitude of the coefficients.

6 Concluding Remark

This paper connects equity markets and local economies, identifying IPOs by high-technology firms as an important but less observable source of inequality within neighborhoods. The results suggest that the effect of high-technology IPOs favors high-skilled workers through knowledge spillover on productivity, as these workers primarily experience a net increase in welfare due to higher real wages. However, low-skilled workers living in the same area bear the brunt of IPOs and are more likely to be displaced from their previous residences and workplaces by higher living costs. Other indicators of gentrification, such as homelessness rates, also increase significantly following high-technology IPOs. In sum, the pre-existing welfare gap between different types of workers is exacerbated by high-technology IPOs.

Overall, the aggregate impact of a typical high-technology IPO on local neighborhoods is substantial and long-lasting. The causal evidence is not limited to metropolitan areas or smaller economies and remains robust when using identification strategies such as withdrawn issuers or the propensity score model as counterfactuals.

Considering the ubiquity of large-scale IPOs by technology firms, this paper emphasizes the need for policymakers to monitor increasing inequality when funding high-technology firms and promoting their IPOs. Further research could focus on designing optimal social subsidy schemes for low-skilled residents vulnerable to displacement. For instance, increasing the supply of amenities or facilitating job searches can help mitigate the side effects brought about by IPOs.

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7 Figures

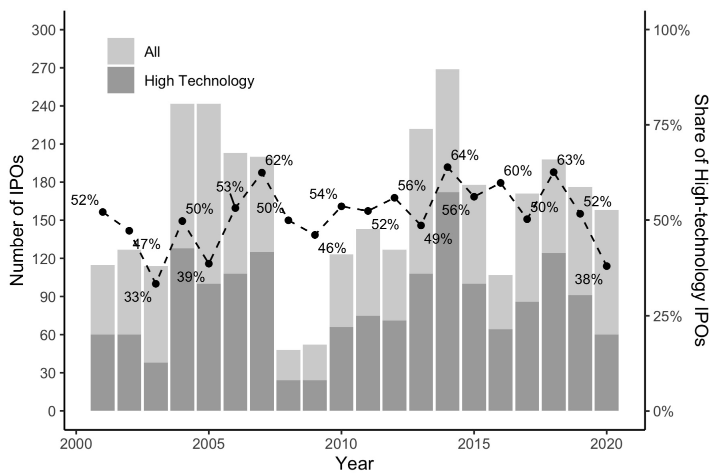


Figure 1: Number of High-technology IPOs

Notes: The plot presents number of IPOs by year. Data are from Audit Analytics, and classification of high-technology follows list of NAICS codes issued by NSF. The bars indicate for number of cases and correspond to the left Y axis. The dotted line describes share of high-technology IPOs and correspond to the right Y axis.

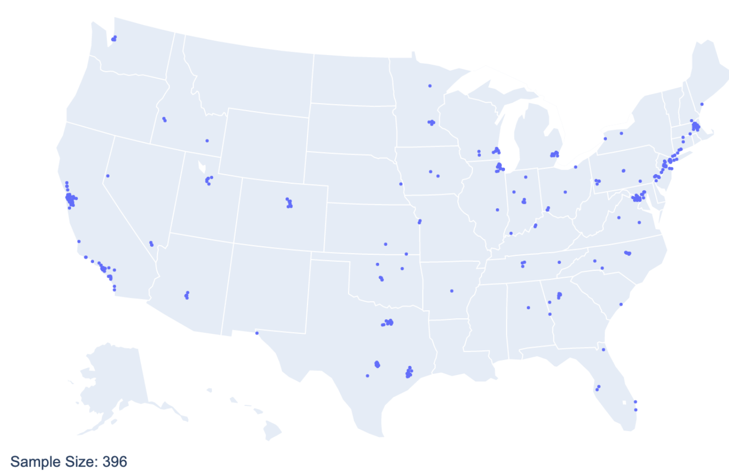


Figure 2: Location of Headquarter of IPO firms

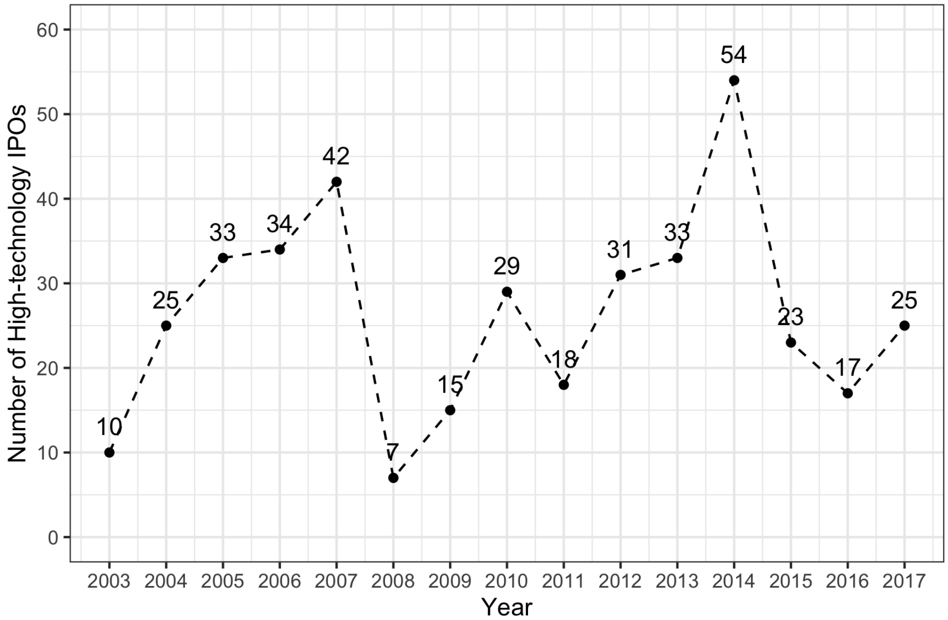


Figure 3: Number of High-technology IPOs in the Sample by Year

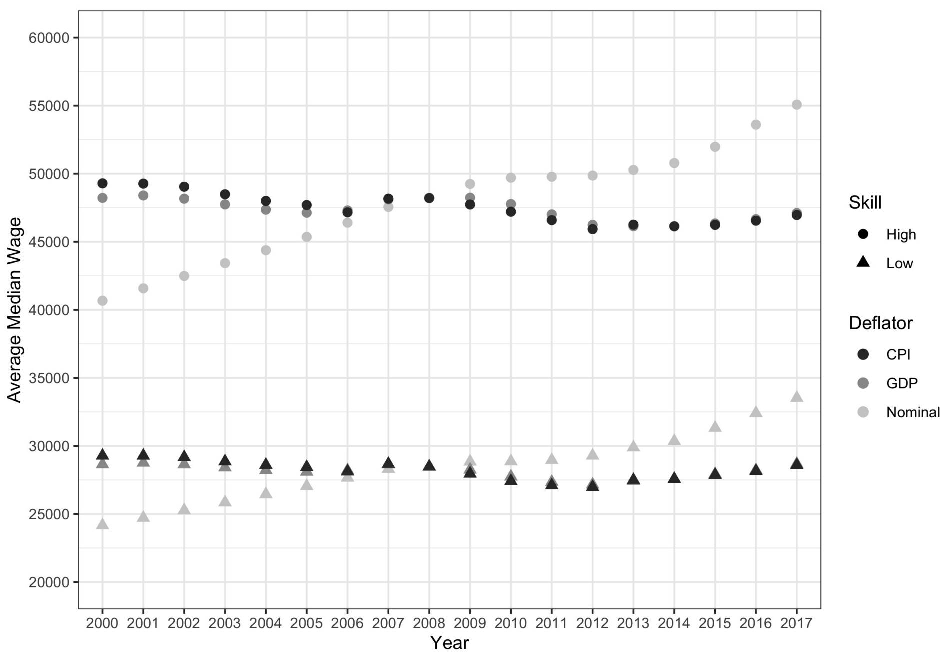


Figure 4: Average Wage by Year

Notes: Wages are median wages in the census tract level from ACS 5-year data. Each point represents the average of all observations in a given year. To balance the panel, I restrict to census tracts with population greater than 100 in 2010, and with complete time series wage observations after imputing missing values. Wages are adjusted to 2010 dollars. Results show that the two adjusted wages are very similar and constant over time, and I use the GDP-adjusted wages for analysis throughout the paper.

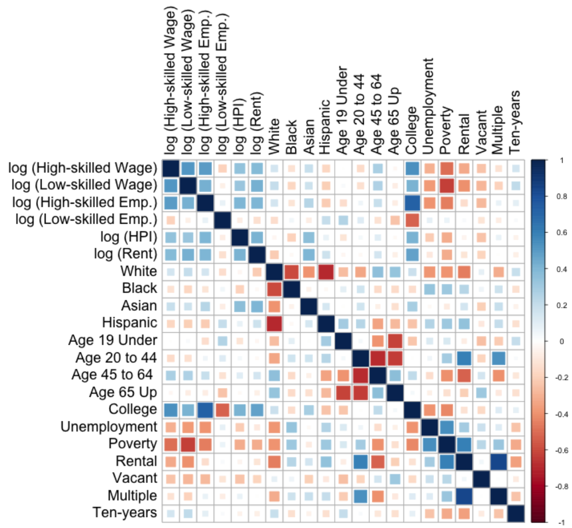
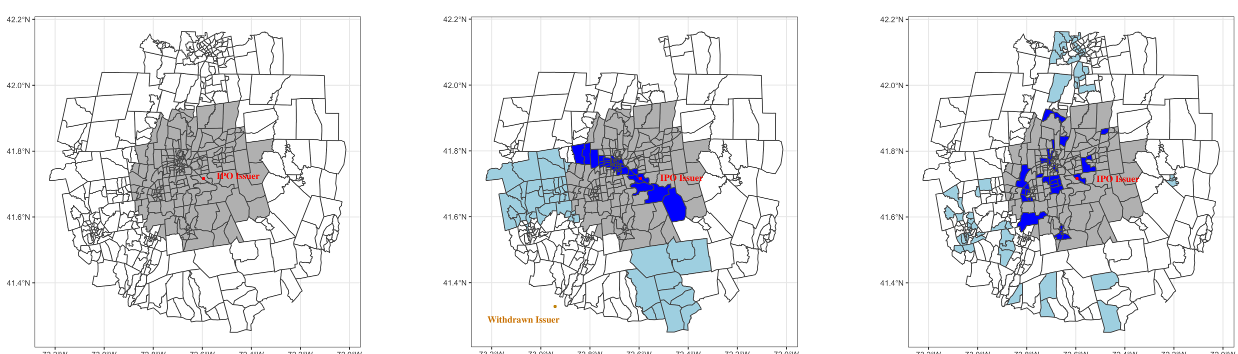


Figure 5: Correlation between Census Characteristics

Notes: The figure plots correlation coefficients between census characteristics. Observations from different years are collapsed into a single panel. Wages and Rents are adjusted to 2010 dollars. Definition of variables follows Table 3.



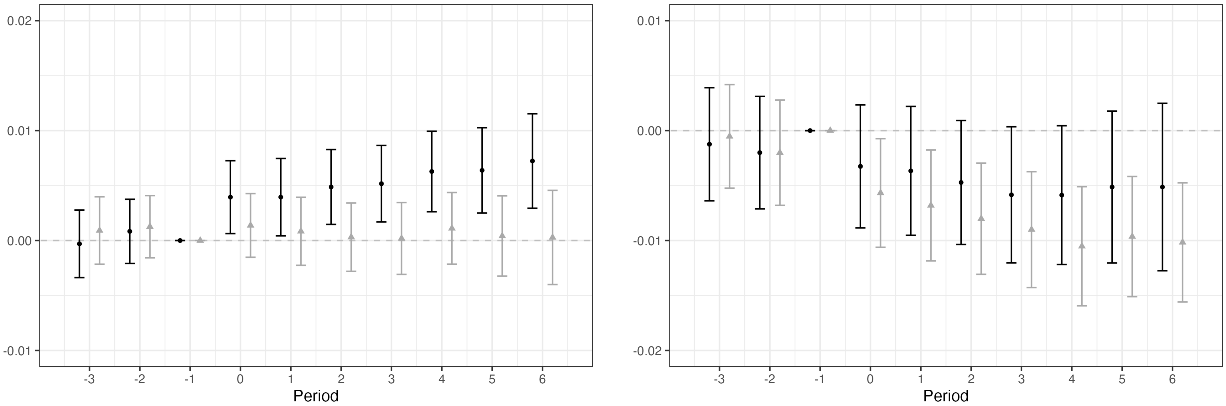
(a) By IPO Proximity only

(b) By Counterfactual IPO

(c) By Propensity Score

Figure 6: Visualization of Identification Strategy

Notes: The figure visualizes the identification strategies by using IPO of Open Solutions Inc as an example. In graph (a), the centering red point identifies location of headquarter of the IPO firm. Shaded area consists of census tracts within 15 miles, and blank area is tracts within 15-30 miles. In graph (b), the dark yellow point in the left bottom indicates the headquarter of closest withdrawn issuer. While the dark blue area and the light blue area share similar proximity to the withdrawn issuer, only the former is close to the real IPO issuer. tracts colored dark blue within the shaded area have similar distance to the withdrawn issuer as tracts colored light blue in the blank area. In graph (c), the only difference is that tracts colored dark blue within the shaded area have similar estimated propensity score as tracts colored light blue in the blank area. The identification strategy compares outcomes of the dark blue area with the light blue area.



(a) Wage

(b) Employment

Figure 7: Estimation of Dynamic Treatment Effect on Labor Market with Withdrawn IPO

Notes: The figure plots the dynamic treatment effect on wage and employment estimated by dynamic difference-in-differences with covariates. Results are by skill group of workers. The horizontal axis is the relative period to the year of IPO, and the period 10+ measures long-term effect over ten years after IPO. The vertical axis is the magnitude of effect relative to effect in period -1, which is normalized to 0. The 95% confidence intervals are simultaneous confidence intervals calculated with covariates. Notice that periods before -1 are falsification tests, and the results indicate that assumption of parallel trend is satisfied, because confidence intervals of estimates contain 0. Standard errors are clustered at the IPO firm level.

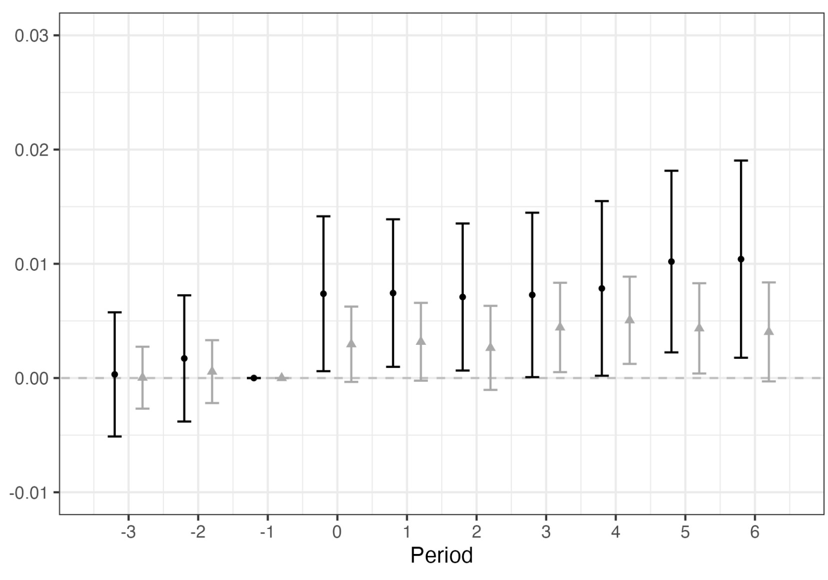


Figure 8: Estimation of Dynamic Treatment Effect on Housing Market with Withdrawn IPO

Notes: The figure plots the dynamic treatment effect on outcomes of housing markets estimated by dynamic difference-in-differences with covariates. Results are by outcomes. The horizontal axis is the relative period to the year of IPO, and the period 10+ measures long-term effect over ten years after IPO. The vertical axis is the magnitude of effect relative to effect in period -1, which is normalized to 0. The 95% confidence intervals are simultaneous confidence intervals calculated with covariates. Notice that periods before -1 are falsification tests, and the results indicate that assumption of parallel trend is satisfied, because confidence intervals of estimates contain 0. Standard errors are clustered at the IPO firm level.

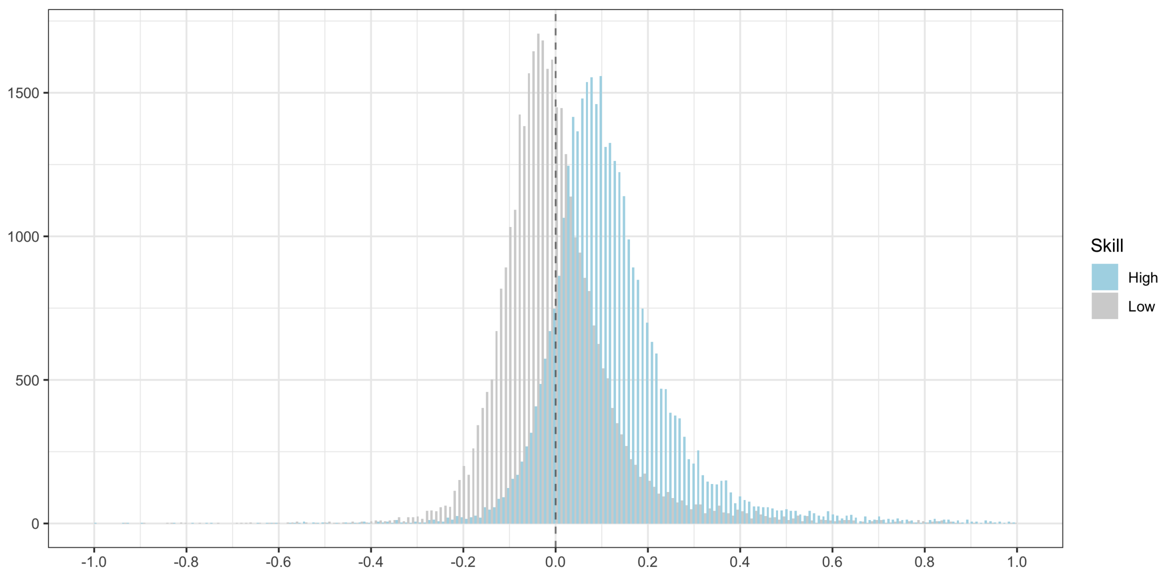
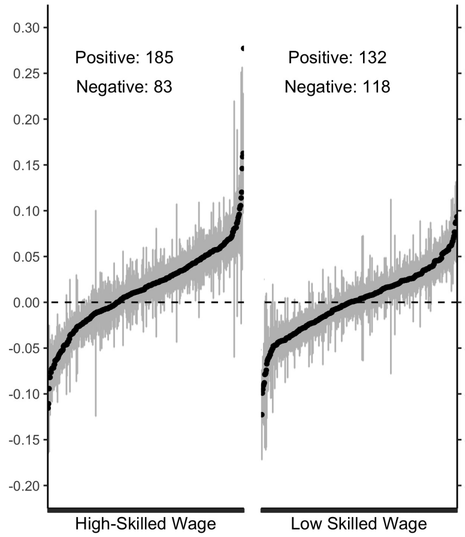
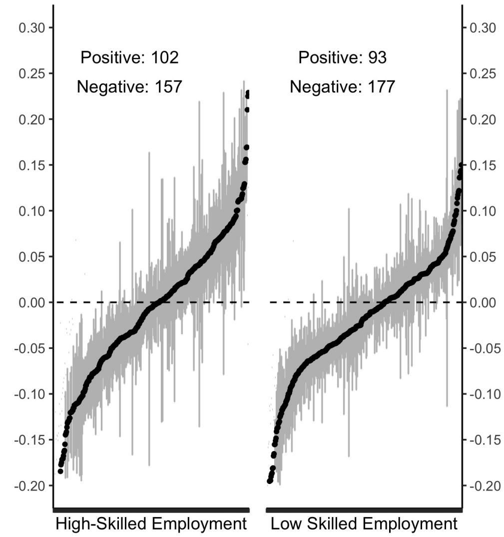


Figure 9: Change in Mean Utility across all Workers by Skill

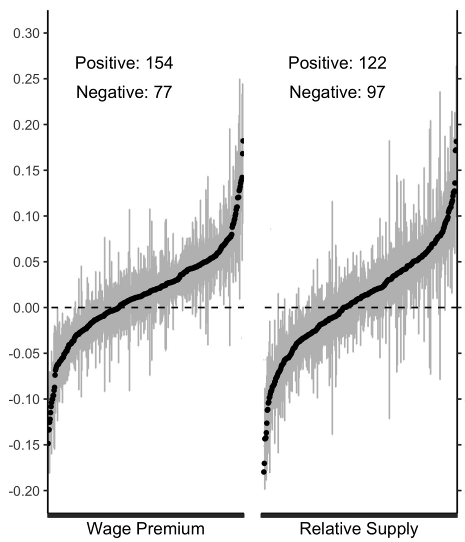
Notes: The histogram represents estimation of changes in utility across all workers by skill in IPO Zones. Mean utility before and after IPO events are estimated by contraction mapping of conditional logistic model on home-workplace commuting flows. Each observation is a three-mile ring of zip codes. On average, utility of high-skilled workers increases after IPOs, but low-skilled workers are hurt. The estimation corresponds with the reduced-form results on welfare outcomes.



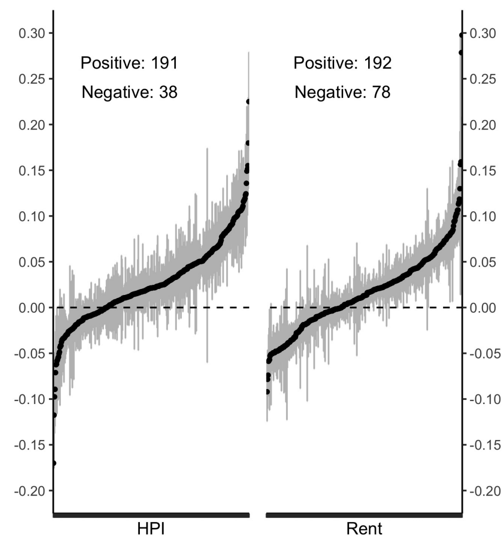
(a) Wage



(b) Employment



(c) Wage and Employment Gap



(d) Housing

Figure 10: Case-by-Case Treatment Effect

Notes: The figure plots the treatment effects by estimating each IPO event separately. They are ranked from lowest to highest, and error bars represent for the 95% confidence interval. For each outcome variables, *Positive (Negative)* refers to number of cases in which coefficient is significantly greater (less) than zero. Due to much fewer observations, the estimation is more noisy. However, one can still easily observe that the majority of IPOs have effects on labor market and housing market in the same direction of previous estimation based on full sample.

8 Tables

Table 1: Areas with Highest Number of High-technology IPO Firms

City	N	County	N	State	N
New York	17	Middlesex, MA	21	CA	93
Houston	13	Santa Clara, CA	20	TX	46
Austin	11	San Mateo, CA	18	MA	29
Cambridge	8	New York, NY	17	NY	24
Dallas	8	Los Angeles, CA	15	IL	18
San Francisco	8	Harris, TX	13	VA	18
Arlington	6	Cook, IL	12	NJ	15
Chicago	6	Alameda, CA	11	PA	15
Seattle	6	Dallas, TX	11	CO	11
Los Angeles	5	Travis, TX	11	MD	11

Note: The table outlines geographical areas with the highest number of high-technology IPOs in the sample by city-, county- and state-level.

Table 2: Top SIC Codes in the Sample of High-Technology IPOs

SIC Code	N	SIC Description
7370	68	Computer Programming, Data Processing, Etc
2836	37	Biological Products, Except Diagnostic Substances
7372	29	Prepackaged Software
1311	25	Crude Petroleum and Natural Gas
3674	21	Semiconductors and Related Devices
2834	17	Pharmaceutical Preparations
7373	13	Computer Integrated Systems Design
4899	12	Communications Services, Not Elsewhere Classified
6282	12	Investment Advice
3845	10	Electromedical and Electrotherapeutic Apparatus
4922	10	Natural Gas Transmission
7374	10	Computer Processing and Data Preparation and Processing Services
7389	8	Business Services, Not Elsewhere Classified
2911	6	Petroleum Refining
8731	6	Commercial Physical and Biological Research

Note: The table outlines four-digit SIC industries with the highest number of high-technology IPOs in the sample. The original list for the definition of high-technology industry is in NAICS Codes(National Science Foundation, 2020).

Table 3: Definition of Local Neighborhood Characteristics

Variable	Description
College	Share of four-year college graduates in total population
Poverty	Share of people in poverty in total population
Unemployed	Share of unemployed people in total population
Asian Hispanic Black White	Share of people with the specific race in total population
Age under 19 Age 20 to 44 Age 45 to 64	People in the age group
Rental	Share of rental housing units in total units
Vacant	Share of vacant housing units in total units
Multiple	Share of housing units with multi-structure in total units
Ten-years	Share of household heads moving into units less than 10 years

Notes: The table includes definition of covariates in the difference-in-difference specification. Variables are calculated from the ACS Data at the census tract level, and are in percentage of the population. Demographic characteristics, such as college graduates and unemployed people, are divided by the total number of residents in the census tract. Housing units is divided by the total number of housing in the census tract. All variables are winsorized at 1% and 99% level.

Table 4: Summary Statistics for IPO Firms and Neighborhoods

	Mean	Median	Min	Max	S.D.
Panel A Firms					
IPO Price	16.35	16.00	5.85	44.00	5.91
IPO Proceeding	389.92	132.00	3.87	17 864.00	1469.61
Current Assets	422.63	148.46	0.14	11 267.00	1159.90
Total Assets	1746.18	315.39	100.17	138 898.00	8029.29
Liability	1032.99	114.44	1.09	101 739.00	5590.30
Revenue	1107.69	191.81	0.00	135 592.00	7071.10
EBIT	63.47	10.89	−3485.58	5955.00	409.71
Net Income	6.05	1.48	−3445.07	6172.00	392.21
Panel B Neighborhoods					
High-skilled Wage	49021.64	47299.07	10530.08	101987.49	16970.84
Low-skilled Wage	29028.13	28109.61	11152.84	56046.71	8558.45
High-skilled Employment	542.24	384.00	0.00	2388.44	493.62
Low-skilled Employment	1055.37	982.88	12.00	2838.00	581.90
Housing Rent	914.80	819.00	27.12	5920.85	410.21
House Price Index	235.73	203.93	95.63	791.08	119.83
White	0.66	0.76	0.01	0.98	0.30
Black	0.14	0.04	0.00	0.97	0.22
Asian	0.05	0.02	0.00	0.49	0.08
Hispanic	0.14	0.06	0.00	0.92	0.20
Age 19 Under	0.26	0.26	0.06	0.44	0.07
Age 20 to 44	0.34	0.33	0.16	0.66	0.09
Age 45 to 64	0.25	0.26	0.07	0.39	0.06
Age 65 Up	0.14	0.13	0.01	0.40	0.07
College	0.27	0.22	0.03	0.79	0.18
Unemployment	0.08	0.06	0.01	0.28	0.05
Poverty	0.15	0.12	0.01	0.55	0.12
Rental	0.35	0.29	0.03	0.98	0.23
Vacant	0.11	0.08	0.00	0.53	0.10
Multiple	0.26	0.17	0.00	0.98	0.26
Ten-years	0.37	0.35	0.01	0.84	0.18

Notes: The table presents summary statistics of financial position of high-technology IPO firms in the year of IPO and neighborhood characteristics. In Panel A, data come from Compustat and Audit Analytic. All variables except for the IPO Price are in million dollars. In Panel B, data are from tract-level ACS data and FHFA for House Price Index. Observations in different years are collapsed together. Wages, housing values and rents are adjusted to 2010 dollars by GDP. Other variables measure the share of race, age group and type of housing in total population or housing units. All variables are winsorized at 1% and 99% percentile.

Table 5: Neighborhood Characteristics by Outcome of IPOs

	Complete IPO (N=396)		Withdrawn IPO (N=118)			
	Mean	S.D.	Mean	S.D.	Diff.	p
Panel A Year 2000						
White	0.672	0.231	0.648	0.249	-0.024	0.350
Black	0.101	0.149	0.103	0.149	0.002	0.892
Asian	0.099	0.100	0.095	0.108	-0.005	0.658
Hispanic	0.107	0.136	0.135	0.163	0.027	0.099
Age 19 Under	0.221	0.098	0.241	0.095	0.020	0.047
Age 20 to 44	0.445	0.118	0.437	0.112	-0.007	0.543
Age 45 to 64	0.219	0.060	0.209	0.060	-0.010	0.129
Age 65 Up	0.112	0.069	0.108	0.067	-0.004	0.613
College	0.437	0.207	0.365	0.194	-0.072	0.001
Unemployment	0.052	0.050	0.057	0.059	0.005	0.400
Poverty	0.114	0.115	0.127	0.126	0.013	0.328
Rental	0.493	0.283	0.476	0.279	-0.017	0.564
Vacant	0.071	0.069	0.071	0.076	0.000	0.951
Multiple	0.494	0.336	0.469	0.319	-0.025	0.455
Ten-years	0.719	0.121	0.710	0.123	-0.008	0.509
Panel B Year of IPO						
White	0.622	0.229	0.607	0.235	-0.015	0.541
Black	0.100	0.134	0.104	0.140	0.004	0.765
Asian	0.131	0.113	0.122	0.123	-0.009	0.490
Hispanic	0.132	0.149	0.149	0.161	0.017	0.316
Age 19 Under	0.207	0.090	0.222	0.096	0.015	0.130
Age 20 to 44	0.421	0.137	0.418	0.124	-0.003	0.811
Age 45 to 64	0.243	0.070	0.243	0.068	0.000	0.985
Age 65 Up	0.123	0.071	0.113	0.070	-0.010	0.173
College	0.503	0.210	0.444	0.199	-0.059	0.006
Unemployment	0.060	0.042	0.066	0.043	0.006	0.216
Poverty	0.122	0.108	0.123	0.112	0.002	0.869
Rental	0.506	0.273	0.463	0.264	-0.043	0.125
Vacant	0.096	0.078	0.104	0.102	0.008	0.456
Multiple	0.516	0.330	0.471	0.325	-0.045	0.187
Ten-years	0.289	0.160	0.331	0.147	0.042	0.009

Notes: The table presents summary statistics of neighborhood characteristics by the outcome of IPOs. Panel A draws data from the 2000 Census, which is surveyed prior to all IPO events. Data for Panel B are from the year of IPO. On average, there is no significant difference between neighborhoods with withdrawn IPOs and with complete IPOs, implying that correlation between outcome of high-technology IPOs and local economy is not a primary concern.

Table 6: Estimation on Market Outcomes by Using Withdrawn Issuers as Counterfactual

	Log (High Skilled Wage)				Log (Low Skilled Wage)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0122***	0.0092***	0.0154***	0.0116***	0.0042***	0.0012	0.0053***	0.0015
	(0.0013)	(0.0011)	(0.0016)	(0.0013)	(0.0014)	(0.0010)	(0.0018)	(0.0013)
Treat	-0.0054***	-0.0041***			-0.0018***	-0.0005		
	(0.0006)	(0.0005)			(0.0006)	(0.0005)		
Covariates		✓		✓		✓		✓
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.78278	0.78707	0.78280	0.78708	0.70654	0.72059	0.70654	0.72059
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (High Skilled Employment)				Log (Low Skilled Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0008	-0.0057***	0.0010	-0.0072***	-0.0122***	-0.0127***	-0.0155***	-0.0160***
	(0.0028)	(0.0022)	(0.0035)	(0.0028)	(0.0023)	(0.0018)	(0.0029)	(0.0023)
Treat	-0.0003	0.0025***			0.0054***	0.0056***		
	(0.0012)	(0.0010)			(0.0010)	(0.0008)		
Covariates		✓		✓		✓		✓
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.91077	0.92942	0.91077	0.92942	0.91146	0.92735	0.91147	0.92735
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (Wage Premium)				Log (Relative Labor Supply)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0085***	0.0086***	0.0108***	0.0109***	0.0106***	0.0046***	0.0134***	0.0058***
	(0.0012)	(0.0011)	(0.0015)	(0.0014)	(0.0029)	(0.0016)	(0.0037)	(0.0020)
Treat	-0.0038***	-0.0038***			-0.0047***	-0.0020***		
	(0.0005)	(0.0005)			(0.0013)	(0.0007)		
Covariates		✓		✓		✓		✓
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.53076	0.53438	0.53077	0.53440	0.93622	0.95940	0.93622	0.95940
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (House Price Index)				Log (Housing Rent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0169***	0.0150***	0.0214***	0.0190***	0.0079***	0.0061***	0.0099***	0.0077***
	(0.0018)	(0.0016)	(0.0023)	(0.0020)	(0.0013)	(0.0011)	(0.0016)	(0.0014)
Treat	-0.0075***	-0.0066***			-0.0035***	-0.0027***		
	(0.0008)	(0.0007)			(0.0006)	(0.0005)		
Covariates		✓		✓		✓		✓
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.95227	0.95346	0.95229	0.95348	0.83869	0.84354	0.83870	0.84355
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Wage premium is the ratio of high-skilled wage by low-skilled wage, and relative supply is the ratio of high-skilled employment by low-skilled employment. Definition of covariates are same as before. I provide the coefficients of covariates in Appendix. All specifications include IPO case-distance-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replaces census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to closest headquarter of withdrawn issuers. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 7: Estimation on Homeless People by Using Withdrawn Issuers as Counterfactual

	Log ($Homeless_{pop}$)				Log ($Homeless_{pov}$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0048***	0.0048***	0.0073***	0.0073***	0.0035**	0.0037**	0.0054**	0.0056**
	(0.0018)	(0.0017)	(0.0026)	(0.0026)	(0.0018)	(0.0018)	(0.0026)	(0.0026)
Treat	-0.0026***	-0.0026***			-0.0019*	-0.0019**		
	(0.0010)	(0.0010)			(0.0010)	(0.0010)		
Covariates		✓		✓		✓		✓
Observations	2,803,711	2,803,711	2,803,711	2,803,711	2,803,711	2,803,711	2,803,711	2,803,711
R^2	0.99578	0.99579	0.99579	0.99580	0.99687	0.99688	0.99688	0.99689
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The number of homeless people in each census tract is constructed by the 2007 - 2017 HUD data and the crosswalk by Glynn et al. (2021). $Homeless_{pop}$ uses total population in census tracts as weights, and $Homeless_{pov}$ uses the number of people in poverty as weights. The coefficient of *TreatXpost* identifies treatment effect of IPO on the number of homeless people. Definition of covariates are same as before. I provide the coefficients of covariates in Appendix. All specifications include IPO case-distance-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replaces census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to closest headquarter of withdrawn issuers. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 8: Estimation of Dynamic Effect with Withdrawn IPO

	Log (High Skilled Wage)	Log (Low Skilled Wage)	Log (High Skilled Employment)	Log (Low Skilled Employment)	Log (House Price Index)	Log (Housing Rent)
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Period=-3	-0.0003	0.0009	-0.0012	-0.0005	0.0003	3.08×10^{-5}
	(0.0010)	(0.0010)	(0.0017)	(0.0016)	(0.0018)	(0.0009)
Treat X Period=-2	0.0008	0.0013	-0.0020	-0.0020	0.0017	0.0006
	(0.0010)	(0.0009)	(0.0017)	(0.0017)	(0.0018)	(0.0009)
Treat X Period=0	0.0039***	0.0014	-0.0033*	-0.0057***	0.0074***	0.0030***
	(0.0011)	(0.0009)	(0.0019)	(0.0017)	(0.0022)	(0.0011)
Treat X Period=1	0.0040***	0.0008	-0.0037*	-0.0068***	0.0074***	0.0032***
	(0.0012)	(0.0010)	(0.0020)	(0.0017)	(0.0021)	(0.0011)
Treat X Period=2	0.0049***	0.0003	-0.0047**	-0.0080***	0.0071***	0.0026**
	(0.0011)	(0.0010)	(0.0019)	(0.0018)	(0.0021)	(0.0012)
Treat X Period=3	0.0052***	0.0002	-0.0058***	-0.0090***	0.0073***	0.0044***
	(0.0012)	(0.0011)	(0.0021)	(0.0018)	(0.0024)	(0.0013)
Treat X Period=4	0.0063***	0.0011	-0.0059***	-0.0105***	0.0078***	0.0051***
	(0.0012)	(0.0011)	(0.0021)	(0.0019)	(0.0025)	(0.0013)
Treat X Period=5	0.0064***	0.0004	-0.0051**	-0.0096***	0.0102***	0.0043***
	(0.0013)	(0.0012)	(0.0023)	(0.0019)	(0.0026)	(0.0013)
Treat X Period=6	0.0072***	0.0003	-0.0051**	-0.0102***	0.0104***	0.0040***
	(0.0014)	(0.0014)	(0.0026)	(0.0019)	(0.0028)	(0.0015)
Treat	-0.0017***	-0.0003	0.0016**	0.0027***	-0.0026***	-0.0012***
	(0.0004)	(0.0003)	(0.0007)	(0.0006)	(0.0007)	(0.0004)
Covariates	✓	✓	✓	✓	✓	✓
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.78704	0.72059	0.92942	0.92734	0.95343	0.84354
Tract fixed effects	✓	✓	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: The table presents estimation result on dynamic effect of high-technology IPOs. *Treat* is the dummy for indicating census tracts belong to the treatment group. The effect on $Period = -1$ is normalized to zero. Critical values and confidence intervals are calculated by the simultaneous method by Montiel Olea and Plagborg-Møller (2019) to account for serial correlation. Definition of covariates follows Table 3. I provide the coefficients of covariates in Appendix. All specifications include census tract fixed effect, IPO case-distance-year fixed effect and county-year fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to the closest withdrawn issuer. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 9: Intensive Margin - Patent Value and Growth

	Log (Patents)		Log (Citations)		Log (Economic Value)	
	(1)	(2)	(3)	(4)	(5)	(6)
Same Industry						
TreatXpost	0.1103**	0.1128**	0.1165**	0.1188**	0.1209*	0.1243**
	(0.0465)	(0.0457)	(0.0559)	(0.0549)	(0.0637)	(0.0631)
Treat	0.0244	0.0232	0.0303	0.0292	0.0580	0.0561
	(0.0483)	(0.0478)	(0.0476)	(0.0473)	(0.0767)	(0.0759)
No Patent	-1.530***	-1.523***	-2.996***	-2.996***	-2.742***	-2.733***
	(0.0247)	(0.0249)	(0.0474)	(0.0469)	(0.0513)	(0.0499)
Covariates		✓		✓		✓
Observations	76,659	76,659	76,659	76,659	76,659	76,659
R^2	0.86334	0.86501	0.87531	0.87672	0.87063	0.87220
Tract fixed effects	✓	✓	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓
	Log (Patents)		Log (Citations)		Log (Economic Value)	
	(1)	(2)	(3)	(4)	(5)	(6)
Different Industry						
TreatXpost	0.0096	0.0138	0.0068	0.0089	-0.0039	0.0036
	(0.0191)	(0.0191)	(0.0239)	(0.0238)	(0.0274)	(0.0271)
Treat	-0.0833***	-0.0843***	-0.0784***	-0.0790***	-0.1052***	-0.1076***
	(0.0227)	(0.0228)	(0.0240)	(0.0243)	(0.0307)	(0.0306)
No Patent	-1.740***	-1.735***	-3.184***	-3.183***	-3.130***	-3.125***
	(0.0159)	(0.0162)	(0.0220)	(0.0223)	(0.0297)	(0.0299)
Covariates		✓		✓		✓
Observations	207,016	207,016	207,016	207,016	207,016	207,016
R^2	0.79884	0.79964	0.83490	0.83591	0.80415	0.80494
Tract fixed effects	✓	✓	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: The table presents treatment effect on patent growth and its economic value measured by Kogan et al. (2017). Sample consists of census tracts with at least one patent in the same first-digit SIC industry as the high-technology IPO over the period 2000-2017. Table *Same Industry* consider patents in the same industry as the IPO firms, while Table *Different Industry* present results for patents in different industries. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 10: Extensive Margin - High-technology Establishments

	Log (HT Establishments)				Log (HT Establishments (employees < 100))			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0065*	-0.0023	0.0083*	-0.0030	0.0070**	-0.0020	0.0088**	-0.0026
	(0.0036)	(0.0029)	(0.0045)	(0.0037)	(0.0035)	(0.0029)	(0.0045)	(0.0037)
Treat	-0.0029*	0.0010			-0.0031**	0.0009		
	(0.0016)	(0.0013)			(0.0016)	(0.0013)		
Covariates		✓		✓		✓		✓
Observations	1,080,819	1,080,819	1,080,819	1,080,819	1,080,819	1,080,819	1,080,819	1,080,819
R^2	0.95800	0.96067	0.95801	0.96067	0.95676	0.95946	0.95676	0.95946
Zipcode fixed effects	✓	✓			✓	✓		
IPO-Zipcode fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents the estimation of effect of IPOs on the number of high-technology establishments on ZIP code level. Columns (1) - (4) include all establishments recorded by NSF, while columns (5) - (8) consider establishments with less than 100 employees only. Standard errors are clustered on the IPO Zone level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 11: Mean Test of Difference in Mean Utility

	High (N=5486272)		Low (N=5486272)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Full Sample	0.0026	0.4186	-0.0091	0.4092	0.0117***	0.0000
< 15 Miles Only	0.0173	0.4116	-0.0033	0.3980	0.0206***	0.0000

Notes: The table compares the changes in the mean utility of high-skilled workers and low-skilled workers in each ZIP code neighborhood. The first row includes samples from all neighborhoods within 30 miles distance to high-technology IPO headquarters, while the second line includes only neighborhoods within 15 miles, which consist of the treatment group in the difference-in-difference specification. There is strong evidence that there is a net increase in the utility of high-skilled workers but a net decrease for low-skilled workers. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 12: Estimation of Gravity Equation

	$log(\pi^L)$		$log(\pi^H)$	
	(1)	(2)	(3)	(4)
ξ^s	-0.0908***	-0.0930***	-0.0908***	-0.0929***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Observations	4,734,754	4,734,754	4,734,710	4,734,710
R^2	0.88799	0.88072	0.88782	0.88075
Home-Period FE	✓	✓	✓	✓
Work-Period FE	✓	✓	✓	✓
Case-Period FE	✓		✓	

Notes: The table presents the estimation of the semi-elasticity of the probability of commuting on commuting distance. The gravity equation (23) is augmented by Case-Period fixed effect and has standard error clustered on the IPO Zone level. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 13: Estimation of Structural Parameters

	High-skilled (1)	Low-skilled (2)	High-skilled (3)	Low-skilled (4)
Real wage elasticity ($\beta^s = \frac{1}{\zeta^s}$)	3.712^{***}	3.428^{***}	3.721^{***}	3.466^{***}
	(1.406)	(1.149)	(1.411)	(1.165)
Preference on amenities (η^s)	1.163^{***}	0.1507	1.157^{***}	0.1190
	(0.1526)	(0.1418)	(0.1507)	(0.1312)
Spillover effect on productivity (λ_0)	0.1965^{***}		0.2006^{***}	
	(0.0061)		(0.0063)	
Spillover effect on productivity (λ_1)	-0.0008^{***}		-0.0008^{***}	
	(0.0003)		(0.0003)	
Calibrated Parameters				
Share of spending on local goods (θ^s) (Diamond (2016) and Moretti (2013))	0.63	0.68	0.62	
Elasticity of substitution of skills (σ) (Katz and Murphy, 1992)	1.4		1.4	

Notes: Estimation includes sample of high-technology IPOs from 2005 to 2010 and ZIP codes within each IPO zone. Real wage elasticity and preference on amenities are identified by shift-share IV on wages using 1900 as the base year, conditional on IPO case fixed effect. Standard errors are clustered at IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 14: Estimation on Outcomes of Labor and Housing Markets

	Log (High Skilled Wage)				Log (Low Skilled Wage)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0116***	0.0088***	0.0146***	0.0111***	0.0052***	0.0022**	0.0065***	0.0027**
	(0.0012)	(0.0010)	(0.0016)	(0.0013)	(0.0013)	(0.0010)	(0.0017)	(0.0013)
Treat	-0.0050***	-0.0038***			-0.0023***	-0.0010**		
	(0.0006)	(0.0005)			(0.0006)	(0.0004)		
Covariates		✓		✓		✓		✓
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.78398	0.78807	0.78400	0.78808	0.70965	0.72313	0.70965	0.72313
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
	Log (High Skilled Employment)				Log (Low Skilled Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	-0.0018	-0.0085***	-0.0023	-0.0107***	-0.0136***	-0.0145***	-0.0172***	-0.0182***
	(0.0027)	(0.0022)	(0.0035)	(0.0028)	(0.0022)	(0.0018)	(0.0028)	(0.0023)
Treat	0.0008	0.0037***			0.0060***	0.0063***		
	(0.0012)	(0.0010)			(0.0010)	(0.0008)		
Covariates		✓		✓		✓		✓
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.91084	0.92989	0.91084	0.92989	0.91203	0.92740	0.91204	0.92740
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
	Log (Wage Premium)				Log (Relative Labor Supply)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0073***	0.0076***	0.0092***	0.0096***	0.0097***	0.0039***	0.0122***	0.0050***
	(0.0012)	(0.0011)	(0.0015)	(0.0014)	(0.0027)	(0.0015)	(0.0034)	(0.0019)
Treat	-0.0032***	-0.0033***			-0.0042***	-0.0017**		
	(0.0005)	(0.0005)			(0.0012)	(0.0007)		
Covariates		✓		✓		✓		✓
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.53151	0.53504	0.53152	0.53505	0.93584	0.95929	0.93584	0.95929
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
	Log (House Price Index)				Log (Housing Rent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0178***	0.0161***	0.0225***	0.0203***	0.0086***	0.0071***	0.0108***	0.0090***
	(0.0018)	(0.0016)	(0.0022)	(0.0020)	(0.0012)	(0.0011)	(0.0015)	(0.0014)
Treat	-0.0078***	-0.0070***			-0.0037***	-0.0031***		
	(0.0008)	(0.0007)			(0.0005)	(0.0005)		
Covariates		✓		✓		✓		✓
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.95470	0.95557	0.95472	0.95558	0.84438	0.84891	0.84439	0.84891
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Wage premium is the ratio of high-skilled wage by low-skilled wage, and relative supply is the ratio of high-skilled employment by low-skilled employment. Definition of covariates are same as before. I provide the coefficients of covariates in Appendix. All specifications include IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 15: Estimation on Outcomes for Non-metropolitan IPOs only

	Log (High Skilled Wage)				Log (Low Skilled Wage)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0104***	0.0068***	0.0129***	0.0085***	0.0069***	0.0025**	0.0086***	0.0031**
	(0.0016)	(0.0013)	(0.0020)	(0.0016)	(0.0015)	(0.0012)	(0.0018)	(0.0014)
Treat	-0.0044***	-0.0029***			-0.0030***	-0.0011**		
	(0.0007)	(0.0006)			(0.0006)	(0.0005)		
Covariates		✓		✓		✓		✓
Observations	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996
R^2	0.77467	0.77904	0.77469	0.77904	0.72577	0.73968	0.72578	0.73968
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (High Skilled Employment)				Log (Low Skilled Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	-0.0009	-0.0070**	-0.0010	-0.0086**	-0.0180***	-0.0163***	-0.0222***	-0.0202***
	(0.0038)	(0.0030)	(0.0047)	(0.0037)	(0.0024)	(0.0020)	(0.0029)	(0.0025)
Treat	0.0004	0.0030**			0.0077***	0.0070***		
	(0.0016)	(0.0013)			(0.0010)	(0.0009)		
Covariates		✓		✓		✓		✓
Observations	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996
R^2	0.90708	0.92608	0.90708	0.92608	0.90779	0.92365	0.90780	0.92366
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (Wage Premium)				Log (Relative Labor Supply)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0042***	0.0050***	0.0052***	0.0062***	0.0141***	0.0068***	0.0175***	0.0084***
	(0.0013)	(0.0013)	(0.0017)	(0.0017)	(0.0033)	(0.0019)	(0.0040)	(0.0023)
Treat	-0.0018***	-0.0021***			-0.0060***	-0.0029***		
	(0.0006)	(0.0006)			(0.0014)	(0.0008)		
Observations	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996
R^2	0.52442	0.52779	0.52442	0.52780	0.93602	0.95932	0.93603	0.95932
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (House Price Index)				Log (Housing Rent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0188***	0.0160***	0.0233***	0.0198***	0.0101***	0.0078***	0.0126***	0.0097***
	(0.0020)	(0.0018)	(0.0025)	(0.0022)	(0.0012)	(0.0012)	(0.0015)	(0.0014)
Treat	-0.0080***	-0.0068***			-0.0043***	-0.0033***		
	(0.0009)	(0.0008)			(0.0005)	(0.0005)		
Covariates		✓		✓		✓		✓
Observations	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996	3,500,996
R^2	0.95691	0.95784	0.95692	0.95785	0.85109	0.85645	0.85110	0.85645
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Wage premium is the ratio of high-skilled wage by low-skilled wage, and relative supply is the ratio of high-skilled employment by low-skilled employment. Definition of covariates are same as before. I provide the coefficients of covariates in Appendix. All specifications include IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 16: Estimation of First-time Treatment on Outcomes of Labor and Housing Markets

	Log (High Skilled Wage)		Log (Low Skilled Wage)	
	(1)	(2)	(3)	(4)
TreatXpost	0.0258***	0.0207***	0.0116*	0.0056
	(0.0055)	(0.0047)	(0.0069)	(0.0061)
Covariates		✓		✓
Observations	536,817	536,817	536,817	536,817
R^2	0.76469	0.76877	0.73683	0.75073
Tract fixed effects	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓
	Log (High Skilled Emp.)		Log (Low Skilled Emp.)	
	(1)	(2)	(3)	(4)
TreatXpost	-0.0018	-0.0263*	-0.0453***	-0.0430***
	(0.0148)	(0.0139)	(0.0130)	(0.0105)
Covariates		✓		✓
Observations	536,817	536,817	536,817	536,817
R^2	0.89942	0.92137	0.90288	0.91830
Tract fixed effects	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓
	Log (Wage Premium)		Log (Relative Labor Supply)	
	(1)	(2)	(3)	(4)
TreatXpost	0.0154**	0.0166**	0.0413***	0.0146*
	(0.0067)	(0.0064)	(0.0125)	(0.0088)
Covariates		✓		✓
Observations	536,817	536,817	536,817	536,817
R^2	0.52837	0.53162	0.92888	0.95525
Tract fixed effects	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓
	Log (House Price Index)		Log (Housing Rent)	
	(1)	(2)	(3)	(4)
TreatXpost	0.0417***	0.0385***	0.0158**	0.0133**
	(0.0068)	(0.0055)	(0.0067)	(0.0065)
Covariates		✓		✓
Observations	536,817	536,817	536,817	536,817
R^2	0.96053	0.96151	0.85525	0.86046
Tract fixed effects	✓	✓	✓	✓
County-Year fixed effects	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment. For each census tract, only the first treatment by IPO is considered. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Wage premium is the ratio of high-skilled wage by low-skilled wage, and relative supply is the ratio of high-skilled employment by low-skilled employment.. Definition of covariates are same as before. I provide the coefficients of covariates in Appendix. All specifications include Tract fixed effect, IPO case-pscore-year fixed effect and county-year fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

A Appendix: Data Imputation for Structural Estimation

A.1 Imputation for Commuting Patterns

In the structural model, the first step is to estimate the mean utility for each pair of neighbourhoods from the commuting pattern of workers. Hence, the actual share of workers commuting between each pair of neighbourhoods should be calculated from observed data. Therefore, I start with calculating π^s_{ijt} as the actual share of workers with skill s living in i and working in j in time t i.e.

$$\pi^s_{ijt} = \frac{n^s_{ijt}}{\sum_{i'} \sum_{j'} n^s_{i'j't}} \tag{26}$$

Hence, it just needs to know n^s_{ijt} as the number of workers with specified commuting pattern. Due to data availability, the measure is not directly observed, so I predict it by the method in Qian and Tan (2021). First, it can be decomposed into two parts

$$n^s_{ijt} = n_{ijt} p^s_{ijt} \tag{27}$$

n_{ijt} is the total commuting flow from i to j, and p^s_{ijt} is the share of workers with skill s in the flow. The LEHD Origin-Destination Employment Statistics (LODES) datasets record the commuting flow of workers from one census block to another. They are available for most states during 2002 - 2015, so n_{ijt} can be directly observed. However, as the dataset does not disclose educational attainment of workers, p^s_{ijt} is unobserved. To overcome the challenge, I complement the data with 2009 NHTS, which is a travel survey on individual level including the education of participants. I run a LASSO model using the 2009 NHTS as the training sample, and predict them based on characteristics from census, RAC and WAC data. Finally, I can calculate π^s_{ijt} for each (i, j).

A.2 Construction for Workplace Wage and IV

Estimation of Equation 17 requires variables on the right-hand sides to be observed. However, the census data include wages of residents in one area, but provide no information on the wage of workers who work in the area. To address the limitation, the workplace wage is imputed by the weighted average of the residential wage

$$w_{jt}^{H} = log(W_{jt}^{H}) = log\left(\frac{\sum_i H_{ijt}W_{it}^{H}}{\sum_i H_{ijt}}\right) \tag{28}$$

$$w_{jt}^{L} = log(W_{jt}^{L}) = log\left(\frac{\sum_i L_{ijt}W_{it}^{L}}{\sum_i L_{ijt}}\right) \tag{29}$$

Second, the shift-share IV for log wage based on 1990 is constructed by the weight average of industry wage

$$\Delta B_{jt\leftarrow 1990}^{H} = \sum_{ind} \left(w_{ind,t}^{H} - w_{ind,1990}^{H}\right) \frac{H_{ind,j,1990}}{H_{j,1990}} \tag{30}$$

$$\Delta B_{jt\leftarrow 1990}^{L} = \sum_{ind} \left(w_{ind,t}^{L} - w_{ind,1990}^{L}\right) \frac{L_{ind,j,1990}}{L_{j,1990}} \tag{31}$$

where $w_{ind,t}^{s}$ represents for the average log wage of workers with skill s in industry ind in year t. $H(L)_{ind,j,1990}$ measures the number of high-skilled (low-skilled) people working in ZIP code j in industry ind and in 1990, while $H(L)_{j,1990}$ is the total number of high-skilled (low-skilled) workers in ZIP code j in 1990.

By its design, the shift-share IV links with contemporaneous real wages by the "shift" part, and thus satisfies the relevance condition. Meanwhile, it is able to identifies shift of labor demand by its industry-level weight average part. For example, since 1990 the reduction in communication cost leaded to boom in the financial services sector, so we shall see greater rising wage in neighborhoods in which employees of financial services sector concentrate. Furthermore, the underlying assumption for exclusion restriction is that geographical distribution of industry in 1990 does not drive residualized amenity changes. To my best knowledge, there is no such evidence in pointing the correlation.

Besides the main data sources, I merge them with a sample of 1990 census data to calculate employment share in 1990. The sample covers 5% U.S. population and information on workers' educational attainment and industry. I crosswalk 1990 industry in census to ACS three-digit industry identifier, and use the latter as industry classification. The 1990 sample doesn't contain ZIP codes as geographical level, and the 1990 ACS data only provide employment in each industry but no information on educational attainment. I calculate the share of high-skilled workers in each industry on the county level by census sample, and then multiply employment in each industry on the ZIP code level by ACS in order to predict ($H_{ind,j,1990}$, $L_{ind,j,1990}$). Formally,

$$H_{ind,j,1990} \approx \underbrace{N_{ind,j,1990}}_{\text{ACS}} * \underbrace{\frac{H_{ind,c(j),1990}}{H_{ind,c(j),1990} + L_{ind,c(j),1990}}}_{\text{sample of 5\% population}} \tag{32}$$

$$L_{ind,j,1990} \approx \underbrace{N_{ind,j,1990}}_{\text{ACS}} * \underbrace{\frac{L_{ind,c(j),1990}}{H_{ind,c(j),1990} + L_{ind,c(j),1990}}}_{\text{sample of 5\% population}} \tag{33}$$

where $c(j)$ represents for the county containing ZIP code j.

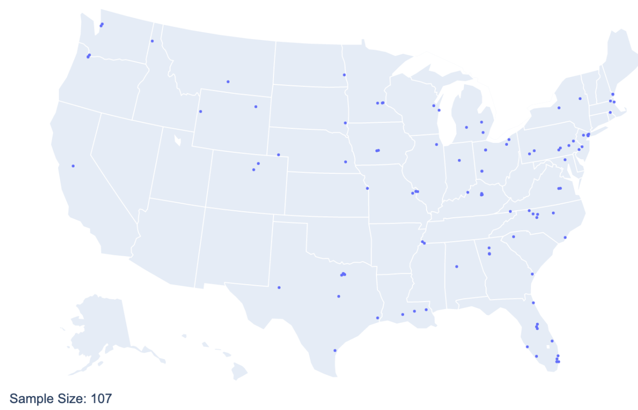
By using the IV to estimate Equation (17), one can separate variation in real wages from unobserved amenity changes. Formally, the exclusion restriction for shift-share IV reads

$$\mathbb{E}[\mathbf{\Delta B_{jt \leftarrow 1990}} \times \mathbf{\Delta \epsilon^{a}_{ijt}}] = \mathbf{0} \tag{34}$$

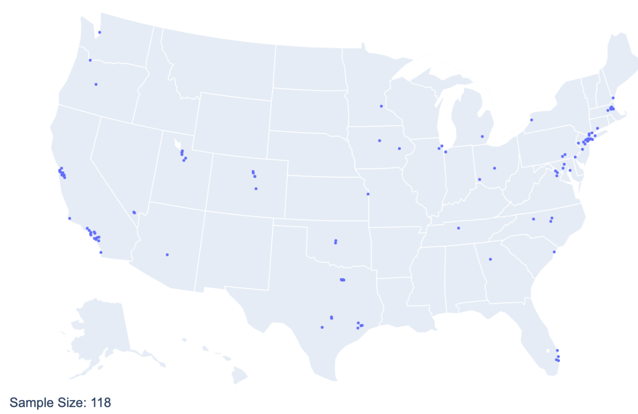
with

$$\mathbf{\Delta B_{jt \leftarrow 1990}} := (\Delta B^{H}_{jt \leftarrow 1990}, \Delta B^{L}_{jt \leftarrow 1990})^{\intercal} \quad \mathbf{\Delta \epsilon^{a}_{ijt}} := (\Delta \epsilon^{a,H}_{ijt}, \Delta \epsilon^{a,L}_{ijt})$$

B Appendix: Additional Figures



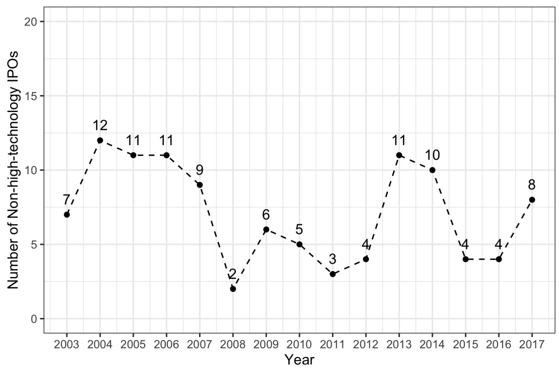
(a) Non-high-technology Firms



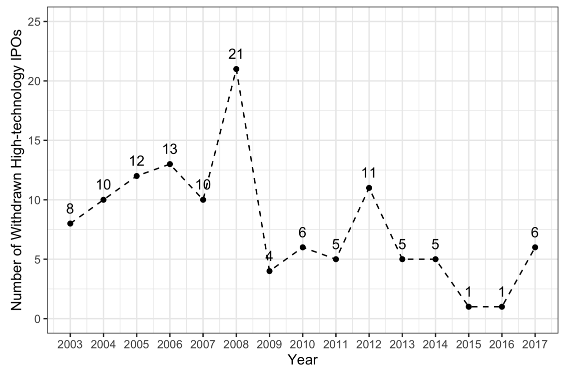
(b) Withdrawn High-technology IPO Issuers

Figure A1: Location of IPO Issuers

Notes: The figure plots headquarter location of non-high-technology IPO issuers and high-technology withdrawn high-technology IPO issuers. Data are from Audit Analytics and Thomson/Refinitiv. Non-high-technology IPO issuers are issuers whose SIC codes are not classified as high-technology by NSF, and are restricted to those located in counties that never host any high-technology IPOs during the sample period 2003 - 2017.



(a) Non-high-technology Firms



(b) Withdrawn High-technology IPO Issuers

Figure A2: Number of IPOs by Year

Notes: The figure plots year of non-high-technology IPO issuers and high-technology withdrawn high-technology IPO issuers. Data are from Audit Analytics and Thomson/Refinitiv. Non-high-technology IPO issuers are issuers whose SIC codes are not classified as high-technology by NSF, and are restricted to those located in counties that never host any high-technology IPOs during the sample period 2003 - 2017.

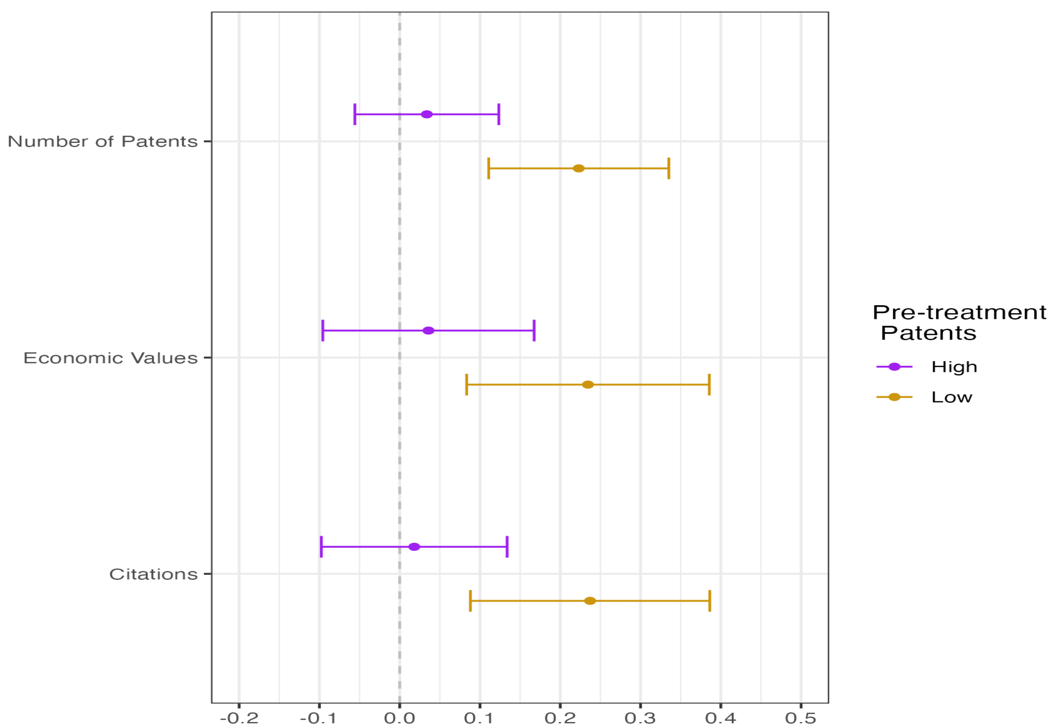
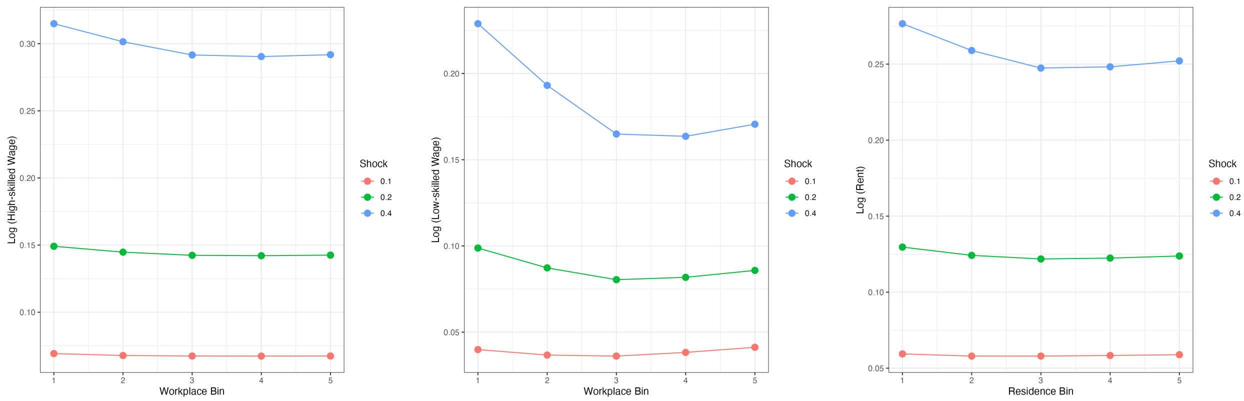


Figure A3: Heterogeneity of Patent Growth by Pre-treatment Productivity

Notes: The figures provides coefficient estimate for the effect of high-technology IPOs on patent outcomes, by the pre-treatment productivity of each census tract. Sampled patents are in the same industry as the high-technology IPO firms, A census tract has High (Low) productivity of patent outputs if it has number of patents above (below) the average in year 2000, which is prior to all sampled high-technology IPOs. The error bars represent for 95% confidence interval. Standard errors are clustered on the IPO Zone level.



(a) High-skilled Wage (b) Low-skilled Wage (c) Rents

Figure A4: Simulation Results for Spatial Equilibrium Model

Notes: The figure plots the simulation results for spatial equilibrium model in Section 4. Structural Parameters are calibrated and estimated values as in Table (13) and (12). Ten thousands workers are assigned to neighborhoods proportionally based on the real commuting flow. Wages and rents are observed in period 0, while productivity and amenity are estimated. In each figure, the horizontal axis represents bin of neighborhoods, while smaller number indicates neighborhoods closer to the centriod of productivity shock (IPO Headquarter). The vertical axis represents the difference of values in logarithm. Each colored line indicates magnitude of productivity shock on high-skilled workers in period 1.

C Appendix: Additional Tables

Table B1: Correlation Coefficients between Census Characteristics

	log (High-skilled Wage)	log (Low-skilled Wage)	log (High-skilled Emp.)	log (Low-skilled Emp.)	log (HPI)	log (Rent)	White	Black	Asian	Hispanic	Age 19 Under	Age 20 to 44	Age 45 to 64	Age 65 Up	College	Unemployment	Poverty	Rental	Vacant	Multiple	Ten-years
log (High-skilled Wage)	1.000	0.511	0.494	-0.194	0.340	0.390	0.152	-0.130	0.200	-0.175	-0.004	-0.156	0.276	-0.031	0.534	-0.304	-0.495	-0.322	-0.240	-0.126	0.150
log (Low-skilled Wage)	0.511	1.000	0.429	-0.064	0.321	0.424	0.206	-0.175	0.170	-0.202	0.030	-0.140	0.262	-0.073	0.418	-0.376	-0.625	-0.404	-0.289	-0.192	0.217
log (High-skilled Emp.)	0.494	0.429	1.000	0.080	0.403	0.400	0.150	-0.111	0.250	-0.215	-0.143	0.052	0.191	-0.078	0.722	-0.395	-0.457	-0.144	-0.277	0.072	0.095
log (Low-skilled Emp.)	-0.194	-0.064	0.080	1.000	-0.075	-0.136	-0.144	0.049	-0.079	0.201	0.257	0.113	-0.124	-0.245	-0.529	0.081	0.070	0.028	-0.116	-0.075	0.022
log (HPI)	0.340	0.321	0.403	-0.075	1.000	0.412	-0.039	-0.199	0.363	0.079	-0.117	0.038	0.107	-0.024	0.413	-0.212	-0.318	-0.049	-0.247	0.075	-0.054
log (Rent)	0.390	0.424	0.400	-0.136	0.412	1.000	-0.220	-0.027	0.404	0.178	-0.035	-0.028	0.152	-0.070	0.471	-0.095	-0.312	-0.112	-0.188	-0.010	-0.068
White	0.152	0.206	0.150	-0.144	-0.039	-0.220	1.000	-0.595	-0.395	-0.698	-0.260	-0.331	0.355	0.332	0.186	-0.390	-0.396	-0.452	0.083	-0.313	0.193
Black	-0.130	-0.175	-0.111	0.049	-0.199	-0.027	-0.595	1.000	-0.056	-0.029	0.098	0.166	-0.153	-0.156	-0.148	0.336	0.313	0.248	0.059	0.171	-0.136
Asian	0.200	0.170	0.250	-0.079	0.363	0.404	-0.395	-0.056	1.000	0.145	-0.008	0.167	-0.061	-0.138	0.287	-0.028	-0.089	0.155	-0.204	0.199	-0.057
Hispanic	-0.175	-0.202	-0.215	0.201	0.079	0.178	-0.698	-0.029	0.145	1.000	0.293	0.245	-0.342	-0.274	-0.249	0.258	0.314	0.345	-0.096	0.205	-0.132
Age 19 Under	-0.004	0.030	-0.143	0.257	-0.117	-0.035	-0.260	0.098	-0.008	0.293	1.000	0.035	-0.391	-0.616	-0.230	0.129	0.132	-0.078	-0.256	-0.218	0.206
Age 20 to 44	-0.156	-0.140	0.052	0.113	0.038	-0.028	-0.331	0.166	0.167	0.245	0.035	1.000	-0.690	-0.634	-0.007	0.052	0.292	0.596	-0.186	0.530	0.025
Age 45 to 64	0.276	0.262	0.191	-0.124	0.107	0.152	0.355	-0.153	-0.061	-0.342	-0.391	-0.690	1.000	0.363	0.220	-0.146	-0.403	-0.522	0.153	-0.406	-0.108
Age 65 Up	-0.031	-0.073	-0.078	-0.245	-0.024	-0.070	0.332	-0.156	-0.138	-0.274	-0.616	-0.634	0.363	1.000	0.031	-0.063	-0.137	-0.200	0.319	-0.095	-0.137
College	0.534	0.418	0.722	-0.529	0.413	0.471	0.186	-0.148	0.287	-0.249	-0.230	-0.007	0.220	0.031	1.000	-0.394	-0.429	-0.125	-0.168	0.112	0.087
Unemployment	-0.304	-0.376	-0.395	0.081	-0.212	-0.095	-0.390	0.336	-0.028	0.258	0.129	0.052	-0.146	-0.063	-0.394	1.000	0.549	0.293	0.183	0.115	-0.244
Poverty	-0.495	-0.625	-0.457	0.070	-0.318	-0.312	-0.396	0.313	-0.089	0.314	0.132	0.292	-0.403	-0.137	-0.429	0.549	1.000	0.600	0.238	0.328	-0.323
Rental	-0.322	-0.404	-0.144	0.028	-0.049	-0.112	-0.452	0.248	0.155	0.345	-0.078	0.596	-0.522	-0.200	-0.125	0.293	0.600	1.000	0.045	0.839	-0.356
Vacant	-0.240	-0.289	-0.277	-0.116	-0.247	-0.188	0.083	0.059	-0.204	-0.096	-0.256	-0.186	0.153	0.319	-0.168	0.183	0.238	0.045	1.000	0.007	-0.088
Multiple	-0.126	-0.192	0.072	-0.075	0.075	-0.010	-0.313	0.171	0.199	0.205	-0.218	0.530	-0.406	-0.095	0.112	0.115	0.328	0.839	0.007	1.000	-0.249
Ten-years	0.150	0.217	0.095	0.022	-0.054	-0.068	0.193	-0.136	-0.057	-0.132	0.206	0.025	-0.108	-0.137	0.087	-0.244	-0.323	-0.356	-0.088	-0.249	1.000

Notes: The table provides correlation coefficients between census characteristics corresponding with Figure 5. Observations from different years are collapsed into a single panel. Wages and Rents are adjusted to 2010 dollars. Definition of variables follows Table 3.

Table B2: Definition of Variables in Propensity Score Model

Category	Variable	Description	Interaction
Gender	Male	Percentage of males in total population	
Household	Urban Rural Poverty Housing Units	Percentage of population living in urban areas Percentage of population living in rural areas Percentage of population in poverty The number of housing units per capita	
Race	White Black Asian Native	Percentage of population with the specific race	
Age	Age 16 under Age 20 to 44 Age 45 to 64	Percentage of population in the specific age group	
Vehicle	Car No Car	Percentage of people commuting to work by car or public transportation Percentage of people commuting to work by bicycle or walk	
Education	High school Some college or associate degree Bachelor Graduate	Percentage of people with the specific educational attainment	Commuting time & Establishment
Employment	Unemployment High-tech Employment	Percentage of unemployed population Percentage of employment in high-technology industry	Commuting time & Establishment
Commuting time	Time 15 under Time 15 to 29 Time 30 to 59	Percentage of people with the specified commuting time	Education & Employment
Establishment	Establishment 10 under Establishment 10 to 49 Establishment 50 to 249	Percentage of establishments with the specified number of employees	Education & Employment

Notes: The table presents definition of variables and their categories in the propensity score model for predicting IPO events. Values are in percentage and based on 2000 Census, while census tracts are adjusted to 2010. For each census tract, each variable is calculated by summing and averaging all census tracts within 0-5, 5-10 and 10-15 miles respectively. Distance between census tracts is from the centriod of one tract to another. If two categories are interacted, it means a fully cross combination of all variables with the same distance zone.

Table B3: Balance of Selected versus Not-selected Non-high-technology Firms

	Not Selected (N=320)		Selected (N=107)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
IPO Price	16.645	4.953	16.809	6.586	0.164	0.821
IPO Proceedings	279.888	353.300	244.591	259.849	-35.297	0.283
Current Assets	388.366	699.023	310.897	400.343	-77.470	0.177
Total Assets	1492.058	3233.463	1402.094	3812.525	-89.964	0.833
Liability	1103.347	3055.110	1072.591	3157.446	-30.756	0.932
Revenue	1355.619	3524.301	1264.932	2129.577	-90.687	0.756
EBIT	112.256	299.306	110.188	151.258	-2.068	0.927
Net Income	23.845	176.478	46.498	186.228	22.654	0.289

Notes: The table presents summary statistics for selected non-high-technology firms versus those not selected. Variables are from Audit Analytics and Compustat and by the year end of IPOs. The result indicates that firms in the sample are very similar in their IPO and financial position to all firms. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B4: Estimation on Outcomes of Labor and Housing Markets by Non-High-Technology IPOs

	Log (High Skilled Wage)				Log (Low Skilled Wage)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0031	0.0035	0.0038	0.0043	0.0042*	0.0047**	0.0051*	0.0057**
	(0.0026)	(0.0024)	(0.0031)	(0.0029)	(0.0025)	(0.0021)	(0.0030)	(0.0025)
Treat	-0.0015	-0.0017			-0.0021	-0.0023**		
	(0.0013)	(0.0012)			(0.0012)	(0.0010)		
Covariates		✓		✓		✓		✓
Observations	669,013	669,013	669,013	669,013	669,013	669,013	669,013	669,013
R^2	0.75970	0.76477	0.75970	0.76477	0.73480	0.75264	0.73481	0.75264
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (High Skilled Employment)				Log (Low Skilled Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0013	-0.0023	0.0015	-0.0028	-0.0009	-0.0029	-0.0011	-0.0035
	(0.0068)	(0.0045)	(0.0082)	(0.0054)	(0.0052)	(0.0041)	(0.0062)	(0.0050)
Treat	-0.0006	0.0011			0.0005	0.0014		
	(0.0033)	(0.0022)			(0.0025)	(0.0020)		
Covariates		✓		✓		✓		✓
Observations	669,013	669,013	669,013	669,013	669,013	669,013	669,013	669,013
R^2	0.89440	0.91994	0.89440	0.91994	0.89907	0.91639	0.89907	0.91640
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (Wage Premium)				Log (Relative Labor Supply)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	-0.0015	-0.0015	-0.0018	-0.0019	0.0016	6.77×10^{-5}	0.0019	9.1×10^{-5}
	(0.0031)	(0.0030)	(0.0037)	(0.0036)	(0.0060)	(0.0032)	(0.0072)	(0.0039)
Treat	0.0007	0.0008			-0.0008	-5.46×10^{-5}		
	(0.0015)	(0.0015)			(0.0029)	(0.0016)		
Covariates		✓		✓		✓		✓
Observations	669,013	669,013	669,013	669,013	669,013	669,013	669,013	669,013
R^2	0.53372	0.53753	0.53372	0.53753	0.92038	0.95132	0.92038	0.95132
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

	Log (House Price Index)				Log (Housing Rent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0099***	0.0098***	0.0120***	0.0120***	0.0047	0.0057*	0.0056	0.0070*
	(0.0034)	(0.0033)	(0.0040)	(0.0039)	(0.0031)	(0.0029)	(0.0037)	(0.0035)
Treat	-0.0048***	-0.0048***			-0.0023	-0.0028*		
	(0.0017)	(0.0016)			(0.0015)	(0.0014)		
Covariates		✓		✓		✓		✓
Observations	669,013	669,013	669,013	669,013	669,013	669,013	669,013	669,013
R^2	0.95006	0.95143	0.95006	0.95143	0.82740	0.83529	0.82740	0.83530
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 107 non-high-technology IPO firms. All observations are collapsed into a single panel for estimation. Same as above, the coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. I provide the coefficients of covariates in Appendix. All specifications include tract fixed effect, IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replaces census tract fixed effect with case-tract fixed effect. Propensity score model is re-estimated by using these non-high-technology IPOs as outcome variable. Standard errors are clustered at the IPO Zone level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B5: Estimation on Wage by Skill Groups with Withdrawn IPO

	Log (High Skilled Wage)				Log (Low Skilled Wage)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatXpost = 1	0.0122***	0.0092***	0.0154***	0.0116***	0.0042***	0.0012	0.0053***	0.0015
	(0.0013)	(0.0011)	(0.0016)	(0.0013)	(0.0014)	(0.0010)	(0.0018)	(0.0013)
treat	-0.0054***	-0.0041***			-0.0018***	-0.0005		
	(0.0006)	(0.0005)			(0.0006)	(0.0005)		
College		0.0674***		0.0674***		0.2041***		0.2041***
		(0.0123)		(0.0122)		(0.0056)		(0.0056)
Asian		0.0201		0.0198		0.2856***		0.2855***
		(0.0189)		(0.0188)		(0.0274)		(0.0274)
Hispanic		-0.1222***		-0.1219***		-0.1825***		-0.1824***
		(0.0047)		(0.0046)		(0.0054)		(0.0054)
Black		-0.4636***		-0.4630***		0.0663***		0.0664***
		(0.0311)		(0.0310)		(0.0244)		(0.0243)
White		0.0629***		0.0626***		0.4851***		0.4850***
		(0.0191)		(0.0190)		(0.0219)		(0.0219)
Poverty		-0.1447***		-0.1446***		-0.5315***		-0.5315***
		(0.0088)		(0.0087)		(0.0066)		(0.0066)
Unemployed		-0.1534***		-0.1533***		-0.2620***		-0.2620***
		(0.0072)		(0.0071)		(0.0081)		(0.0081)
Age under 19		0.5013***		0.5000***		0.4404***		0.4402***
		(0.0163)		(0.0163)		(0.0108)		(0.0107)
Age 20 to 44		0.2219***		0.2206***		-0.0832***		-0.0833***
		(0.0180)		(0.0179)		(0.0142)		(0.0141)
Age 45 to 64		0.3461***		0.3457***		0.0443***		0.0442***
		(0.0168)		(0.0168)		(0.0163)		(0.0162)
Rental		-0.2311***		-0.2309***		-0.1589***		-0.1588***
		(0.0073)		(0.0073)		(0.0063)		(0.0063)
Vaccant		0.0255***		0.0253***		-0.0403***		-0.0403***
		(0.0086)		(0.0086)		(0.0066)		(0.0066)
Multiple		-0.1046***		-0.1047***		-0.0227***		-0.0228***
		(0.0082)		(0.0082)		(0.0036)		(0.0036)
Ten-years		-0.0240***		-0.0238***		0.0507***		0.0507***
		(0.0040)		(0.0040)		(0.0038)		(0.0038)
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.78278	0.78707	0.78280	0.78708	0.70654	0.72059	0.70654	0.72059
Within R^2	0.00032	0.02005	0.00040	0.02009	4.05×10^{-5}	0.04794	5.1×10^{-5}	0.04793
Tract fixed effects	✓	✓			✓	✓		
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Tract fixed effects			✓	✓			✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Definition of covariates follows Table 3. All specifications include IPO case-distance-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to the closest withdrawn IPO issuer. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B6: Estimation on Employment by Skill Groups with Withdrawn IPO

	Log (High Skilled Employment)				Log (Low Skilled Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatXpost = 1	0.0008	-0.0057***	0.0010	-0.0072***	-0.0122***	-0.0127***	-0.0155***	-0.0160***
	(0.0028)	(0.0022)	(0.0035)	(0.0028)	(0.0023)	(0.0018)	(0.0029)	(0.0023)
treat	-0.0003	0.0025***			0.0054***	0.0056***		
	(0.0012)	(0.0010)			(0.0010)	(0.0008)		
College		2.763***		2.763***		-1.811***		-1.811***
		(0.0225)		(0.0224)		(0.0157)		(0.0157)
Asian		-0.2927***		-0.2924***		0.8164***		0.8169***
		(0.0846)		(0.0844)		(0.0585)		(0.0584)
Hispanic		-0.1041***		-0.1043***		0.1864***		0.1861***
		(0.0212)		(0.0212)		(0.0073)		(0.0073)
Black		-0.8063***		-0.8067***		0.0594		0.0586
		(0.0768)		(0.0766)		(0.0412)		(0.0411)
White		-0.9511***		-0.9508***		-0.4133***		-0.4128***
		(0.0419)		(0.0418)		(0.0251)		(0.0251)
Poverty		-0.3139***		-0.3140***		-0.5127***		-0.5127***
		(0.0133)		(0.0133)		(0.0120)		(0.0120)
Unemployed		-0.7815***		-0.7815***		-0.9392***		-0.9394***
		(0.0208)		(0.0208)		(0.0110)		(0.0110)
Age under 19		0.7100***		0.7108***		1.431***		1.433***
		(0.0443)		(0.0443)		(0.0198)		(0.0198)
Age 20 to 44		1.962***		1.963***		2.343***		2.345***
		(0.0497)		(0.0496)		(0.0218)		(0.0217)
Age 45 to 64		1.879***		1.879***		1.913***		1.914***
		(0.0493)		(0.0492)		(0.0233)		(0.0233)
Rental		-0.1051***		-0.1052***		0.0769***		0.0766***
		(0.0142)		(0.0141)		(0.0112)		(0.0112)
Vacant		-0.9920***		-0.9919***		-1.013***		-1.013***
		(0.0254)		(0.0253)		(0.0144)		(0.0143)
Multiple		0.2265***		0.2265***		0.2803***		0.2804***
		(0.0124)		(0.0124)		(0.0111)		(0.0110)
Ten-years		-0.0422***		-0.0423***		-0.0139		-0.0142
		(0.0111)		(0.0110)		(0.0108)		(0.0107)
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.91077	0.92942	0.91077	0.92942	0.91146	0.92735	0.91147	0.92735
Tract fixed effects	✓	✓			✓	✓		
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Tract fixed effects			✓	✓			✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Definition of covariates follows Table 3. All specifications include IPO case-distance-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to the closest withdrawn IPO issuer. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B7: Estimation on Wage and Employment Gap with Withdrawn IPO

	Log (Wage Premium)				Log (Relative Labor Supply)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatXpost = 1	0.0085***	0.0086***	0.0108***	0.0109***	0.0106***	0.0046***	0.0134***	0.0058***
	(0.0012)	(0.0011)	(0.0015)	(0.0014)	(0.0029)	(0.0016)	(0.0037)	(0.0020)
treat	-0.0038***	-0.0038***			-0.0047***	-0.0020***		
	(0.0005)	(0.0005)			(0.0013)	(0.0007)		
College		-0.1540***		-0.1540***		4.622***		4.622***
		(0.0096)		(0.0096)		(0.0132)		(0.0131)
Asian		-0.1307***		-0.1310***		-0.9896***		-0.9898***
		(0.0282)		(0.0281)		(0.0581)		(0.0580)
Hispanic		0.0480***		0.0482***		-0.2761***		-0.2759***
		(0.0085)		(0.0084)		(0.0199)		(0.0198)
Black		-0.4787***		-0.4781***		-0.8164***		-0.8161***
		(0.0379)		(0.0377)		(0.0579)		(0.0577)
White		-0.3713***		-0.3716***		-0.5314***		-0.5316***
		(0.0266)		(0.0265)		(0.0367)		(0.0367)
Poverty		0.3804***		0.3804***		0.1784***		0.1784***
		(0.0103)		(0.0103)		(0.0136)		(0.0136)
Unemployed		0.0897***		0.0899***		0.2077***		0.2078***
		(0.0110)		(0.0110)		(0.0198)		(0.0197)
Age under 19		0.0808***		0.0795***		-0.7338***		-0.7345***
		(0.0195)		(0.0195)		(0.0290)		(0.0290)
Age 20 to 44		0.2882***		0.2870***		-0.4385***		-0.4391***
		(0.0221)		(0.0221)		(0.0394)		(0.0393)
Age 45 to 64		0.2904***		0.2900***		-0.0948**		-0.0950**
		(0.0233)		(0.0232)		(0.0438)		(0.0436)
Rental		-0.0586***		-0.0584***		-0.1678***		-0.1677***
		(0.0102)		(0.0101)		(0.0089)		(0.0088)
Vaccant		0.0535***		0.0533***		0.0358**		0.0357**
		(0.0080)		(0.0080)		(0.0142)		(0.0141)
Multiple		-0.0783***		-0.0783***		-0.0496***		-0.0497***
		(0.0087)		(0.0087)		(0.0080)		(0.0080)
Ten-years		-0.0494***		-0.0493***		-0.0325***		-0.0324***
		(0.0054)		(0.0054)		(0.0065)		(0.0064)
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.53076	0.53438	0.53077	0.53440	0.93622	0.95940	0.93622	0.95940
Tract fixed effects	✓	✓			✓	✓		
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Tract fixed effects			✓	✓			✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Wage premium is the ratio of high-skilled wage by low-skilled wage, and relative supply is the ratio of high-skilled employment by low-skilled employment. Definition of covariates follows Table 3. All specifications include IPO case-distance-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to the closest withdrawn IPO issuer. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B8: Estimation on Housing Market Outcomes with Withdrawn IPO

	Log (House Price Index)				Log (Housing Rent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0169***	0.0150***	0.0214***	0.0190***	0.0079***	0.0061***	0.0099***	0.0077***
	(0.0018)	(0.0016)	(0.0023)	(0.0020)	(0.0013)	(0.0011)	(0.0016)	(0.0014)
treat	-0.0075***	-0.0066***			-0.0035***	-0.0027***		
	(0.0008)	(0.0007)			(0.0006)	(0.0005)		
College		0.0327***		0.0328***		0.2158***		0.2158***
		(0.0046)		(0.0045)		(0.0088)		(0.0088)
Asian		0.7861***		0.7855***		0.5649***		0.5646***
		(0.0221)		(0.0220)		(0.0253)		(0.0252)
Hispanic		-0.0546***		-0.0541***		0.0008		0.0010
		(0.0031)		(0.0031)		(0.0058)		(0.0058)
Black		0.3235***		0.3244***		0.2607***		0.2611***
		(0.0301)		(0.0300)		(0.0218)		(0.0217)
White		0.5124***		0.5117***		0.5649***		0.5646***
		(0.0181)		(0.0180)		(0.0223)		(0.0222)
Poverty		-0.1388***		-0.1388***		-0.1594***		-0.1594***
		(0.0086)		(0.0085)		(0.0050)		(0.0050)
Unemployed		-0.0694***		-0.0691***		0.0215***		0.0216***
		(0.0104)		(0.0104)		(0.0077)		(0.0077)
Age under 19		0.3765***		0.3744***		0.2484***		0.2475***
		(0.0183)		(0.0182)		(0.0123)		(0.0122)
Age 20 to 44		-0.0120		-0.0140		0.1504***		0.1496***
		(0.0127)		(0.0127)		(0.0153)		(0.0153)
Age 45 to 64		-0.0550***		-0.0556***		0.0217		0.0215
		(0.0151)		(0.0151)		(0.0161)		(0.0160)
Rental		-0.0744***		-0.0740***		0.1353***		0.1355***
		(0.0066)		(0.0066)		(0.0083)		(0.0083)
Vaccant		0.0136		0.0133		0.0213***		0.0212***
		(0.0097)		(0.0096)		(0.0073)		(0.0073)
Multiple		0.0820***		0.0819***		-0.4119***		-0.4120***
		(0.0049)		(0.0049)		(0.0093)		(0.0093)
Ten-years		0.0413***		0.0416***		0.1417***		0.1418***
		(0.0035)		(0.0035)		(0.0072)		(0.0071)
Observations	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277	4,848,277
R^2	0.95227	0.95346	0.95229	0.95348	0.83869	0.84354	0.83870	0.84355
Tract fixed effects	✓	✓			✓	✓		
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Distance-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Tract fixed effects			✓	✓			✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Definition of covariates follows Table 3. All specifications include IPO case-distance-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on distance to the closest withdrawn IPO issuer. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B9: Estimation on Wage by Skill Groups with Propensity Score

	Log (High Skilled Wage)				Log (Low Skilled Wage)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0116***	0.0088***	0.0146***	0.0111***	0.0052***	0.0022**	0.0065***	0.0027**
	(0.0012)	(0.0010)	(0.0016)	(0.0013)	(0.0013)	(0.0010)	(0.0017)	(0.0013)
Treat	-0.0050***	-0.0038***			-0.0023***	-0.0010**		
	(0.0006)	(0.0005)			(0.0006)	(0.0004)		
College		0.0673***		0.0674***		0.2018***		0.2019***
		(0.0119)		(0.0119)		(0.0055)		(0.0054)
Asian		-0.0207		-0.0212		0.2438***		0.2437***
		(0.0176)		(0.0175)		(0.0271)		(0.0270)
Hispanic		-0.1140***		-0.1137***		-0.1810***		-0.1809***
		(0.0042)		(0.0042)		(0.0056)		(0.0056)
Black		-0.4351***		-0.4347***		0.0451*		0.0453*
		(0.0309)		(0.0307)		(0.0250)		(0.0249)
White		0.0754***		0.0750***		0.4663***		0.4663***
		(0.0207)		(0.0206)		(0.0213)		(0.0212)
Poverty		-0.1359***		-0.1359***		-0.5247***		-0.5247***
		(0.0084)		(0.0084)		(0.0062)		(0.0062)
Unemployed		-0.1525***		-0.1524***		-0.2577***		-0.2577***
		(0.0071)		(0.0071)		(0.0077)		(0.0076)
Age under 19		0.4931***		0.4919***		0.4392***		0.4389***
		(0.0153)		(0.0152)		(0.0105)		(0.0104)
Age 20 to 44		0.2345***		0.2335***		-0.0453***		-0.0455***
		(0.0175)		(0.0174)		(0.0136)		(0.0136)
Age 45 to 64		0.3638***		0.3634***		0.0795***		0.0794***
		(0.0162)		(0.0161)		(0.0146)		(0.0146)
Rental		-0.2256***		-0.2254***		-0.1566***		-0.1566***
		(0.0070)		(0.0069)		(0.0062)		(0.0061)
Vacant		0.0204**		0.0202**		-0.0387***		-0.0387***
		(0.0083)		(0.0083)		(0.0069)		(0.0069)
Multiple		-0.1039***		-0.1040***		-0.0261***		-0.0261***
		(0.0079)		(0.0079)		(0.0036)		(0.0036)
Ten-years		-0.0206***		-0.0204***		0.0519***		0.0519***
		(0.0039)		(0.0039)		(0.0037)		(0.0037)
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.78398	0.78807	0.78400	0.78808	0.70965	0.72313	0.70965	0.72313
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Definition of covariates follows Table 3. All specifications include IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replaces census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B10: Estimation on Employment by Skill Groups with Propensity Score

	Log (High Skilled Employment)				Log (Low Skilled Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	-0.0018	-0.0085***	-0.0023	-0.0107***	-0.0136***	-0.0145***	-0.0172***	-0.0182***
	(0.0027)	(0.0022)	(0.0035)	(0.0028)	(0.0022)	(0.0018)	(0.0028)	(0.0023)
Treat	0.0008	0.0037***			0.0060***	0.0063***		
	(0.0012)	(0.0010)			(0.0010)	(0.0008)		
College		2.806***		2.806***		-1.794***		-1.795***
		(0.0226)		(0.0226)		(0.0158)		(0.0158)
Asian		-0.0429		-0.0423		0.9868***		0.9878***
		(0.0810)		(0.0808)		(0.0622)		(0.0621)
Hispanic		-0.1068***		-0.1070***		0.1757***		0.1753***
		(0.0182)		(0.0181)		(0.0080)		(0.0080)
Black		-0.6562***		-0.6566***		0.1093**		0.1087**
		(0.0742)		(0.0740)		(0.0456)		(0.0454)
White		-0.8289***		-0.8285***		-0.3637***		-0.3630***
		(0.0464)		(0.0463)		(0.0247)		(0.0247)
Poverty		-0.3271***		-0.3272***		-0.5295***		-0.5296***
		(0.0120)		(0.0120)		(0.0119)		(0.0119)
Unemployed		-0.7802***		-0.7804***		-0.9448***		-0.9451***
		(0.0182)		(0.0181)		(0.0112)		(0.0112)
Age under 19		0.7950***		0.7962***		1.474***		1.476***
		(0.0431)		(0.0430)		(0.0207)		(0.0207)
Age 20 to 44		1.929***		1.930***		2.299***		2.300***
		(0.0473)		(0.0471)		(0.0219)		(0.0218)
Age 45 to 64		1.772***		1.773***		1.829***		1.829***
		(0.0446)		(0.0444)		(0.0232)		(0.0232)
Rental		-0.1296***		-0.1298***		0.0599***		0.0595***
		(0.0126)		(0.0125)		(0.0104)		(0.0103)
Vacant		-0.9706***		-0.9704***		-0.9967***		-0.9964***
		(0.0233)		(0.0232)		(0.0139)		(0.0138)
Multiple		0.2369***		0.2369***		0.2842***		0.2843***
		(0.0121)		(0.0120)		(0.0112)		(0.0111)
Ten-years		-0.0561***		-0.0563***		-0.0220**		-0.0223**
		(0.0104)		(0.0104)		(0.0106)		(0.0105)
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.91084	0.92989	0.91084	0.92989	0.91203	0.92740	0.91204	0.92740
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Definition of covariates follows Table 3. All specifications include IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B11: Estimation on Wage and Employment Gap with Propensity Score

	Log (Wage Premium)				Log (Relative Labor Supply)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0073***	0.0076***	0.0092***	0.0096***	0.0097***	0.0039***	0.0122***	0.0050***
	(0.0012)	(0.0011)	(0.0015)	(0.0014)	(0.0027)	(0.0015)	(0.0034)	(0.0019)
Treat	-0.0032***	-0.0033***			-0.0042***	-0.0017**		
	(0.0005)	(0.0005)			(0.0012)	(0.0007)		
College		-0.1528***		-0.1528***		4.647***		4.647***
		(0.0095)		(0.0094)		(0.0136)		(0.0136)
Asian		-0.1562***		-0.1567***		-0.9282***		-0.9284***
		(0.0274)		(0.0273)		(0.0498)		(0.0497)
Hispanic		0.0569***		0.0571***		-0.2711***		-0.2710***
		(0.0081)		(0.0080)		(0.0174)		(0.0173)
Black		-0.4380***		-0.4377***		-0.7410***		-0.7409***
		(0.0377)		(0.0376)		(0.0495)		(0.0493)
White		-0.3492***		-0.3495***		-0.4770***		-0.4772***
		(0.0263)		(0.0262)		(0.0343)		(0.0342)
Poverty		0.3847***		0.3847***		0.1823***		0.1823***
		(0.0099)		(0.0099)		(0.0128)		(0.0127)
Unemployed		0.0890***		0.0891***		0.2156***		0.2157***
		(0.0108)		(0.0107)		(0.0175)		(0.0175)
Age under 19		0.0656***		0.0645***		-0.6984***		-0.6990***
		(0.0184)		(0.0183)		(0.0277)		(0.0276)
Age 20 to 44		0.2675***		0.2666***		-0.4296***		-0.4301***
		(0.0224)		(0.0223)		(0.0375)		(0.0374)
Age 45 to 64		0.2825***		0.2822***		-0.1126***		-0.1127***
		(0.0235)		(0.0234)		(0.0409)		(0.0408)
Rental		-0.0527***		-0.0525***		-0.1746***		-0.1746***
		(0.0096)		(0.0096)		(0.0082)		(0.0082)
Vacant		0.0478***		0.0476***		0.0381***		0.0380***
		(0.0078)		(0.0078)		(0.0130)		(0.0130)
Multiple		-0.0763***		-0.0763***		-0.0421***		-0.0421***
		(0.0085)		(0.0085)		(0.0079)		(0.0078)
Ten-years		-0.0453***		-0.0452***		-0.0359***		-0.0358***
		(0.0053)		(0.0053)		(0.0063)		(0.0063)
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.53151	0.53504	0.53152	0.53505	0.93584	0.95929	0.93584	0.95929
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on workers by their educational attainment and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Wage premium is the ratio of high-skilled wage by low-skilled wage, and relative supply is the ratio of high-skilled employment by low-skilled employment. Definition of covariates follows Table 3. All specifications include IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B12: Estimation on Housing Market Outcomes with Propensity Score

	Log (House Price Index)				Log (Housing Rent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TreatXpost	0.0178***	0.0161***	0.0225***	0.0203***	0.0086***	0.0071***	0.0108***	0.0090***
	(0.0018)	(0.0016)	(0.0022)	(0.0020)	(0.0012)	(0.0011)	(0.0015)	(0.0014)
Treat	-0.0078***	-0.0070***			-0.0037***	-0.0031***		
	(0.0008)	(0.0007)			(0.0005)	(0.0005)		
College		0.0232***		0.0232***		0.2126***		0.2126***
		(0.0044)		(0.0044)		(0.0085)		(0.0085)
Asian		0.6663***		0.6653***		0.5222***		0.5218***
		(0.0232)		(0.0232)		(0.0270)		(0.0269)
Hispanic		-0.0472***		-0.0467***		0.0117**		0.0119**
		(0.0034)		(0.0034)		(0.0052)		(0.0052)
Black		0.2323***		0.2330***		0.2549***		0.2552***
		(0.0290)		(0.0289)		(0.0220)		(0.0219)
White		0.4721***		0.4715***		0.5540***		0.5537***
		(0.0176)		(0.0176)		(0.0211)		(0.0211)
Poverty		-0.1159***		-0.1158***		-0.1560***		-0.1559***
		(0.0075)		(0.0075)		(0.0052)		(0.0051)
Unemployed		-0.0568***		-0.0566***		0.0156**		0.0157**
		(0.0099)		(0.0098)		(0.0072)		(0.0072)
Age under 19		0.3178***		0.3155***		0.2059***		0.2049***
		(0.0160)		(0.0160)		(0.0126)		(0.0126)
Age 20 to 44		0.0163		0.0145		0.1495***		0.1487***
		(0.0116)		(0.0115)		(0.0155)		(0.0155)
Age 45 to 64		-0.0101		-0.0107		0.0284*		0.0281*
		(0.0134)		(0.0134)		(0.0155)		(0.0155)
Rental		-0.0555***		-0.0551***		0.1391***		0.1392***
		(0.0051)		(0.0051)		(0.0080)		(0.0079)
Vacant		0.0053		0.0050		0.0061		0.0059
		(0.0099)		(0.0099)		(0.0075)		(0.0074)
Multiple		0.0712***		0.0711***		-0.4146***		-0.4146***
		(0.0041)		(0.0041)		(0.0091)		(0.0090)
Ten-years		0.0508***		0.0511***		0.1437***		0.1439***
		(0.0031)		(0.0032)		(0.0069)		(0.0069)
Observations	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853	5,038,853
R^2	0.95470	0.95557	0.95472	0.95558	0.84438	0.84891	0.84439	0.84891
Tract fixed effects	✓	✓			✓	✓		
Case-Tract fixed effects			✓	✓			✓	✓
County-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case-Pscore-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Sample consists of tract-level ACS 5-year data on housing market outcomes and 396 high-technology IPO firms. All observations are collapsed into a single panel for estimation. The coefficient of *TreatXpost* identifies treatment effect of IPO on welfare outcomes. Definition of covariates follows Table 3. All specifications include IPO case-pscore-year fixed effect and county-year fixed effect, while columns (3)(4)(7)(8) replace census tract fixed effect with case-tract fixed effect. An IPO case corresponds with an IPO Zone, which is the collection of census tracts within 30 miles of headquarter of IPO firms. IPO Zone is further split into bins $h \in \{1, 2, 3, 4, 5\}$ based on prediction of propensity score model. Standard errors are clustered at the IPO case level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.