THREE ESSAYS IN CORPORATE FINANCE

by

XIAO REN

(Under the Direction of Jie He)

ABSTRACT

This dissertation comprises three independent essays in empirical corporate finance, with a focus on labor and finance and entrepreneurial finance. In the first chapter, I study the implication of within-firm labor heterogeneity for firm performance through the lens of employee political ideology. Using individual campaign donation information to capture political ideology, I find that political ideology conflicts, both those within employees and those between CEOs and employees, negatively affect firms' future operating performance. To establish causality, I use an instrumental variable approach which relies on the exogenous variation in political ideology caused by local television station ownership changes. The second chapter studies the large decline in U.S. IPOs since 2000. This essay first finds that the dramatic reduction in U.S. IPOs is not due to a weaker economy. Second, this essay finds evidence strongly supports the hypotheses that the decline in U.S. IPOs is due to the public firms' greater sensitivity to product market competition and the greater supply of private equity financing in the post-2000 period. Finally, this essay finds mixed evidence regarding the explanations based on the smaller net financial benefits of being standalone public firms or the increased need for confidentiality after 2000. The third chapter examines an emerging phenomenon that talented employees leave successful entrepreneurial firms to join less mature ones. This essay finds that these "entrepreneurial diffusers", by potentially passing on entrepreneurial knowledge and institutional wisdom, can enhance their new colleagues' innovation productivity and help their new employers successfully exit. This essay further finds that these diffusers are motivated by an entrepreneurial culture that prizes risk-taking rather than by the prospect of monetary gain. Finally, the departure of entrepreneurial diffusers contributes to the well-documented long-run IPO underperformance in accounting and stock returns.

INDEX WORDS: Labor and finance, Political ideology, Worker-management conflict, Within-firm labor heterogeneity, IPOs, Exit choices, Private equity, Entrepreneurship, Innovation

THREE ESSAYS IN CORPORATE FINANCE

by

XIAO REN

B.B.A., University of Georgia, 2015

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial

Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2021

THREE ESSAYS IN CORPORATE FINANCE

by

XIAO REN

Major Professor: Jie He
Committee: Jeffry Netter
Annette Poulsen
Tao Shu

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
May 2021

DEDICATION

To my parents and grandparents for their love and support.

And, to Dr. Huan Yang, who was a dear friend and mentor to me. May him rest in peace.

ACKNOWLEDGEMENTS

I would like to express the deepest appreciation to my dissertation chair Professor Jie He. His insights and encouragement were instrumental to my successful completion of this dissertation, and without his guidance this dissertation would not have been possible.

I would like to thank my committee members Professor Jeffry Netter, Professor Annette Poulsen, and Professor Tao Shu for their valuable comments.

TABLE OF CONTENTS

CHAPTER 1

Within-firm Labor Heterogeneity and Firm Performance: Evidence from Employee Political Ideology Conflicts[1]

[1] Xiao Ren. To be submitted to *Journal of Financial Economics*.

Abstract

This paper explores the implication of within-firm labor heterogeneity for firm performance through the lens of employee political ideology. Using individual campaign donation information to capture political ideology, I find that political ideology conflicts, both those within employees and those between CEOs and employees, are negatively associated with firms' future operating performance. This effect is stronger for firms whose employees are more geographically concentrated and more sophisticated. The reduced labor productivity and abnormal employee turnover are two plausible mechanisms through which employee political ideology conflicts hurt firm performance. To establish causality, I use an instrumental variable approach which relies on the exogenous variation in political ideology caused by local television station ownership changes.

1.1 Introduction

The recent U.S. presidential elections have witnessed and brought public attention to numerous heated debates among people with different political ideology, even those living in the same neighborhood or working for the same employer. When people in a social environment (e.g., a family, neighborhood, or workplace) express different political views in the public or attempt to convince one another of such views, conflicts, either verbal or physical, could take place and adversely affect their relationship, which might eventually impose severe negative externalities on the entire social group. The welfare implication of heterogenous political views in the same social group is both an important and an interesting topic not only to academics, but also to business practitioners and policy makers. However, even though the recent presidential elections has revealed tremendous heterogeneity in political beliefs among seemingly homogeneous social groups, the consequences of such ideology conflicts on the real economy remain underexplored. In particular, much of the literature to date, with a few exceptions (to be discussed later), has treated a firm’s employees as a homogeneous group whose decisions can be made by a “representative” agent. As a result, few studies have explored the implications of within-firm labor heterogeneity, especially the differential political views among workers in the same workplace, for firm performance and policies. My paper aims to fill in this gap by empirically investigating the political ideology conflicts among employees and their effects on corporate performance.

As the modern society has been pushing for diversity at workplace over the past few decades, a typical firm’s employees nowadays are likely to exhibit heterogeneous political ideology, which might lead to workplace conflicts due to such different political views. In general, there are two types of employee political ideology conflicts in a firm. The first type of conflicts exits among all the employees of a firm. According to a CNBC news article (Rooney (2020)), the CEO of Coinbase, Brian Armstrong, believes that the political conversations among employees at workplace have the potential to destroy firm value by “being a distraction” and by “creating internal division”. Therefore, Coinbase banned political discussions at work and offered generous severance packages to those employees who did not want to abide by the rule and wanted to quit the company. According to another example from a Bloomberg news article (Weise (2017)), conservative employees in the Silicon Valley feel ostracized in the workplace because of their political ideology, which they are afraid of revealing to coworkers because the latter might take it as a “personal affront”. Therefore, it is reasonable to expect that a firm’s teamwork efficiency and labor productivity will suffer when the firm’s employees have political ideology conflicts among each other, or when they are distracted from work by political issues.

The second type of employee political ideology conflicts exists between employees and the CEO. For example, according to a Bloomberg news article (Hymowitz and Greenfield (2017)), in November 2016, Ginni Rometty, the CEO of IBM, sent an open letter to Donald Trump, congratulating him for winning the presidential election. This letter provoked a storm of protest from Democratic employees at IBM. For example, a software engineer, Daniel Hanley, drafted a petition that urged the CEO to "do what's right for IBMers" and got more than 1,600 supporting signatures from his fellow workers. Meanwhile, a senior content strategist at IBM, Elizabeth Wood, decided to quit the company, and published an open letter stating that she left the company because of the CEO's political ideology. In this example, the employees and the CEO of a firm have strong political ideology conflicts, which lead to negative consequences for the firm, in terms of distraction at workplace and voluntary departure of skillful employees.

Despite the abundant anecdotal evidence suggesting that within-firm heterogeneity in employee political ideology will negatively affect firms, one could argue that such heterogeneity might actually improve firm value by reducing managers' empire-building incentives (e.g., retaining/promoting incapable employees sharing similar political ideology with that of themselves). In fact, Lee, Lee, and Nagarajan (2014) show that the alignment of political views between a firm's CEO and its board members increases managerial entrenchment and decreases shareholder value. In other words, they find that a larger difference in political ideology between the CEO and board members will benefit the shareholders. If the CEO-employee relationship is similar to the CEO-board relationship, then a larger difference in political views between employees and the CEO might make the latter less incentivized to please the former out of entrenchment motives (e.g., via wage increases, as documented by studies such as Cronqvist et al. (2009)), which leads to an improvement of firm value. Similarly, greater heterogeneity in a firm's political ideology among employees might also improve its performance because a more diverse workforce (which usually accompanies a more vibrant corporate culture) might inspire more thought-provoking conversations at the workplace and lead to more skill-complementarity among employees with different backgrounds, which boosts corporate innovation and ultimately enhances firm value (see, e.g., Mayer, Warr, and Zhao (2018), Ostergaard, Timmermans, and Kristinsson (2010), and Richard (2000)). Hence, whether within-firm heterogeneity in employee political ideology affects firm performance/value positively or negatively is an empirical question.

In this paper, I formally examine the above two competing hypotheses by analyzing the impact of employee political ideology conflicts on firm performance. Following the literature, I capture an employee's political ideology using individual political campaign donation data provided by Federal Election Commission (FEC). To capture the political ideology conflicts within the employees, I calculate the percentage of strongly polarized employees (i.e., those with much stronger support for one party relative to the other) in a given firm-year, and assign a score ranging from one to five to the firm-year based on its relative proportion of such strongly polarized employees. To measure the conflicts between the employees and the CEO, for each person in a given year, I calculate her Democratic tendency (i.e., *DEM%*) as the dollar amount of her donation to Democratic recipients divided by the dollar amount of her donation to both the Democratic recipients and Republican recipients. A higher value of *DEM%* indicates that the person is more Democratic-oriented. For a given firm-year, I then use the absolute value of the difference between the CEO's *DEM%* and the average employees' *DEM%* as the proxy for the political ideology conflict between employees and the CEO.

The baseline ordinary least squares (OLS) regression results show that there is a significantly negative association between a firm's operating performance (i.e, return on assets, ROA) and both the political ideology conflicts within the employees and those between its CEO and the average employees. In terms of economic magnitudes, a firm with the strongest within-employee conflicts (i.e., with more than 40% strong Democratic employees and more than 40%

strong Republican employees) has a 2.8 percentage points lower ROA, which is about 34.5% of its standard deviation, than a firm with the weakest within-employee conflicts (i.e., with less than 10% Democratic employees or less than 10% strong Republican employees). A one standard deviation increase in CEO-employee political ideology conflicts is associated with a 0.23 percentage points decrease in ROA. Using information from Execucomp and Capital IQ, I further decompose the CEO-employee political ideology conflicts into the conflicts between the CEO and employees of different ranks within the firm, and find that the negative association of political ideology conflicts with firm performance manifests for most hierarchies of employees.

I then conduct multiple subsample analyses to explore the cross-sectional heterogeneity of the relation between employee political ideology conflicts and firm performance. First, the negative association between ROA and employee political ideology conflicts should be stronger for firms with more geographically concentrated employees. When employees live and work in the same geographic location, they tend to interact and communicate with each other more often, which increases the effect of within-employee political ideology conflicts on firm performance. Furthermore, it makes it easier for them to unite together and collectively oppose the CEO if the latter's political ideology contradicts with theirs, leading to more destructive dynamics at the workplace and hurt firm performance. Using the residential address information provided by the FEC for each registered donor, I find that the negative associations between ROA and employee political ideology conflicts are indeed more pronounced when a larger fraction of a firm's employees live in its headquarter.

Second, I expect the associations between employee political ideology conflicts and firm performance to be stronger for firms with more sophisticated/skillful employees, who tend to have more polarized political views and contribute more to firm value. Using the labor skill index (see, e.g., Belo et al. (2017) and Ghaly, Dang, and Stathopoulos (2017)) to proxy for employee sophistication/skill, I find evidence consistent with this prediction.

Furthermore, I exploit the channel through which employees' political ideology conflict affects firm performance. Edmans (2011) argues that employee satisfaction is positively associated with firm value because employees, if satisfied with their employers, tend to have higher productivity and are less likely to leave the firm. In a similar vein, Oswald, Proto, and Sgroi (2015) argue that employees' happiness increases their productivity at workplace. The recent work by Babenko, Fedaseyeu, and Zhang (2020) show that the employees whose political donations are not aligned with their CEOs are more likely to leave their firms. Hence, I conjecture that the lower ROA resulting from greater employee political ideology conflicts could be caused by two possible channels, namely, lower productivity and abnormal employee turnover, when employees are not satisfied or happy due to the conflicts in political ideology at workplace. To test the first channel, I use operating income before depreciation per employee and output per employee as the empirical measures of labor productivity and find that both the within-employee and CEO-employee political ideology conflicts are negatively associated with labor productivity. I further use the number of patents filed and the average number of citations received per patent by individual inventors as proxies of labor productivity, and find consistent results. To study the turnover channel, I identify the departure events of key employees using information from the Execucomp and Capital IQ databases and examine whether employee political ideology conflicts increase the turnover of key employees. I find that both the conflicts between the key employee and other employees in the firm and those between a key employee and her CEO are positively associated with the likelihood that the employee leaves the firm, which is consistent but not limited to the findings in Babenko, Fedaseyeu, and Zhang (2020).

While the OLS results suggest that there is a negative relation between employee political ideology conflicts and firm performance, endogeneity concerns could arise due to either omitted variables or reverse causality. For example, according to the evidence presented by Babenko, Fedaseyeu, and Zhang (2020), CEOs could exert influence on employees' political decisions to increase shareholder value, which makes the CEO-employee political ideology conflict an endogenously determined variable. Moreover, entrenched CEOs, under empire-building incentives, may hire or retain more employees who share similar political ideology with themselves. To alleviate such endogeneity concerns, I implement a two-stage least-squares (2SLS) estimation framework, using the acquisitions of local television stations by Sinclair Broadcast Group (Sinclair) as an instrumental variable (IV) for employee political ideology conflicts. Sinclair, as the largest television station operator in the United States in terms of both the number of stations owned and the total coverage of local TV audience, has long been known to have a strong conservative orientation. Martin and McCrain (2018) document a significant rightward shift in the ideological slant of TV coverage in a community after its local television stations are acquired by Sinclair. As previous literature shows that mass media (such as television programs) has a strong persuasive effect on people's political orientation (e.g., DellaVigna and Kaplan (2007) and Martin and Yurukoglu (2017)), it is reasonable to believe that the acquisitions of local television stations by Sinclair would shift the political ideology of people (including working professionals) living in the same location, influence the conflicts of political views at workplace, and ultimately affect the performance of firms employing these employees. Meanwhile, the incidences of such acquisitions appear not to be driven by local economic conditions (e.g., Martin and McCrain (2018)) and should not influence the performance of affected firms through channels other than employee political ideology conflicts. Thus, this instrument is likely to satisfy both the relevance condition and the exclusion restriction.

Specifically, I first identify whether the local television stations at each sample employee's city of residence are acquired by Sinclair in a given year, and then aggregate this shock to the firm-year level as the instrumental variable for employee political ideology conflicts. I show that the Sinclair shock makes affected employees more Republican-oriented. As the distribution of my employee political ideology measure (i.e., DEM%) ranges from zero (indicating strong Republican) to one (indicating strong Democratic), the Sinclair shock would shift an individual employee towards the left end of this distribution, which tends to reduce the distances in political ideology among individual employees (i.e., reduces the within-employee political ideology conflicts). Similarly, the Sinclair shock reduces the CEO-employee political ideology conflicts because CEOs are predominantly more Republican-oriented than employees and thus less affected by the Sinclair shock than an average employee in the same workplace. Using the Sinclair acquisition shock as the IV, I show that an exogenous decrease in the within-employee political ideology conflicts and the CEO-employee conflicts indeed causes an improvement in firm performance.

This paper sheds new light on the effect of within-firm labor heterogeneity and labor-management relationship on firm performance through the lens of political ideology. It is the first to explicitly examine the differences in political ideology among the average employees as well as the differences between CEOs and employees of all ranks along the corporate ladder. In this sense, the current paper supplements the findings in the recent literature on the association between CEOs'/employees' political contribution and firm value, which mostly treats a firm's executives or employees as a homogeneous group of decision makers. I propose a new measure of political ideology conflicts among average employees. Using this measure, I examine not only the CEO-employee conflicts, but also the within-employee conflicts, and contrast their differential effects on firm performance. Last but not least, my paper proposes a new identification strategy to the literature on political ideology, namely, the acquisition of local TV stations by Sinclair, which could possibly provide an exogenous variation to local people's political ideology and improve the causal inference of studies on stakeholders' political views and participation.

1.2 Relation and Contribution to the Existing Literature

My paper is related to the literature on employee satisfaction and firm value. Edmans (2011) shows that a value-weighted portfolio of the 100 companies with the highest employee satisfaction in the United States created an annual four-actor alpha of 3.5% from 1984 to 2009, suggesting that employee satisfaction creates shareholder value in the long run. Oswald, Proto, and Sgroi (2015) use both experimental and real-world evidence to show that individuals' happiness increases their productivity. Huang et al. (2015) study the association between employee satisfaction and corporate performance in the context of family firms. They find that family firms enhance their performance by providing an employee-friendly corporate culture. Researchers have also shown that labor-management relationship, as an important factor of employee satisfaction, significantly affects firm performance. For example, Guiso, Sapienza, and Zingales (2015) find that firm performance is stronger when employees perceive top managers as trustworthy and ethical. My paper contributes to the literature by studying the association between firm performance and employees' political ideology conflict, which is a significant factor of employee satisfaction and labor-management relationship but cannot be captured in standard employee welfare measures such as KLD score. Consistent with the predictions in the literature, I find that firm performance is lower when employee satisfaction is lower and when labor-management relationship is worse in the context of political orientation.

My paper is also related to the literature that studies the relationship between CEO political ideology and corporate behavior. Di Giuli and Kostovetsky (2014) show that firms with Democratic CEOs spend more on corporate social responsibility (CSR), which is associated with a decrease in firm value. Hutton, Jiang, and Kumar (2014) show that republican managers adopt and maintain more conservative corporate policies. Francis, Hasan, Sun, and Wu (2016) show that political polarized CEOs are associated with more corporate tax sheltering. While Republican CEOs use tax sheltering for idiosyncratic reasons, Democratic CEOs use it for economic reasons. Unsal, Hassan, and Zirek (2016) show that Republican managers lobby a larger number of bills and have higher lobbying expenditures, which offset the benefit from lobbying.

Lee, Lee, and Nagarajan (2014) is the first paper to study the political ideology conflict between the CEO and other stakeholders of the firm. They show that when CEO and board members share similar political ideology, the empathy and acceptance between them increase. As a result, board monitoring is weakened, CEO entrenchment increases and firm value decreases. While my paper uses similar methodology, I study the impact of the difference in terms of political ideology between the CEOs and non-CEO employees, instead of that between the CEOs and the board members. Since employees do not have monitoring duty, shared values and belief systems between the CEO and rank-and-file employees in a firm should result in more efficient decision making, execution, and better teamworking. On the other hand, if employees do not share the same political ideology with their CEOs, the efficiency of teamworking and execution could suffer, which could negatively impact labor productivity and firm performance.

Another stream of literature focuses on the relationship between employees' political ideology and firm behavior. Gupta, Briscoe, and Hambrick (2016) show that firms with liberal employees have larger CSR spending. Borghesi (2018) shows that the impact of employees' political ideology on firm CSR intensity is even more significant than the impact of executives' political ideology. While the above papers treat a firm's employees as a group with homogenous political ideology, I study the impact of with-firm heterogeneity in employee political ideology on firm performance.

Babenko, Fedaseyeu, and Zhang (2020) is the first paper to study the relation between CEOs and employees' political participation. They show that in the same election cycle, a firm's employees are more likely to make campaign donations to the candidates who receive donations from the firm's CEO. They claim that CEOs exert influence on employees' political participation to support the candidates whose policies will benefit the firm more. While the action increases shareholder value, it is not likely that the employees' economic values are perfectly correlated with shareholder value. Therefore, the CEOs' influence decreases employees' economic gain from campaign donations. While the authors have done a very thorough study on the relation between CEO and employees' political participation, some interesting questions arise from their findings. It can be inferred from their results that the employees' ex ante political ideology differs from that of the CEOs. If they always share the same ideology, there will be no need for the CEO to influence the employees' donations. Assume there are two types of employees: those whose donations are affected by the CEO, and those whose donations are not affect by the CEO. The first type could be the individuals who have very strong political affiliation, which cannot be easily affected by CEO's effort. When the CEO makes the attempt to affect their campaign donations, tension is likely to arise between these employees and the CEO and results in negative consequences for the firm. For the second type of individuals, even if their donations are affected by the CEO, it does not necessarily mean that shift their political ideology to be consistent with the CEO. On the contrary, the influence exerted by the CEO could exacerbate the conflict between these employees and CEO, since the employees are influenced to make donations that do not provide them with economic gains. Therefore, their study provides a motivation of my research: when the political ideology conflict arises between CEO and employees, how does it affect firm performance? In addition, my paper focuses on not only the political ideology conflict between the CEO and employees, but also that among the average employees.

Finally, my paper is broadly related to the literature that studies the relation between firm value and political connection/participation, such as Political Action Committee (PAC) campaign donation made by firms (Akey (2015) and Cooper, Gulen, and Ovtchinnikov (2010)), acquisition of political information by hedge fund managers (Gao and Huang (2016)), political connections of board members (Goldman, Rocholl, and So (2013)), and campaign donation made by individuals (Ovtchinnikov and Pantaleoni (2012)). On one hand, the political alignment between CEO and employees can be viewed as a form of connection. Consistent with the literature, the connection should create value for firms. On the other hand, both CEOs' and employees' campaign donations are forms of political participation. My study shows that in the context of labor-management relationship and within-firm labor heterogeneity, political participation might have a negative impact on firm value.

1.3 Data Construction and Summary Statistics

1.3.1 Data and Sample Selection

Following the literature on political ideology and finance (e.g., Hong and Kostovetsky (2012) and Di Giuli and Kostovetsky (2014)), I use the individual campaign donation data provided by Federal Election Commission (FEC) starting in 1992 to construct proxies for employees' political ideology.[2] The FEC individual contributions file contains information at transaction level about each contribution from an individual to a political committee/candidate, which is disclosed by the donation recipients under the requirement of federal law. It is notable that not all individual donations are subject to mandatory disclosure. In 1989-2014, a contribution would be reported if the reporting period amount is $200 or more. After the year 2014, a contribution is reported if the election cycle-to-date amount is over $200 for contributions to candidate committees and if the calendar year-to-date amount is over $200 for contributions to political action committees (PACs) and party committees.[3] I include only the donations subject to mandatory disclosure in the sample, to avoid the potential selection bias of voluntary disclosure.

I include contributions to candidate committees, party committees, hybrid PACs and super PACs with strong party affiliation in the sample. The party affiliation of candidate and party committees are obtained from the committee master file provided by FEC. For hybrid PACs and super PACs which have more than 1,000 transaction records, I manually search for the political orientation of the PAC on OpenSecrets.org and Google.com.[4] For each individual donation, I obtain the date and dollar amount of the donation, employer and location information of the donor, and party affiliation of the recipient. FEC does not provide a unique identifier for donors. Therefore, I first create a standardized name for each donor, capitalizing the characters and

[2] The database is available at https://www.fec.gov/data/browse-data/?tab=bulk-data.
[3] Information obtained from the Federal Election Commission website at https://www.fec.gov/campaign-finance-data/contributions-individuals-file-description/ .
[4] Previous papers in the literature include only donations to candidate and party committees. However, some hybrid PACs and super PACs have strong political orientation and account for a significant amount of donations made by individuals. For example, Hillary Victory Fund raised a total of $424 million in the 2016 election cycle, which accounted for 11.16% of total contributions from individuals in the cycle. Not including these contributions will significantly reduce sample size and potentially introduce selection bias.

removing the prefixes and suffixes, and then use a combination of the standardized name and employer of the individual to create a unique identifier for each donor.

The employer of each donor is reported in the FEC database. However, the self-reported employer information is noisy. For example, an employee of Google might report her employer as "Google", "Google Inc", "Google.com", "Alphabet Inc", etc. Some donors also include their job title in their employer information field, such as "Bank of America Banker", "Home Depot Sales", etc. Therefore, I use a three-step approach to link employer from FEC files to Compustat records. First, I standardize the employer names by deleting special characters and standardizing the suffixes such as "Inc", "Corp", "Company", etc., and match the standardized employer names to company names in Compustat, CRSP, and Capital IQ database. Matching to company names from several different databases minimizes the number of observations I lose due to unknown limitations in the company name collecting process of data vendors. Second, I employee a fuzzy-matching algorithm using two SAS functions "compare" and "complev". "Compare" returns the position of the leftmost character by which two strings differ. "Complev" returns the Levenshtein edit distance between two strings. I calculate the "compare" and "complev" value for each pair of employer name from FEC dataset and company name from standard financial databases. I require a pair of names to have a "compare" value of no less than 10 and a "complev" value of no larger than 9 to be a valid match. Adjusting the threshold slightly upwards or downwards does not change the empirical results qualitatively. Finally, to reduce the errors caused by fuzzy matching, I use Google search returns to verify the reliability of the matched employers. Specifically, for each pair of matched employer from the FEC database and company from the financial databases, I obtain the first 30 Google search results for both the two identities. A matched pair is treated as a valid pair if the two identities share at least 10 common search results. As a result, the individual contribution sample with matched employers ranges from the years 1992 to 2019, containing 543,509 transactions made by 241,842 employees from 5,409 firms.

1.3.2 Measuring Employees' political Ideology Conflict

1.3.2.1 Measuring Person-level Political Ideology

For each employee in year *t*, I define the individual's democratic tendency (*DEM%*) as the total dollar amount of her donations to Democratic recipients divided by the total dollar amount of her donations to both Democratic and Republican recipients in year *t*. The variable *DEM%* is continuous, ranging from zero to one. A higher *DEM%* value indicates that the person is more Democratic-oriented.

I further identify each employee's rank in the company using person-level information from Execucomp and Capital IQ People Intelligence database. An employee is identified as the CEO if her name matches the CEO's name from Execucomp or Capital IQ in a given year. An employee is identified as a key employee if her name matches the name of a non-CEO employee in Execucomp or Capital IQ. Board members are identified in a similar fashion. The employees whose names do not match with any records from Execucomp or Capital IQ are treated as rank-and-file employees.

Table 1.1 presents the descriptive statistics of person-level political ideology by employee rank. In Panel A, Column (1) shows the number of person-year observations in each rank, Column (2) shows the average dollar amount of donation per person-year, and Column (3) shows the mean Democratic tendency. The statistics reveal some interesting patterns of employees' political ideology. First, employees in higher ranks donate more than employers in lower ranks. The average dollar amount of donation per CEO-year is \$6,110.68, which is approximately 4.5 times the size of average donation made by rank-and-file employees. Second, employees in lower ranks are more

Democratic-oriented on average. The mean Democratic tendency of rank-and-file employees is 59.48%, compared to 37.68% of the CEOs. Panel B presents the distribution of employee-years within each bracket of *DEM%* by employee rank. Specifically, for employees in a given rank, I calculate the fraction of employee-years when an employee's *DEM%* falls in the following ranges: 0%, (0%, 25%], (25%, 50%), 50%, (50%, 75%), [75%, 100), 100%. The results show that, 56% of the CEOs are strongly Republican-oriented (i.e., all of their contributions are made to Republican recipients), which is 1.72 times the fraction of strong Democratic CEOs (i.e. those who only make contributions to the Democratic recipients), while the fraction of rank-and-file employees who are strongly Republican-oriented is 0.68 times the fraction of rank-and-file employees who are strongly Democratic-oriented. Furthermore, employees in lower ranks are more polarized than employees in higher ranks. For example, 11% of the CEOs donate to both the Republican party and the Democratic party in a given year, whereas only 1% of the rank-and-file employees donate to both parties. Combined together, the results presented in Table 1.1 suggest that there are strong political ideology conflicts both within each rank of employees and across different ranks of employees.

1.3.2.2 Measuring Political Ideology Conflicts

Measuring the within-employee political ideology conflicts is a difficult task. Simple measures of dispersion such as standard deviation or interquartile range are not applicable since they capture only the spread of employees' *DEM%*, but not whether the employees are Republican or Democratic. For example, a uniform distribution of employees' *DEM%* on [25%, 75%] and a uniform distribution on [0%, 50%] will have the same standard deviation, but they obviously have different implications in terms of political ideology conflict, as the first one consists of both Democratic and Republican employees, whereas the second one consists of only Republicans.

Conceptually, a measure of the within-employee political ideology conflicts should capture 1) whether the individual employees are Republican or Democratic, 2) whether the individual employees are strongly polarized, and 3) the fraction of employees with strong polarization. To construct the empirical measure, I first define an individual as strong Democratic (Republican) if she donates more than $2,000 only to Democratic (Republican) recipients in a given year.[5] Then, I calculate the percentage of strong Democratic employees (*%StrongDEM*) and strong Republican employees (*%StrongREP*) in a firm. All possible pairs of *%StrongDEM* and *%StrongREP* create a [0,1] by [0,1] grid. Since the sum of *%StrongDEM* and *%Strong REP* cannot exceed 100%, the grid can be illustrated as an isosceles right triangle, as shown in Figure 1.1. The two sides of the triangle represent the percentages of strong Republican employees and strong Democratic employees in a firm. I divide the grid into five areas so that each area is assigned with a score (*EmpConflict*) that represents a level of within-employee political ideology conflict. This is a strict definition of conflict between employees, because conflict increases if and only if both *%StrongDEM* and *%StrongREP* increase. For example, firms with *EmpConflict* that equals five have the highest level of conflict, as these firms have both more than 40% strong Republican employees and more than 40% strong Democratic employees. Area four represents the second highest level of conflict, including firms with more than 30% strong Republicans, more than 30% strong Democrats, and at least one of the percentages is below 40%. Area three and two can be interpreted in similar fashion. Firms with *EmpConflict* that equals one have the lowest level of conflict, as at least one of the percentages of strong Republicans and strong Democrats are below 10%. I exclude firms with fewer than ten employees to ensure that the value of *EmpConflict* is not

[5] Hong and Kostovetsky (2012) define strong Democratic (Republican) as individuals who made more than $2,000 donation to Democrats (Republicans), net of donation to Republicans (Democrats). However, the interpretation of the $2,000 difference varies in the total dollar amount of donations made by an individual. Thus, I apply a stricter definition of strong polarization.

driven by small denominators in *%StrongRep* and *%StrongDem*. The summary statistics of *EmpConflict* is presented in Table 1.2, Panel A. The variable has a mean of 2.424 and a median of 2.

The measure of CEO-employee political ideology conflict is constructed by comparing the *DEM%* of a firm's CEO and the average *DEM%* of the firm's non-CEO employees. Specifically, for each firm-year, I calculate the CEO's *DEM%* (*DEMCEO*) as the proxy for CEO's political ideology. I then measure the overall non-CEO employees' political orientation for a firm-year as the average of non-CEO employees' *DEM%* (*DEMemp*). The measure of CEO-employee political ideology conflict (*CEOempDiff*) is calculated by taking the absolute value of the difference between a firm's *DEMCEO* and the firm's *DEMemp*. A larger value of *CEOempDiff* indicates that the CEO and the employees have larger conflicts in terms of political ideology.

I further separate the political orientation measure by the rank of the non-CEO employees, i.e. the key employees and rank-and-file employees. Employees with higher ranks are likely to be wealthier and more educated than rank-and-file employees. They are more likely to have stronger political affiliation and have larger impacts on the firm's performance. They also work more closely with the CEO and have similar ideology to the CEO than rank-and-file employees, as shown in Table 1.1. Therefore, I further calculate the ideology measure for key employees (*DEMkey*), board members (*DEMboard*), and rank-and-file employees (*DEMempRf*). Lee, Lee and Nagarajan (2014) argue that the political alignment between CEO and board members decreases firm value. To exclude the confounding effect, I further create a subsample of key employees who are not board members of their firms and calculate the political ideology of these non-board key employees (*DEMkeyNb*). The political ideology conflicts between the CEO and the key employees (*CEOkeyDiff*), between the CEO and the board members (*CEOboardDiff*), between the CEO and the non-board key employees (*CEOkeyNbDiff*), and between the CEO and the rank-and-file employees (*CEOempRfDiff*), are calculated in a similar fashion to that of *CEOempDiff*.

The summary statistics of the CEO-employee political conflict measures are presented in Table 1.2, Panel A. The statistics indicate that there is a 30.09% difference between CEO's and employees' political ideologies on average. The difference increases as the rank of the employees goes down. The average difference between the CEO and the rank-and-file employees is 32.05%, which is the highest among all the employee ranks, while the key employees have lower conflicts in political ideology with their CEOs. The results presented in Table 1.2, Panel A indicate that there are significant conflicts between the CEO and non-CEO employees in all ranks, which is consistent with the findings presented in Table 1.1.

1.3.3 Measuring Firm Performance and Controls Variables

The main dependent variable in my study is return on assets (*ROA*), defined as the ratio of operating income before depreciation to lagged total assets. I control for a set of variables that are commonly known to impact firm performance (e.g., Ovtchinnikov and Pantaleoni, 2012; Cao et al., 2018), including market-to-book ratio (*MB*), book leverage (*Lev*), the natural logarithm of total asset (*LnAsset*), capital expenditure (*CAPEX*), the ratio of net property, plant, and equipment to total assets (*PPE*), research and development expenses (*RD*), and the natural logarithm of one plus firm age (*LnFirmAge*), approximated by the number of years that the firm has been listed on Compustat. I further control for several CEO characteristics that might impact both CEO political ideology and firm performance, which include the natural logarithm of a CEO's age (*LnCEOage*), a dummy variable that equals one if a CEO also serves as the chair of the board of directors, and zero otherwise (*CEOchair*), the natural logarithm of the sum of the CEO's salary and bonus (*LnCEOpay*), and the natural logarithm of one plus the CEO tenure at the firm (*LnCEOtenure*).

The firm-level control variables are obtained from Compustat. The CEO-level control variables are obtained from Execucomp and Capital IQ. Detailed definitions of the variables are provided in Appendix A. Table 1.2, Panel B summarizes the firm performance measure and the control variables. The mean and standard deviation of *ROA* in the sample are 12.4% and 8.1%, respectively.

1.4. Baseline Empirical Analyses

In this section, I conduct OLS regression analyses on the association between employee political ideology conflicts and firm performance. I further break down CEO-employee political ideology conflicts into the conflicts between CEOs and employees in different ranks and separately examine their associations with firm performance. Finally, I inspect the cross-sectional heterogeneity in the impacts of employee political ideology conflicts on firm performance in terms of employee geographic concentration and sophistication.

1.4.1 Association between Employee Political Ideology Conflicts and Firm Performance

To test the association between within-employee political ideology conflict and firm performance, I conduct the following OLS regression analysis:

$$ROA_{i,t+1} = \alpha_1 + \beta_1 EmpConflict_{i,t} + \gamma_1 Controls_{i,t} + \varepsilon_{i,t}, \tag{1.1}$$

where *ROA* is return on assets, defined as operating income before depreciation divided by lagged total assets. The independent variable of interest, *EmpConflict*, measures the within-firm political ideology conflict among all employees in a firm. *Controls* is a vector of control variables for firm and CEO characteristics. The firm-level control variables include market-to-book ratio, leverage, firm size, capital expenditure, plant, property, and equipment, R&D expenditure, and firm age. The CEO-level control variables include CEO age, compensation, tenure, and duality. The dependent variable is measured at year *t+1*, while the independent variables are measured at year *t*. Detailed definitions of the variables are provided in Appendix A. I include firm fixed effects and year fixed effects in the regressions. Standard errors are clustered at the firm level.

Columns (1) and (2) in Table 1.3 report the results of estimating Equation (1.1). Column (1) reports the regression with firm-level control variables. Column (2) reports the regression with both firm-level and CEO-level control variables. The coefficients on *EmpConflict* are significantly negative in both specifications, suggesting that there is a negative association between within-employee political ideology conflict and future firm performance. By definition, *EmpConflict* is a score ranging from one to five. A higher score means the firm has larger conflicts among its employees. Therefore, the coefficient estimate in Column (2) indicates that a firm with the highest within-employee political ideology conflicts (with more than 40% strong Republican employees and more than 40% strong Democratic employees) has a 2.8 percentage point lower *ROA*, which is approximately 34.5% of its standard deviation, compared to a firm with the lowest conflicts (with less than 10% strong Republican employees or less than 10% strong Democratic employees).

To test the association between CEO-employee political ideology conflict and firm performance, I run a similar regression to that specified by Equation (1.1), where I use *CEOempDiff* as the independent variable of interest, instead of *EmpConflict*. *CEOempDiff*, is the absolute value of the difference between the CEO's Democratic tendency and the non-CEO employees' average Democratic tendency in a firm. Other specifications are similar to those of Equation (1.1). The results are presented in Columns (3) and (4) of Table 1.3. Column (3) reports the regression with firm-level control variables. Column (4) reports the regression with both firm-level and CEO-level control variables. The coefficients on *CEOempDiff* are significantly negative in both specifications, suggesting that there is a negative association between CEO-employee political ideology conflict and future firm performance. As for the economic magnitude, the coefficient estimate on *CEOempDiff* in Column (4) indicates that a one standard deviation increase in CEO-employee political ideology conflict is associated with a 0.23 percentage point decrease in *ROA*, which is approximately 2.9% of its standard deviation. Taken together, the results presented in Table 1.3 indicate that both the within-employee political ideology conflict and the CEO-employee ideology conflict are negatively associated with firm performance, in terms of both statistical and economic magnitude.

1.4.2 CEO-Employee Political Ideology Conflicts by Employee Rank

The baseline results presented in Table 1.3 show that the CEO-employee political ideology conflict is negatively associated with future firm performance. It would be interesting to separately inspect such association for employees in different ranks for several reasons. First, as shown by the summary statistics in Table 1.1 and Table 1.2, employees in higher ranks are, on average, more active in political participation, more Republican oriented, and closer to their CEOs in terms of political ideology. Second, employees in higher ranks are more likely to work closely to their CEOs and have a greater chance of exposure to their CEOs' political ideology. Third, employees in higher ranks may have a larger impact on firm performance. Therefore, it would be interesting to examine whether the impact of CEO-employee political ideology conflict on firm performance is prevalent in all employee ranks, and whether there is heterogeneity across different ranks.

Empirically, I identify the key employees using information from Execucomp and Capital IQ People Intelligence database. An employee is defined as a key employee if her name matches the name of a non-CEO employee in Execucomp and Capital IQ. I then calculate the CEO-key employee conflicts (*CEOkeyDiff*) and CEO-rank-and-file employees' conflicts (*CEOempRfDiff*), and regress *ROA* on the conflict measures separately. Table 1.4 presents the results. Columns (1) and (4) show that both the conflicts between the CEO and the key employees and those between the CEO and rank-and-file employees, respectively, have a significantly negative association with firm performance. The economic magnitudes of the coefficients do not appear to be significantly different, suggesting that the CEO-employee political ideology conflict plays an important role in determining firm performance, regardless of the rank of employees.

Lee, Lee, and Nagarajan (2014) argue that the political ideology alignment between the CEO and board members have a negative impact on firm value as it increases managerial entrenchment. Since some key employees also serve as board members of their firms, there might be a confounding effect in the findings on the impact of CEO-key employees' political ideology conflict and firm performance. Thus, I further separate key employees into two groups: those who also serve as the firms' board members and those who do not. In Columns (2) and (3) of Table 1.4, I regress ROA on the conflict between the CEO and the board members (*CEOboardDiff*) and that between the CEO and the non-board key employees (*CEOkeyNbDiff*), respectively. Results show that there is a significant negative association between firm performance and the conflicts between the CEO and the key employees, regardless of whether they serve on the board of directors. The results are inconsistent with the finds of Lee, Lee, and Nagarajan (2014), who argue that the difference in political ideology between the CEO and board members should decrease managerial entrenchment and improve firm value. It is worth noting that the sample used by Lee, Lee, and Nagarajan (2014) includes only independent directors, whereas my sample consists of only dependent directors (i.e., those who are recorded as employees of their firms by Execucomp or Capital IQ). While the independent directors mainly serve as monitors of the CEO, the dependent directors contribute to firm value both indirectly through the monitoring duty and directly by working for the firms as employees. The results in this paper suggest that, despite having a potential positive impact on monitoring efficiency, the political ideology conflicts between the CEO and dependent board members are negatively associated with future firm performance.

1.4.3 Cross-sectional Heterogeneity in the Association between Employee Political Ideology Conflicts and Firm Performance

In this subsection, I inspect the cross-sectional heterogeneity in the impacts of employee political ideology conflicts on firm performance. Specifically, I examine whether such impacts are stronger for firms whose employees are more geographically concentrated, and for firms whose employees are more sophisticated.

1.4.3.1 Cross-sectional Heterogeneity in Employee Geographical Concentration

When a firm's employees live and work in more concentrated geographic areas, they interact and communicate with each other more often, and have higher chances of getting involved in political conversations with each other. In this case, if the employees disagree with each other in terms of political ideology, the disagreement is likely to cause a larger negative effect on the workplace environment, which causes a larger negative impact on firm performance. Furthermore, when the employees are clustered in a concentrated area, it is easier for them to unite against the CEO if they disagree with the CEO's political views, leading to more destructive dynamics at the workplace and hurt firm performance. Therefore, I hypothesize that, the impacts of employee political ideology conflicts on firm performance are stronger for firms whose employees are more geographically concentrated.

To empirically test the hypothesis, I first obtain each donating employee's state of residence from the FEC database and her employer's headquarter location from the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) maintained by the U.S. Securities and Exchange Commission (SEC). For each firm-year, I calculate the percentage of donating employees who live in the state where the firm's headquarter is located. A higher percentage of employees living in a firm's headquarter state indicates that the firm's employees are more geographically concentrated. I then estimate two OLS regressions where *ROA* is regressed on the interaction between *EmpConflict* and *HighHqStatePct* and that between *CEOempDiff* and *HighHqStatePct*. *HighHqStatePct* is a dummy variable that equals one if the firm's percentage of employees living in its headquarter state is above the sample median, and zero otherwise. All other specifications are the same as those of Equation (1.1).

The results of the cross-sectional regressions are presented in Columns (1) and (2) of Table 1.5. Column (1) reports the regression with the interaction of *EmpConflict* and *HighHqStatePct*. Column (2) reports the regression with the interaction of *CEOempDiff* and *HighHqStatePct*. The control variables at the firm level and the CEO level are included but not reported to conserve space. The results show that, both the within-employee political ideology conflict and the CEO-employee conflict has a significantly larger impact on future firm performance when the firm has more employees living in its headquarter state, which is consistent with the hypothesis.

1.4.3.2 Cross-sectional Heterogeneity in Employee Sophistication

The association between employee political ideology conflicts and firm performance should be more pronounced if a firm's employees are more sophisticated for two reasons. First, more sophisticated employees contribute more to the firm's operating performance. Second, more sophisticated employees are more likely to have stronger political orientation and more likely to have a larger reaction when they disagree with each other's political ideology or their CEO's political ideology. Thus, I hypothesize that the impacts of employee political ideology conflicts on firm performance should be stronger for firms with more sophisticated employees.

To empirically test the hypothesis, I first construct the industry-level labor skill index (*LSI*) following Belo et al. (2017) and Ghaly, Dang, and Stathopoulos (2017). Specifically, I obtain the classification of occupations based on skill level from the U.S. Department of Labor's O*NET program and industry-level employee occupation information from the Bureau of Labor Statistics (BLS). I calculate the labor skill index as

$$LaborSkill_{i,t} = \sum_{j=1}^{O}(E_{j,i,t} * Z_{j,t}), \qquad (1.2)$$

where $E_{j,i,t}$ is the fraction of employees in industry i (three-digit SIC industry for pre-2002 period and four-digit NAICS industry for 2002 and beyond) working in occupation j, O is the total number of occupations in industry i, and $Z_{j,t}$ is the skill level of occupation j. A higher value of *LaborSkill* indicates that the industry has a higher average employee skill level. I then assign each industry's labor skill index to the firms in the industry and estimate two OLS regressions where *ROA* is regressed on the interaction between *EmpConflict* and *HighLaborSkill* and that between *CEOempDiff* and *HighLaborSkill*. *HighLaborSkill* is a dummy variable that equals one if a firm's labor skill index is above the sample median, and zero otherwise. All other specifications are the same as those of Equation (1.1).

The results of the cross-sectional regressions are presented in Columns (3) and (4) of Table 1.5. Column (3) reports the regression with the interaction of *EmpConflict* and *HighLaborSkill*. Column (4) reports the regression with the interaction of *CEOempDiff* and *HighLaborSkill*. The control variables at the firm level and the CEO level are included but not reported to conserve space. The results show that, the impacts of both the within-employee political ideology conflict and the CEO-employee conflict on firm performance are significantly stronger when a firm's employee skill level is above the sample median, which is consistent with the prediction.

1.5 Labor Productivity and Employee Turnover

The baseline results suggest that there is a negative association between employee political ideology conflicts and firm performance. In this section, I examine the potential channels of the impact. Several papers argue that employee satisfaction affects firm value by affecting labor productivity and employer turnover. For example, Edmans (2011) suggests that employee satisfaction increases firm value by increasing labor productivity and reducing employee turnover. In a similar vein, Oswald, Proto, and Sgroi (2015) argue that people's happiness increases their productivity. The recent work by Babenko, Fedaseyeu, and Zhang (2020) show that the employees whose political donations are not aligned with their CEOs are more likely to leave their firms. Employee satisfaction should be arguably low when political ideology conflicts in the workplace are high. Thus, I hypothesize that employees' political ideology conflict has a negative impact on firm performance by decreasing labor productivity and inducing abnormal employee turnover.

1.5.1 Association between Employee Political Ideology Conflicts and Labor Productivity

I study the association between employee political ideology conflicts and labor productivity at both the firm level and the individual employee level. At the firm level, I construct two empirical measures for labor productivity following Kale, Ryan Jr., and Wang (2016). The first measure, *LaborProd*, defined as operating income before depreciation scaled by total number of employees, captures the value added by employees. The second measure, *OutputPerEmp*, is defined as the sum of sales and change in inventory scaled by total number of employees. Using the two measures for firm-level labor productivity, I estimate a model similar to that of Equation (1.1), where I substitute *ROA* with one of the labor productivity measures. In addition to the firm-level and CEO-level control variables included in Equation (1.1), I further control for labor input (*LnEmp*), defined as the natural logarithm of total number of employees, and asset intensity

(*AssetInt*), defined as the natural logarithm of total assets divided by total number of employees, which are shown by researchers to be associated with labor productivity (see, e.g., Kale, Ryan Jr., and Wang (2016)). All other specifications are the same as those of Equation (1.1).

Table 1.6 reports the results of regressing the labor productivity measures on employee political ideology conflicts. The dependent variable in Columns (1) and (2) (Columns (3) and (4)) is *LaborProd* (*OutputPerEmp*). The independent variable of interest in Columns (1) and (3) (Columns (2) and (4)) is *EmpConflict* (*CEOempDiff*). The results show that, both the within-employee political ideology conflict and the CEO-employee conflict have a significantly negative association with the two measures for labor productivity, which is consistent with the prediction that employee political ideology conflicts hurt firm performance by reducing labor productivity.

I further provide more detailed evidence on the association between employee political ideology conflicts and labor productivity at the individual employee level. Specifically, I examine the association between individual inventors' innovation output and the political ideology conflict between the inventors and other employees in their firms, and that between the inventors and their CEOs. Patent and inventor information are obtained from the National Bureau of Economic Research (NBER) database and the Harvard Business School (HBS) patent database.[6] Following standard practice in the literature (see, e.g., Liu, Mao, and Tian (2017)), I treat the assignee of an inventor's patent as her employer. The inventor dataset is matched to the donation dataset by matching both an inventor's name and her employer's name in a given year. For each inventor-year, I measure the inventor's productivity by the natural logarithm of one plus the number of patents filed (*LnPatent*) and the natural logarithm of one plus the average number of citations received per patent (*LnCitePat*) by the inventor in year *t+1*. To measure an inventor's conflict with

[6] The NBER patent database is available at https://sites.google.com/site/patentdataproject/Home/downloads. The HBS patent database is available at https://dataverse.harvard.edu/dataverse/patent.

other employees in her firm (*InventorOtherDiff*), I calculate the absolute value of the difference between the inventor's *DEM%* and the average *DEM%* of other employees in her firm. To measure an inventor's conflict with her CEO (*InventorCEODiff*), I calculate the absolute value of the difference between the inventor's *DEM%* and her CEO's *DEM%*.

Table 1.7 presents the regression analyses of individual inventor productivity on the inventors' workplace political ideology conflicts. In each column, I regress one of the inventor productivity measures on one of the inventor political ideology conflict measures. Specifically, Columns (1) and (2) (Columns (3) and (4)) report the regressions using *LnPatent* (*LnCitePat*) as the dependent variable. Columns (1) and (3) (Columns (2) and (4)) report the regressions using *InventorOtherDiff* (*InventorCEODiff*) as the independent variable. All regressions include firm-level and CEO-level control variables similar to those of Equation (1.1). I further include inventor-firm fixed effects, following Liu, Mao, and Tian (2017). Standard errors are clustered at the inventor level. In all specifications, the inventor political conflict measures are significantly negatively correlated with the inventor productivity measures, suggesting that both the conflict between an inventor and other employees in her firm and that between the inventor and her CEO are associated with lower quantity and quality of works done by the inventor.

1.5.2 Association between Employee Political Ideology Conflicts and Employee Turnover

The second channel through which employee political ideology conflicts could hurt firm performance is by inducing abnormal employee turnover. An employee can choose to leave a firm if she has large conflicts with other employees in her firm or the CEO of her firm (see, e.g., by Babenko, Fedaseyeu, and Zhang, 2020). It is costly for firm to replace workers due to labor market frictions. The adjustment costs could eventually be reflected in firm performance. Thus, I hypothesize that employee political ideology conflicts hurt firm performance by inducing abnormal employee turnover.

Empirically, I identify the turnovers of key employees using the Execucomp database and the Capital IQ People Intelligence database. Execucomp provides the exact date when an employee left a company (LEFTCO). Capital IQ does not provide such information, but the year when an employee left a company can be inferred from the year when her last job function in the firm ended (ENDYEAR). For each employee *i* of firm *j* in year *t*, *Leave* is defined as a dummy variable that equals one if the employee leaves the firm in year *t+1*, and zero otherwise. The political ideology conflict between a key employee and other employees in her firm (*KeyOtherDiff*), and that between the key employee and the CEO of her firm (*KeyCEODiff*), are measured by taking the absolute value of the difference between the key employee's *DEM%* and the average *DEM%* of other employees in her firm, and that between the key employee's *DEM%* and her CEO's *DEM%*, respectively.

Table 1.8 presents the estimation of a linear probability model where I regress *Leave* on the two measures of key employee political ideology conflicts separately. Firm-level and CEO-level control variables similar to those of Equation (1.1) are included in both regressions. I further include employee-firm fixed effects. Standard errors are clustered at the employee level. Column (1) reports the regression of *Leave* on *KeyOtherDiff*. The result shows that a key employee is more likely to leave a firm when the misalignment between her political ideology and that of her coworkers is larger. Column (2) reports the regression of *Leave* on *KeyCEODiff*. The result suggests that a key employee is more likely to leave a firm when her political ideology is more different with that of her CEO. The result shown in Column (2) is consistent with the finds of Babenko, Fedaseyeu, and Zhang (2020). My study supplements their finds by showing that not only the conflicts between an employee and her CEO, but also the conflicts between an employee and her coworkers are associated with a higher likelihood of the employee leaving a firm.

Notably, an alternative explanation of the association between the CEO-employee political ideology conflicts and employee turnover is that the CEOs are more likely to fire the employees who differ from them in terms of political orientation. While I cannot observe whether the employee turnover is voluntary or involuntary, the alternative explanation does not change the implication of the results. That is, an increase in political ideology conflict increases the probability of abnormal employee turnover, which affects firm performance negatively.

1.6 Endogeneity Concerns and 2SLS Analysis

While the OLS results suggest that there is a negative association between employee political ideology conflicts and firm performance, several endogeneity concerns arise when interpreting the results. First, there could be omitted variables that are simultaneously correlated with political ideology conflict and firm performance. For example, Babenko, Fedaseyeu, and Zhang (2020) suggest that CEOs exert influence on their employees' political choices in order to increase shareholder value. If that is the case, the CEOs' incentives could drive both political ideology conflicts and firm performance. Furthermore, entrenched CEOs may have the power to hire employees who are more aligned with them in terms of political ideology, and CEO entrenchment is also correlated with firm performance. Second, the results could be driven by reverse causality. That is, worse firm performance could lead to disagreements in political ideology between the CEO and the employees or among the employees.

To at least partially address the endogeneity concerns, the independent variables are lagged by one year in all the OLS regressions in this paper. However, an exogenous variation in employee political ideology conflicts is needed in order to establish causality. In this section, I use the acquisitions of local television stations by Sinclair Broadcast Group as the source of exogenous variation in political ideology conflicts and implement a two-stage least squares (2SLS) analysis to establish causality of employee political ideology conflicts on firm performance.

1.6.1 The Acquisitions of Local Television Stations by Sinclair Broadcast Group

Sinclair Broadcast Group (Sinclair) is the largest television station operator in the United States in terms of number of stations (191 stations) and total coverage (89% of U.S. markets).[7] The acquisitions of local television stations are made over a span of more than 30 years, starting in 1984. Sinclair is well known to have strong conservative orientation and has long been criticized for pushing conservative news coverage and commentary. For example, in March 2018, journalists from all the local television stations owned by Sinclair across the whole country were asked by Sinclair to read the same script supporting President Donald Trump's Twitter feed regarding "biased and false news" (Glaser (2018)). Using textual analysis on television news scripts, Martin and McCrain (2018) document a significant rightward shift in the ideological slant of coverage after local television stations are acquired by Sinclair.

Researchers have shown that mass media has strong persuasive effects and often affects people's political orientation. Using voting data in presidential elections, DellaVigna and Kaplan (2007) show that Republicans gained vote shares in towns where Fox News entered the cable markets. Similarly, Martin and Yurukoglu (2017) show that Fox News increases Republicans' vote shares by 0.3 points among viewers induced into watching 2.5 additional minutes of television news per week. According to a survey conducted by Pew Research Center, 37% of U.S. adults often get news from local television, which is larger than the population who often get news from

[7] Information obtained from the official website of Sinclair Broadcast Group at http://sbgi.net/.

cable television (28%).[8] Therefore, the acquisitions of local television stations by Sinclair, a firm with strong political orientation, is likely to have a strong Republican-oriented impact on local residents' political ideology.

When a firm's employees are affected by Sinclair acquisitions in their city of residence, the acquisitions create a rightward pressure on the employees' political ideology. As the distribution of employee political ideology (*DEM%*) is a continuum bounded between zero and one, the pressure that pushes the employees' ideology towards the Republican end (where *DEM%* equals zero) is going to condense the distribution and reduce the distance among the employee's political ideology. Therefore, the Sinclair acquisitions should reduce the within-employee political ideology conflicts. The Sinclair acquisitions should also reduce the CEO-employee political ideology conflicts as the CEOs are more Republican-oriented in the first place (as shown in Table 1.1), and should be less affected by the Sinclair acquisitions than the non-CEO employees. The acquisitions should push the non-CEO employees' ideology towards the Republican end and therefore reduce the distance between the average non-CEO employees' political ideology and that of their CEOs.

There is no evidence suggesting that the acquisitions by Sinclair are correlated with local economic conditions. Moreover, since a firm's employees may live in various locations across the whole country, it is unlikely that Sinclair has the ability to track the residential address of all the firm's employees, which makes it hard to believe that Sinclair can attempt to affect the firm's performance by acquiring television stations in the residential area of its employees.[9] Thus, the Sinclair acquisitions provide a unique setting for my analyses as it directly impacts employees'

---

[8] Information obtained from the website of Pew Research Center at http://www.pewresearch.org/fact-tank/2018/01/05/fewer-americans-rely-on-tv-news-what-type-they-watch-varies-by-who-they-are/ft_18-01-04_localtv_demographic/.

[9] In my sample, only 16.6% of employees live in the city where their employers' headquarters are located in.

political ideologies but does not affect firm performance through channels. Empirically, I conduct a 2SLS analysis, using Sinclair acquisitions to predict employee political ideology conflicts and then regressing firm performance on the fitted value of conflicts.

1.6.2 2SLS Analysis

Starting from 1984, Sinclair has made 163 acquisitions in 96 designated market areas (DMA). I obtain the acquisition information from RabbitEars, a website which provides detailed and comprehensive information on media markets in the United States. For the employees in my sample, I match each employee's city of residence to the DMA it belongs to using the DMA-county/city matching information obtained from Wikipedia.[10] For each employee-year, I identify whether a Sinclair acquisition happened in the employee's city of residence in the year. To verify that the Sinclair acquisitions cause a rightward pressure on the employees' political ideology, I regress individual employees' *DEM%* in year *t* on *SinclairIndiv*, a dummy variable that equals one if at least one of the local television stations in an employee's city of residence is acquired by Sinclair in year *t-1*, and zero otherwise. The regression results are presented in Table 1.9. Column (1) reports the regression in the sample of non-CEO employees. The coefficient on *SinclairIndiv* is significantly negative, indicating that Sinclair acquisitions indeed make the employees more Republican-oriented. Column (2) reports the regression in the sample of CEOs. The coefficient on *SinclairIndiv* is positive and insignificant, suggesting that the CEOs are indeed less affected by Sinclair acquisitions, compared to the non-CEO employees. Taken together, the results presented in Table 1.9 supports the hypothesis that the Sinclair acquisitions would reduce the within-employee political ideology conflict and the CEO-employee conflict.

[10] Information obtained from Wikipedia at https://en.wikipedia.org/wiki/List_of_United_States_television_markets.

To capture the Republican-oriented ideological pressure caused by the Sinclair acquisitions on a firm's employees, for each firm-year, I calculate the percentage of employees who are affected by a Sinclair acquisition (*SinclairFirm*) in year *t-1*. Lagging the variable by one year allows the Sinclair acquisitions to have time to exert influence on the affected employees' political ideology. Intuitively, a Sinclair acquisition happened in an employee's city of residence in year *t-1* affects the employee's political ideology and changes her donating pattern in year *t*, which affects her employer's employee political ideology conflicts in year *t*. Then, I estimate a set of 2SLS regressions, where *EmpConflict* and *CEOempDiff* are instrumented by *SinclairFirm*.

Table 1.10 presents the results of estimating the 2SLS model. Columns (1) and (2) report the first-stage regressions with *EmpConflict* and *CEOempDiff*, respectively, as the dependent variables. The coefficients of *SinclairFirm* are significant in both regressions, indicating that the Sinclair acquisitions indeed reduce both the within-employee political ideology conflict and the CEO-employee conflict. The Kleibergen-Paap Wald F-statistics on the weak instrument test for *EmpConflict* and *CEOempDiff* are 13.47 and 9.24, respectively, suggesting that the instrument does not suffer from weak instrument problems. Columns (3) and (4) report the second-stage regressions with *FittedEmpConflict* and *FittedCEOempDiff*, respectively, as the independent variables. The coefficients on both the two variables of interest are significantly negative, indicating that the exogenous decreases in within-employee political ideology conflicts and CEO-employee conflicts caused by the Sinclair acquisitions have a positive impact on future firm performance.

1.7 Conclusion

Despite the public attention to workplace political ideology conflicts and their negative consequences, there is a lack of evidence on the association between employees' political ideology conflicts and firm performance. This paper fills in the gap by measuring employee political ideology conflicts using individual campaign donation data and explicitly studying the association between the conflicts and future operating performance.

I find that both the political ideology conflicts among the employees and those between the CEOs and employees are negatively associated with future operating performance. Cross-sectional analyses show that the association is stronger for firms with more geographically concentrated and more sophisticated employees. Furthermore, I show that employee political ideology conflicts affect firm performance negatively by decreasing labor productivity and inducing abnormal employee turnover. Using the acquisitions of local television stations by Sinclair Broadcast Group as a source of exogenous variation in employees' political ideology, I establish causality between employee political ideology conflicts and firm performance.

Overall, my paper suggests that employee political ideology conflicts have a negative impact on firm performance, shedding new light on the importance of within-firm labor heterogeneity and labor-management relationship.

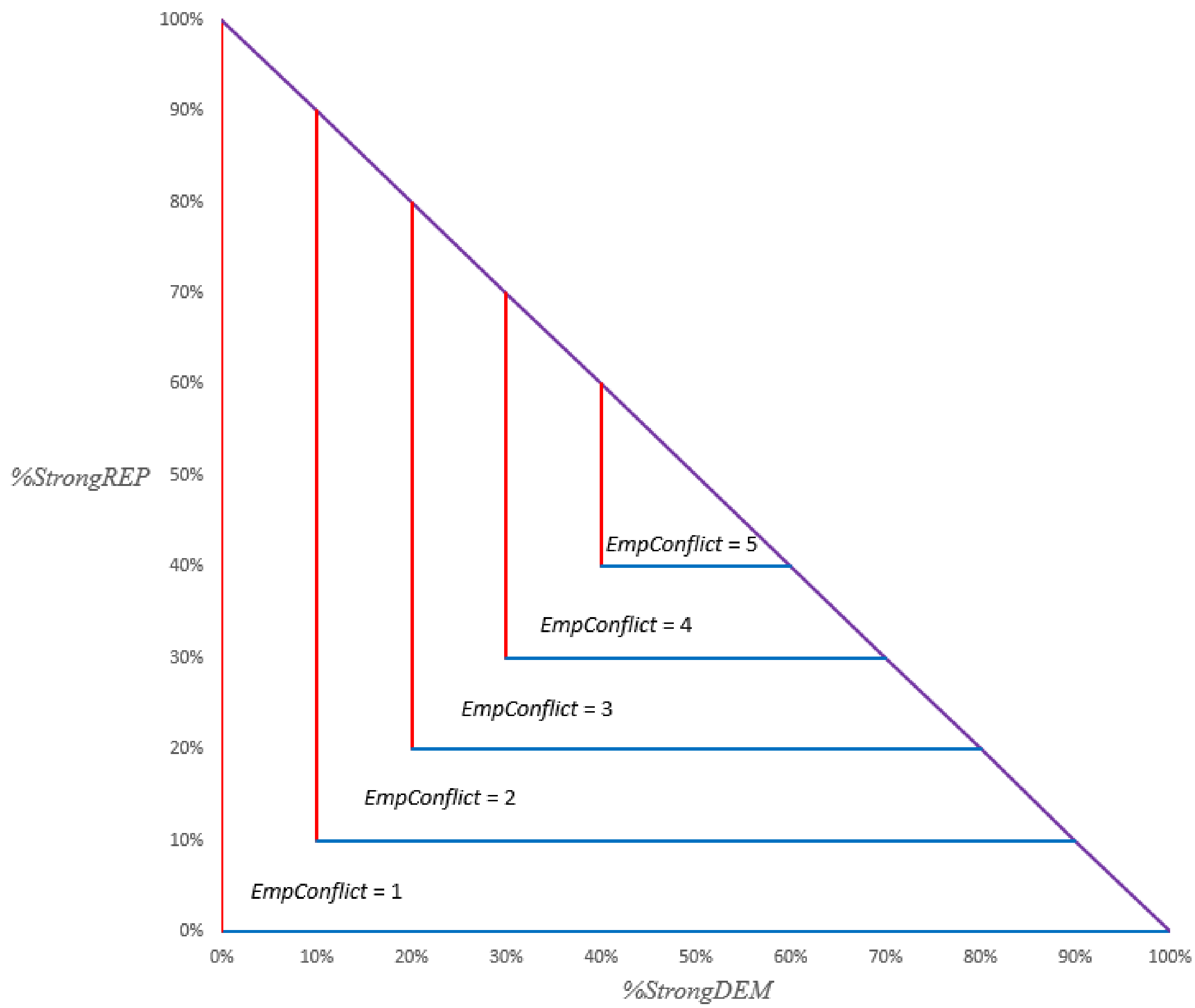


Figure 1.1: Illustration of Within-Employee political Ideology Conflict Measure
This figure depicts the construction of *EmpConflict*, the measure of within-employee political ideology conflicts. *%StrongREP* and *%StrongDEM* are the percentages of strong Republican employees and strong Democratic employees, respectively, in a firm-year. An employee is defined as strong Republican (Democratic) if she donates more than $2,000 to only Republican (Democratic) recipients in a given year. The possible combinations of *%StrongREP* and *%StrongDEM* for a firm can be illustrated in the right triangle. The triangle is divided into five areas, each assigned with an *EmpConflict* score. A higher score represents higher within-employee political ideology conflicts.

Table 1.1: Summary Statistics of Person-level Political Ideology Variables

This table reports the summary statistics of political ideology variables constructed at the person-year level by employee ranks using individual campaign donation data provided by Federal Election Commission (FEC) and employee rank information from Execucomp and Capital IQ. Panel A reports the summary statistics of employees' campaign donations. Column (1) reports the number of person-year observations for each rank. Column (2) reports the average dollar amount of donation made by an individual in a two-year rolling window. Column (3) reports the mean of Democratic tendency (*DEM%*). Panel B reports the distribution of *DEM%* within each employee rank.

Panel A: Summary Statistics of Employees' Campaign Donations

Rank	# Person-years	Mean $ of donation	Mean *DEM%*
	(1)	(2)	(3)
CEO	15,337	6,110.68	37.68%
Board	11,916	5,295.11	41.52%
Nonboard Key	33,741	2,324.16	51.07%
Rank-and-file	252,654	1,352.56	59.48%

Panel B: Distribution of Employees' Political Ideology

Rank				*DEM%*			
	0%	(0%,25%]	(25%,50%)	50%	(50%,75%)	[75%,100)	100%
CEO	56.002%	2.973%	2.875%	1.578%	2.452%	1.584%	32.536%
Board	54.062%	1.678%	2.232%	1.284%	1.989%	1.334%	37.420%
Nonboard Key	45.944%	0.880%	1.405%	1.301%	1.461%	0.945%	48.063%
Rank-and-file	39.831%	0.198%	0.308%	0.325%	0.362%	0.234%	58.743%

Table 1.2: Summary Statistics of Main Dependent and Independent Variables

Panel A reports the summary statistics of political conflict variables at the firm-year level. *EmpConflict* is a score which indices within-employee political ideology conflicts. *CEOempDiff, CEOkeyDiff*, *CEOboardDiff*, *CEOkeyNbDiff*, and *CEOempRfDiff* are the political ideology conflicts between CEO and all non-CEO employees, key employees, board members, non-board key employees, and rank-and-file employees, respectively. Panel B reports the summary statistics of firm performance and control variables. All the continuous variables in Panel B are winsorized at the 1st and 99th percentiles. Detailed definitions of all the variables are presented in Appendix A.

Panel A: Summary Statistics of Employee Political Ideology Conflict Variables

Variable	Mean	SD	Min	P25	Median	P75	Max	N
EmpConflict	2.424	1.280	1.000	1.000	2.000	4.000	5.000	4,055
CEOempDiff	0.301	0.234	0.000	0.105	0.253	0.455	1.000	2,004
CEOkeyDiff	0.247	0.275	0.000	0.000	0.159	0.413	1.000	1,347
CEOboardDiff	0.245	0.313	0.000	0.000	0.106	0.406	1.000	1,002
CEOkeyNbDiff	0.254	0.289	0.000	0.000	0.160	0.429	1.000	939
CEOempRfDiff	0.320	0.243	0.000	0.122	0.278	0.489	1.000	1,784

Panel B: Summary Statistics of Firm Performance and Control Variables

Variable	Mean	SD	Min	P25	Median	P75	Max	N
ROA	0.124	0.081	-0.108	0.070	0.116	0.170	0.360	4,055
MB	1.970	1.356	0.827	1.105	1.475	2.252	8.158	4,055
Lev	0.202	0.148	0.000	0.087	0.178	0.297	0.698	4,055
LnAsset	10.045	1.778	5.730	8.827	10.115	11.145	14.485	4,055
CAPEX	0.217	0.140	0.000	0.117	0.193	0.288	0.716	4,055
PPE	0.229	0.234	0.000	0.047	0.135	0.350	0.856	4,055
RD	0.027	0.045	0.000	0.000	0.000	0.036	0.221	4,055
LnFirmAge	3.368	0.744	1.099	2.890	3.555	4.007	4.234	4,055
LnCEOage	4.046	0.105	3.714	3.989	4.060	4.111	4.331	2,745
LnCEOpay	7.225	1.212	0.001	6.909	7.184	7.689	9.347	2,745
LnCEOtenure	1.739	0.864	0.000	1.099	1.792	2.303	3.555	2,745
CEOchair	0.666	0.472	0.000	0.000	1.000	1.000	1.000	2,745

Table 1.3: Regressions of Firm Performance on Employee Political Ideology Conflicts

This table presents the OLS regression results of firm performance (*ROA*) on employee political ideology conflict measures. Columns (1) and (2) report the regressions of *ROA* on within-employee political ideology conflicts (*EmpConflict*). Columns (3) and (4) report the regressions of *ROA* on CEO-employee political ideology conflicts (*CEOempDiff*). Definitions of the variables are provided in Appendix A. All independent variables are lagged by one year. Firm and year fixed effects are included in all regressions. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*ROA*			
	(1)	(2)	(3)	(4)
EmpConflict	-0.007***	-0.007***		
	(-2.612)	(-2.604)		
CEOempDiff			-0.010**	-0.010**
			(-2.342)	(-2.130)
MB	0.019***	0.019***	0.017***	0.018***
	(8.396)	(6.882)	(6.737)	(6.755)
Lev	-0.048***	-0.048**	-0.062***	-0.053**
	(-2.903)	(-2.454)	(-2.924)	(-2.448)
LnAsset	-0.005	-0.009*	-0.014***	-0.014***
	(-1.113)	(-1.844)	(-3.065)	(-3.099)
CAPEX	0.047***	0.063***	0.070***	0.064***
	(3.115)	(3.697)	(3.573)	(3.213)
PPE	0.059**	0.031	0.027	0.013
	(1.977)	(0.967)	(0.811)	(0.380)
RD	0.209	0.339**	0.391**	0.405**
	(1.632)	(2.185)	(2.218)	(2.380)
LnFirmAge	0.018**	0.023*	0.042***	0.045***
	(2.116)	(1.831)	(3.271)	(3.112)
LnCEOage		-0.016		-0.013
		(-0.908)		(-0.710)
LnCEOpay		0.003		0.002
		(1.608)		(1.558)
LnCEOtenure		0.002		0.002
		(1.315)		(0.835)
CEOchair		0.005*		0.004
		(1.810)		(1.253)
Constant	0.066	0.128	0.070	0.098
	(1.225)	(1.250)	(1.127)	(0.938)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,055	2,745	2,004	1,885
Adj. R-squared	0.827	0.836	0.844	0.843

Table 1.4: Regression of Firm Performance on CEO-Employee Political Ideology Conflicts by Employee Rank

This table reports the OLS regression results of firm performance (*ROA*) on CEO-employee political ideology conflict by employee rank. *CEOkeyDiff*, *CEOboardDiff*, *CEOkeyNbDiff*, and *CEOempRfDiff* are the political ideology conflicts between the CEOs and key employees, board members, non-board key employees, and rank-and-file employees, respectively. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one year. All columns include firm, industry, and year fixed effects. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*ROA*			
	(1)	(2)	(3)	(4)
CEOkeyDiff	-0.009**			
	(-2.056)			
CEOboardDiff		-0.009**		
		(-2.433)		
CEOkeyNbDiff			-0.013***	
			(-2.633)	
CEOempRfDiff				-0.009**
				(-1.997)
MB	0.016***	0.018***	0.018***	0.017***
	(5.591)	(5.500)	(5.133)	(6.227)
Lev	-0.053**	-0.052	-0.067**	-0.053**
	(-2.031)	(-1.599)	(-2.016)	(-2.287)
LnAsset	-0.012**	-0.010	-0.008	-0.014***
	(-2.289)	(-1.315)	(-0.984)	(-3.062)
CAPEX	0.053**	0.041	0.020	0.069***
	(1.974)	(1.302)	(0.667)	(3.501)
PPE	0.013	0.032	0.038	0.018
	(0.291)	(0.601)	(0.662)	(0.501)
RD	0.415**	0.460**	0.407*	0.310*
	(2.059)	(2.032)	(1.682)	(1.953)
LnFirmAge	0.045***	0.060**	0.066***	0.039***
	(3.034)	(2.588)	(2.617)	(3.019)
LnCEOage	-0.009	-0.012	-0.006	-0.013
	(-0.481)	(-0.534)	(-0.253)	(-0.714)
LnCEOpay	0.002	0.002	0.001	0.002
	(1.274)	(0.834)	(0.961)	(1.478)
LnCEOtenure	0.001	-0.000	-0.000	0.001
	(0.318)	(-0.121)	(-0.057)	(0.735)
CEOchair	0.003	0.001	0.002	0.004
	(0.859)	(0.190)	(0.373)	(1.266)
Constant	0.074	0.010	-0.060	0.122
	(0.751)	(0.076)	(-0.439)	(1.190)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,347	1,002	939	1,784
Adj. R-squared	0.845	0.850	0.853	0.843

Table 1.5: Cross-sectional Analyses Based on Employee Geographical Concentration and Sophistication

This table reports the subsample analyses based on employee geographic concentration and sophistication. *HighHqStatePct* is a dummy variable that equals one if a firm's fraction of employees living in its headquarter state is above the sample median, and zero otherwise. *HighLaborSkill* is a dummy variable that equals one if a firm's labor skill index is above the sample median, and zero otherwise. Columns (1) to (4) report the regressions of *ROA* on the interaction between *EmpConflict* and *HighHqStatePct*, that between *CEOempDiff* and *HighHqStatePct*, that between *EmpConflict* and *HighLaborSkill*, and that between *CEOempDiff* and *HighLaborSkill*, respectively. Firm-level and CEO-level control variables are included but not reported to conserve space. All independent variables are lagged by one year. All regressions include firm and year fixed effects. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*ROA*			
	(1)	(2)	(3)	(4)
EmpConflict×HighHqStatePct	-0.009**			
	(-2.482)			
CEOempDiff×HighHqStatePct		-0.020**		
		(-2.347)		
EmpConflict×HighLaborSkill			-0.007**	
			(-1.964)	
CEOempDiff×HighLaborSkill				-0.014**
				(-2.194)
EmpConflict	0.003		-0.002	
	(1.259)		(-0.636)	
CEOempDiff		-0.000		0.004
		(-0.031)		(0.522)
HighHqStatePct	0.005	0.007		
	(1.604)	(1.493)		
HighLaborSkill			0.003	-0.010**
			(0.584)	(-2.124)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,722	1,868	2,237	1,545
Adj. R-squared	0.834	0.841	0.824	0.837

Table 1.6: Regressions of Labor Productivity on Employee Political Ideology Conflicts

This table analyzes the association between employee political ideology conflicts and firm-level labor productivity. *LaborProd* is defined operating income before depreciation scaled by total number of employees. *OutputPerEmp* is defined as the sum of sales and change in inventory scaled by total number of employees. Definitions of other variables are provided in Appendix A. All independent variables are lagged by one year. All columns include firm and year fixed effects. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*LaborProd*		*OutputPerEmp*	
	(1)	(2)	(3)	(4)
EmpConflict	-0.019**		-0.034*	
	(-2.491)		(-1.773)	
CEOempDiff		-0.025*		-0.066**
		(-1.907)		(-2.423)
MB	0.012***	0.014***	0.029***	0.025***
	(4.015)	(3.578)	(3.828)	(3.097)
Lev	0.006	0.015	-0.000	0.057
	(0.201)	(0.390)	(-0.001)	(0.703)
LnAsset	0.092***	0.076***	0.186***	0.160***
	(8.141)	(5.391)	(6.822)	(5.390)
CAPEX	0.024	-0.003	0.104	0.143*
	(0.859)	(-0.098)	(1.511)	(1.941)
PPE	-0.023	-0.145***	-0.399***	-0.504***
	(-0.493)	(-2.663)	(-3.570)	(-4.364)
RD	-0.003	0.010	0.424	0.539
	(-0.014)	(0.042)	(0.965)	(1.091)
LnFirmAge	-0.034**	-0.003	0.044	0.157***
	(-2.041)	(-0.119)	(1.079)	(3.350)
LnCEOage	0.042	0.059	0.176**	0.189**
	(1.228)	(1.405)	(2.088)	(2.107)
LnCEOpay	-0.000	-0.002	0.008	-0.002
	(-0.159)	(-0.549)	(1.337)	(-0.285)
LnCEOtenure	0.002	0.000	-0.008	-0.008
	(0.609)	(0.101)	(-0.830)	(-0.807)
CEOchair	0.012*	0.020**	0.009	0.016
	(1.838)	(2.499)	(0.616)	(0.910)
LnEmp	-0.106***	-0.101***	-0.208***	-0.211***
	(-9.516)	(-7.143)	(-7.667)	(-7.097)
AssetInt	0.005**	0.015***	0.017***	0.013*
	(2.098)	(4.647)	(3.241)	(1.850)
Constant	0.251	0.181	-0.002	-0.069
	(1.630)	(0.942)	(-0.006)	(-0.170)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,511	1,741	2,532	1,755
Adj. R-squared	0.824	0.849	0.892	0.922

Table 1.7: Regressions of Inventor Output on Inventors' Political Ideology Conflicts with Coworkers and CEOs

This table analyzes the association between individual inventors' innovation output and their political ideology conflicts with other employees and the CEOs in their firms. *LnPatent* is defined as the natural logarithm of one plus the number of patents filed by an inventor in a given year. *LnCitePat* is defined as the natural logarithm of one plus the average number of citations received per patent by an inventor in a given year. *InventorOtherDiff* is the absolute value of the difference between an employee's *DEM%* and the average *DEM%* of other employees in her firm. *InventorCEODiff* is defined as the absolute value of the difference between an inventor's *DEM%* and her CEO's *DEM%*. Definitions of other variables are provided in Appendix A. All independent variables are lagged by one year. All regressions include inventor-firm fixed effects and year fixed effects. Standard errors are clustered by inventor. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*LnPatent*		*LnCitePat*	
	(1)	(2)	(3)	(4)
InventorOtherDiff	-0.125**		-0.178*	
	(-2.111)		(-1.694)	
InventorCEODiff		-0.086*		-0.195**
		(-1.983)		(-2.165)
MB	-0.011	-0.033	-0.022	-0.057
	(-0.611)	(-1.217)	(-0.429)	(-0.861)
Lev	-0.463*	-0.343	-0.528	-0.119
	(-1.790)	(-1.128)	(-1.164)	(-0.210)
LnAsset	0.122*	0.000	0.135	0.150
	(1.906)	(0.003)	(1.506)	(0.551)
CAPEX	0.393**	0.164	0.587*	0.034
	(2.178)	(0.765)	(1.695)	(0.057)
PPE	0.756	-0.643	-0.317	-1.026
	(1.426)	(-0.957)	(-0.347)	(-0.808)
RD	0.933	0.308	2.521	4.566
	(0.851)	(0.168)	(1.235)	(1.249)
LnFirmAge	-0.593**	-0.524	-0.778	-1.322*
	(-2.461)	(-1.248)	(-1.348)	(-1.676)
LnCEOage	0.015	0.063	-0.279	-0.453
	(0.039)	(0.176)	(-0.477)	(-0.549)
LnCEOpay	-0.002	0.018	-0.008	0.043*
	(-0.136)	(1.039)	(-0.265)	(1.700)
LnCEOtenure	0.010	0.034	-0.019	-0.034
	(0.258)	(0.909)	(-0.247)	(-0.357)
CEOchair	-0.053	-0.108	0.010	-0.057
	(-0.825)	(-1.169)	(0.076)	(-0.356)
Constant	0.964	2.047	2.782	5.088
	(0.587)	(0.783)	(0.989)	(1.028)
Inventor-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,072	1,435	2,072	1,435
Adj. R-squared	0.573	0.580	0.564	0.556

Table 1.8: Regressions of Key Employee Turnover on Political Ideology Conflicts

This table analyzes the association between key employee turnover and political ideology conflicts. *Leave* is a dummy variable that equals one if the employee leaves the company in a given year, and zero otherwise. *KeyOtherDiff* is the absolute value of the difference between a key employee's *DEM%* and the average *DEM%* of other employees in her firm. *KeyCEODiff* is the absolute value of the difference between a key employee's *DEM%* and her CEO's *DEM%*. Definitions of other variables are provided in Appendix A. All independent variables are lagged by one year. All regressions include employee-firm fixed effects and year fixed effects. Standard errors are clustered by employee. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*Leave*	
	(1)	(2)
KeyOtherDiff	0.037***	
	(2.659)	
KeyCEODiff		0.014*
		(1.786)
MB	0.007	0.008*
	(1.614)	(1.922)
Lev	-0.011	0.068*
	(-0.235)	(1.676)
LnAsset	-0.003	0.000
	(-0.306)	(0.035)
CAPEX	-0.021	-0.044
	(-0.792)	(-1.470)
PPE	0.008	0.010
	(0.117)	(0.155)
RD	0.041	0.113
	(0.143)	(0.405)
LnFirmAge	-0.021	-0.014
	(-0.824)	(-0.517)
LnCEOage	0.034	0.098**
	(0.718)	(2.063)
LnCEOpay	-0.006**	-0.007**
	(-2.173)	(-2.056)
LnCEOtenure	-0.004	-0.005
	(-0.857)	(-0.982)
CEOchair	-0.006	0.002
	(-0.694)	(0.220)
Constant	0.063	-0.262
	(0.289)	(-1.205)
Employee-Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	14,116	14,196
Adj. R-squared	0.296	0.306

Table 1.9: Regressions of Individual Employees' Political Ideology on Sinclair Acquisitions

This table presents the OLS regression results of individual employee's political ideology on Sinclair Acquisitions. *DEM%* is an employee's donation to Democratic recipients divided by her total donations to either Democratic recipients or Republican recipients in a given year. *SinclairIndiv* is a dummy variable that equals one if at least one of the local television stations in an employee's city of residence is acquired by Sinclair in year *t-1*. All other variables are defined in Appendix A. Columns (1) and (2) report the regressions of *DEM%* on *SinclairIndiv* for the non-CEO employees and the CEOs, respectively. Both regressions include employee and year fixed effects. Standard errors are clustered by employee. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*DEM%*	
	Non-CEO Employees	CEOs
	(1)	(2)
SinclairIndiv	-0.097***	0.014
	(-7.940)	(0.490)
MB	0.002	-0.003
	(0.755)	(-0.447)
Lev	0.106***	0.016
	(3.872)	(0.262)
LnAsset	0.019***	-0.032
	(4.958)	(-1.550)
CAPEX	0.036	-0.105*
	(1.539)	(-1.805)
PPE	-0.146***	-0.231**
	(-4.840)	(-2.146)
RD	0.663***	-0.042
	(4.582)	(-0.089)
LnFirmAge	-0.031***	0.014
	(-2.795)	(0.299)
LnCEOage	-0.104***	-0.127
	(-2.862)	(-0.731)
LnCEOpay	-0.009***	-0.022***
	(-4.340)	(-3.063)
LnCEOtenure	0.003	-0.001
	(0.847)	(-0.048)
CEOchair	-0.018***	-0.017
	(-3.082)	(-0.836)
Constant	0.925***	1.355**
	(6.302)	(2.171)
Employee FE	Yes	Yes
Year FE	Yes	Yes
Observations	106,175	6,331
Adj. R-squared	0.742	0.581

Table 1.10: 2SLS Analyses Using Sinclair Acquisitions as the Instrumental Variable for Employee Political Ideology Conflicts

This table presents the 2SLS estimation of *ROA* on employee political ideology conflicts, using Sinclair acquisitions as the instrumental variable for conflicts. *SinclairFirm* is defined as the percentage of a firm's employees who are affected by Sinclair acquisitions in year *t-1*. Columns (1) and (2) report the first-stage regressions where I regress *EmpConflict* and *CEOempDiff*, respectively, on *SinclairFirm*. Columns (3) and (4) report the second-stage regressions where I regress *ROA* on the fitted values of *EmpConflict* and *CEOempDiff*, respectively. Definitions of other variables are provided in Appendix A. Independent variables are lagged by one year. All regressions include firm and year fixed effects. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	*EmpConflict*	*CEOempDiff*	*ROA*	
	(1)	(2)	(3)	(4)
SinclairFirm	-0.205***	-0.121***		
	(-3.670)	(-3.040)		
FittedEmpConflict			-0.006***	
			(-2.778)	
FittedCEOempDiff				-0.010*
				(-1.845)
MB	0.005	0.001	0.019***	0.018***
	(0.545)	(0.233)	(6.911)	(6.726)
Lev	0.065	-0.036	-0.048**	-0.052**
	(1.028)	(-0.868)	(-2.461)	(-2.409)
LnAsset	0.013	0.027***	-0.009*	-0.014***
	(0.948)	(5.244)	(-1.836)	(-3.155)
CAPEX	0.008	0.074	0.063***	0.063***
	(0.131)	(1.491)	(3.706)	(3.158)
PPE	-0.072*	-0.072**	0.031	0.013
	(-1.773)	(-2.222)	(0.962)	(0.376)
RD	-0.353	0.313*	0.339**	0.403**
	(-1.452)	(1.883)	(2.189)	(2.371)
LnFirmAge	-0.049	-0.003	0.022*	0.045***
	(-1.575)	(-0.216)	(1.816)	(3.106)
LnCEOage	-0.114	0.196***	-0.016	-0.015
	(-1.095)	(3.322)	(-0.931)	(-0.797)
LnCEOpay	0.024***	-0.005	0.003	0.002
	(2.804)	(-0.944)	(1.598)	(1.568)
LnCEOtenure	0.014*	-0.007	0.002	0.002
	(1.665)	(-0.912)	(1.341)	(0.880)
CEOchair	0.026	0.002	0.005*	0.004
	(1.216)	(0.141)	(1.786)	(1.218)
Constant	1.381***	-0.703***	0.130	0.107
	(3.581)	(-2.959)	(1.276)	(1.021)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,745	1,885	2,745	1,885
Adj. R-squared	0.067	0.094	0.249	0.288
F-stat	13.472	9.244		

CHAPTER 2

The Disappearing IPO Puzzle:

New Insights from Proprietary U.S. Census Data on Private Firms[11]

[11] Xiao Ren, Thomas Chemmanur, Jie He, and Tao Shu. To be submitted to *Review of Financial Studies*. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1091. All results have been reviewed to ensure that no confidential information is disclosed.

Abstract

The U.S. equity markets have experienced a remarkable decline in IPOs since 2000, both in terms of smaller IPO volume and entrepreneurial firms' greater tendency to exit through acquisitions rather than IPOs. Using proprietary U.S. Census data on private firms, we conduct a comprehensive analysis of the above two notable trends and provide several new insights. First, we find that the dramatic reduction in U.S. IPOs is not due to a weaker economy that is unable to produce enough "exit-eligible" private firms: in fact, the average total factor productivity (TFP) of private firms is slightly higher post-2000 compared to pre-2000. Second, we find little evidence that *small* firms experience a greater decline in IPO propensity than large firms. Third, we do not find a significant change in the characteristics of private firms exiting through acquisitions from pre- to post-2000. Fourth, the decline in IPO propensity persists even after we account for the changing characteristics of private firms over time. Fifth, we show that the difference in TFP between IPO firms and acquired firms (and between IPO firms and firms remaining private) went up considerably post-2000 compared to pre-2000. Finally, the post-exit long-term TFP of venture-capital-backed (VC-backed) IPO firms, relative to matched VC-backed private firms, is significantly lower in the post-2000 era than in the pre-2000 era, while this pattern is absent among IPO and matched private firms without VC backing. Overall, our results strongly support the explanations based on standalone public firms' greater sensitivity to product market competition and entrepreneurial firms' access to more abundant private equity financing in the post-2000 era. We find mixed evidence regarding the explanations based on the smaller net financial benefits of being standalone public firms or the increased need for confidentiality after 2000.

2.1 Introduction

It is now well known that the volume of private firms going public in the U.S. equity market has declined significantly after the year 2000 (see, e.g., Figure 1 in Gao, Ritter, and Zhu (2013)).[12] A related phenomenon is that, among the private firms that do choose to "exit" (i.e., to change ownership structures to allow early equity investors such as entrepreneurs and venture capitalists to cash out), a much larger proportion choose to be acquired by another firm rather than have an IPO to become a standalone public firm.[13] This paper aims to provide new insights into the causes of the above salient trends by empirically analyzing two related research questions using a comprehensive dataset on private firms from the U.S. Census Bureau. First, what explains the tremendous decline in IPOs in the U.S. after the year 2000? Second, what drives the dramatic shift toward acquisitions rather than IPOs in the case of exiting private firms after the year 2000?

A number of hypotheses have been advanced and empirically analyzed to explain the above two phenomena. For example, Gao, Ritter, and Zhu (2013), who propose an "economy of scope" hypothesis, argue that the ongoing changes in the U.S. competition environment reduce the profitability of small companies, whether public or private. As a result, many small firms can create greater operating profits by selling out in trade sales (acquisitions) rather than going public

[12] Using the universe of firms in the U.S. economy, we confirm in Figure 2.1 of our paper that the probability of IPOs among private U.S. firms significantly drops after the year 2000. Doidge, Karolyi, and Stulz (2017) document that the number of listed U.S. firms peaked in 1996. Since the number of listed firms is affected by both IPOs and delistings, the listing peak differs from the IPO peak (year 2000).

[13] See, for example, Chemmanur, He, He, and Nandy (2018), who empirically analyze private firms' choices between going public, getting acquired, and remaining private. The literature that focuses on the exit choices of private firms between IPOs and acquisitions includes, e.g., Aggarwal and Hsu (2014), Bayar and Chemmanur (2012), Poulsen and Stegemoller (2008), and Brau, Francis, and Kohers (2003). A closely related literature, e.g., Cumming (2008) or Ball, Chiu, and Smith (2011), focuses exclusively on the exit choices of venture-backed private firms.

to become standalone firms.[14,15] Further, Gao, Ritter, and Zhu (2013) suggest that the decline in IPOs is unlikely due to the higher costs to public firms imposed by the Sarbanes-Oxley Act of 2002 and the Global Settlement of 2003. On the other hand, Doidge, Karolyi, and Stulz (2017) document a decline in the propensity of U.S. firms to be listed after 1996 and attribute this tendency to a decrease in the net benefits of listing for U.S. firms, especially for smaller firms. They conjecture that this decline in net benefits may arise from the increasing costs of being listed together with the non-increasing benefits of being listed (such as the ability to raise large amounts of capital in the public equity markets).[16]

More recently, Ewens and Farre-Mensa (2020) argue that the deregulation in securities laws in the 1990s, especially the National Securities Markets Improvement Act (NSMIA) of 1996, facilitated the process of raising capital privately and thus allowed private firms to grow larger without accessing the public equity markets until later in their life cycle. Thus, in their view, the decline in IPOs is a result of private firm founders taking advantage of the greater abundance and the lower cost of private equity financing by choosing to remain private for a longer period. Further, Doidge, Kahle, Karolyi, and Stulz (2018) link the decline in listed firms in the U.S. (and by implication, the decline in IPOs) to the growing importance of intangible investments such as intellectual property and human capital in the U.S. economy. They conjecture that raising capital in public markets causes confidentiality concerns for young and R&D-intensive firms so that such firms choose to remain private for a longer period of time. Finally, consistent with the

[14] Bayar and Chemmanur (2011) develop such a hypothesis using a theoretical model of a firm's choice between IPOs and acquisitions. In their setting, where entrepreneurs have private information about a firm's future viability, only firms with the strongest business models choose to go public, while weaker firms choose to be acquired in order to benefit from the acquirers' help in product market competition.

[15] In a companion study, Ritter, Signori, and Vismara (2013) argue that the "economy of scope" also explains the disappearing IPOs in Europe.

[16] Consistent with Gao, Ritter, and Zhu (2013), Doidge, Karolyi, and Stulz (2013, 2017) find little evidence that the lower propensity to be listed is caused by regulatory changes in early 2000s.

two papers discussed above, Stulz (2020) proposes a framework in which the decline in publicly listed firms is explained by the increased supply of private equity funds and the firms' increased demand of confidentiality.

While the above analyses provide useful insights, most of them have been conducted from the point of view of firms that have already gone public. As a result, many interesting questions regarding the disappearing IPO puzzle and the growing trend in exiting through acquisitions are left unanswered. For example, is the decline in IPOs driven by a dearth of "exit-eligible" private firms (i.e., with large enough productivity and size) in the U.S. economy? Is it possible that the changes in characteristics of an average U.S. private firm post the year 2000 lead to the observed changes in exit choices even if the economic and product market conditions remain the same? Further, in recent years, do private firms that choose to delay their IPOs with the possible help of private equity financing perform better relative to their peers that choose to go public? To fully answer such questions, it is essential to conduct a comprehensive analysis of private firms' exit decisions over time.

Differing from previous studies, our paper examines the implications of various existing and new hypotheses from the point of view of private firms that contemplate exiting through IPOs or acquisitions. To that end, we make use of the restricted-access version of the Longitudinal Business Database (LBD) of the U.S. Census Bureau, which contains establishment-level data for virtually the entire universe of U.S. firms, both public and private. We further use the combined data from the Census of Manufacturing Firms (CMF) and the Annual Survey of Manufacturers (ASM), which cover a comprehensive set of public and private firms in the manufacturing sector and contain rich operational and financial information such as sales, capital intensity, and the ingredients for calculating a firm's total factor productivity (TFP), thus allowing us to examine various hypotheses at greater depth than previous studies.[17] Our unique data and the focus on private firms allow us to provide a more complete picture of the two salient phenomena in entrepreneurial finance, namely, the reduction in IPO volume and the greater likelihood of exiting through acquisitions in lieu of IPOs.[18]

Our empirical analyses test five different hypotheses that are not mutually exclusive:

1) *Hypothesis 1 "Weaker economy"*: The number of private firms that are "eligible" to exit successfully (either through an IPO or an acquisition) went down significantly after the year 2000 relative to pre-2000 levels.[19]

2) *Hypothesis 2 "Greater sensitivity to product market competition"*: A standalone public firm is more prone to product market competition in the post-2000 period than in the pre-2000 period, so that a greater fraction of exiting private firms would choose to be acquired rather than going public. These firms are not strong enough to sustain the increased product market rivalry post-2000 as standalone public firms, but can survive by selling out to other companies, who can help the exiting firms on the product markets (Bayar and Chemmanur (2011)). This hypothesis is closely related to the "economy of scope" hypothesis of Gao, Ritter, and Zhu (2013) but the latter focuses on firm size and predicts that the disappearing

[17] The CMF and ASM datasets together were previously known as the Longitudinal Research Database (LRD).

[18] Some recent papers analyze hypotheses more distantly related to our paper. For example, Bowen, Fresard, and Hoberg (2020) show that there has been a steady decline in the number of firms with rapidly evolving innovations between 1930 and 2010, which explains a significant fraction of the disappearing IPOs. Further, Lattanzio, Megginson, and Sanati (2019) argue that the listing gap identified by Doidge, Karolyi, and Stulz (2017) was caused by an unprecedented merger wave occurring between 1997 and 2001. Similarly, Eckbo and Lithell (2020) find that, after including the capital flowing into the public firms through mergers, the number of U.S. listings did not fall significantly in the last decade. Focusing on deregulated industries between 1973 and 2017, Loveland, Mulherin, and Okoeguale (2018) find that not only mergers, but also new listings and delistings of firms cluster in deregulated industries, with new listings preceding delistings.

[19] As pointed out by Doidge, Karolyi, and Stulz (2017), the reduced listing volume could result from either the smaller number of eligible candidates (lower base) or the reduced propensity to go public. However, their analysis uses only the public version of LBD, which measures eligibility solely by firm size proxied by the number of employees but not quality (e.g., TFP or sales growth), and contains only aggregate data for firms across size bins rather than individual firm-level data.

IPO puzzle is mainly caused by the increasingly tougher competition facing smaller firms in the economy.[20]

3) *Hypothesis 3 "More abundant private equity financing"*: The greater supply of private equity financing in the post-2000 period led to the decline in IPOs. This hypothesis is motivated by the argument of Ewens and Farre-Mensa (2020) that the deregulation in securities laws in late 1990s made private equity financing more abundant to late-stage entrepreneurial firms in the post-2000 period. However, instead of focusing on the implications of securities regulations for the private equity industry, we directly examine the changing relationship between private firms' exit decisions and the corresponding private-equity-financing metrics from pre-2000 to post-2000.

4) *Hypothesis 4 "Smaller net financial benefits from being a standalone public firm"*: On the one hand, the financial benefits of going public (arising from the lower information asymmetry and therefore greater stock liquidity) may have declined (or at least remained the same) after early 2000s. In fact, some have argued that the financial benefits declined partly due to a decrease in the number of sell-side analysts after 2002 (see, e.g., Gao, Ritter, and Zhu (2013)). On the other hand, the additional regulatory requirements imposed on public firms in the early 2000s (namely, Regulation Fair Disclosure (Reg FD) in the year 2000; the Sarbanes-Oxley Act (SOX) in the year 2002; and the Global Settlement in the year 2003) may have led to higher financial costs of becoming a stand-alone listed firm in the post-2000 period. These regulatory changes have been widely blamed as the cause of declining IPOs (see, e.g., Zweig (2010), Weild (2011)).

[20] Note that this hypothesis does not depend on whether the level of product market competition in the U.S. has gone up or down. Some of the literature (e.g., Rajan and Zingales (2001), Grullon, Larkin, and Michaely (2019), Kahle and Stulz (2017)) seems to suggest that there has been an increase in U.S. product market concentration over the last several decades.

5) *Hypothesis 5 "Increased need for confidentiality"*: The importance of intangible assets has gone up significantly starting in the early 2000s, which, coupled with the unavoidable release of confidential information at the time of and subsequent to IPO, implies that a greater fraction of U.S. private firms, especially those concerned with leaking valuable information to competitors, will choose to remain private or delay going public to the extent possible.[21] We do not expect a similar effect on private firms' exiting through acquisitions.

Our empirical analysis starts by confirming the phenomenon of disappearing IPOs in our sample, which includes all U.S. firms in the LBD data from 1990-2014. Consistent with the existing literature, we observe a significant decrease in IPO propensity after the year 2000. The proportion of private firms that go public drops dramatically from 0.005% in 1999 to 0.001% in 2001, and remains at a low level afterwards. This is in sharp contrast to the acquisition propensity of private firms, which is not lower in the post-2000 period relative to the pre-2000 period.[22] While the decline in IPO propensity is pervasive across industries, states, and firm size groups, two notable patterns stand out. First, California and Massachusetts experience the largest declines in IPO propensity, possibly due to the increasing abundance of private equity supply in these two states. This finding is consistent with the *more abundant private equity financing hypothesis*. Second, using the number of employees as a proxy for firm size, we find little evidence that small firms experience a greater decline in IPO propensity than large firms. Thus, our evidence based on micro-level data of private firms does not support the common conjecture that the puzzle of

[21] Doidge, Kahle, Karolyi, and Stulz (2018) show that the R&D expenditures have exceeded capital expenditures for the average U.S. firm from 2002. Consistent with the negative impact of disclosure concerns on IPO decisions, Dambra, Field, and Gustafson (2015) document that the JOBS Act, which was enacted in April 2012 aiming to alleviate IPOs' disclosure requirements, led to a 25% increase in the number of IPOs after its passage. Further, Chaplinsky, Hanley, and Moon (2017) find that while the JOBS Act increased IPO underpricing within the first three years of its passage, it has not reduced the direct costs of going public.
[22] In untabulated analysis, we find that these patterns hold if we only examine the manufacturing sector using the ASM/CMF database.

disappearing IPOs predominantly manifests in small firms.

Next, we test the *weaker economy hypothesis* by examining whether the population of private firms in the U.S. economy indeed becomes weaker post 2000 so that fewer private firms are eligible of going public. Using the LBD data of all U.S. private firms, we document an increase in the total number of private firms from 1990 to 2007. The number drops from 2008 (possibly due to the financial crisis) but quickly bounces back after 2011.[23] More importantly, the proportion of large private firms (with 200 or more employees) among all private firms increases throughout our sample period of 1990-2014. We further use private manufacturing firms in the U.S. (i.e., the sample from the ASM/CMF database) for which we have available information on their sales and total factor productivity (TFP).[24] We find that the average TFP and sales for these private firms, as well as the proportion of high-sales or high-TFP private firms in the manufacturing sector, increase from pre-2000 to post-2000. These results, taken together, are against the *weaker economy hypothesis*.

The *greater sensitivity to product market competition hypothesis* and the *more abundant private equity financing hypothesis* both predict that the quality threshold of going public becomes higher in the post-2000 period than in the pre-2000 period, because only higher-quality firms can fend off the greater product market threat or need additional public financing in the presence of more abundant private equity supply after 2000. In contrast, neither hypotheses clearly predicts the quality threshold of being acquired to be higher in the post-2000 period. We therefore use the rich data of private firms in the manufacturing sector (ASM/CMF database) and find that,

[23] These results do not contradict Decker, Haltiwanger, Jarmin, and Miranda (2016b), who find that the entry rates of U.S. firms decline in recent years. They show that the entry rates, despite the decline, are higher than the exit rates until 2008, suggesting an increase in the total number of U.S. firms until 2008.

[24] Although we rely on TFP to capture a firm's performance following the existing literature (e.g., Schoar (2002), Chemmanur, He, and Nandy (2009), Giroud (2013), and Krishnan, Nandy, and Puri (2015)), our results are qualitatively similar if we use sales growth as an alternative measure of firm performance.

consistent with these two hypotheses, the differences in TFP and sales between IPO firms and acquired firms and those between IPO firms and private firms have both increased after the year 2000. In contrast, the differences in TFP and sales between acquired and private firms remain unchanged. These results suggest that the quality threshold has been raised for IPOs but not acquisitions.

While our univariate analyses above provide useful insights, they do not explicitly consider the possible changes in firm characteristics over time. For example, the lower IPO propensity post the year 2000 may be caused by changes in some firm characteristics that are related to exit decisions. Hence, we turn to multivariate analyses using the rich financial information on manufacturing firms from the ASM/CMF database. Specifically, we build a multinomial logit model of private firms' exit decisions on going public, getting acquired, or remaining private. The independent variables include various firm-, industry-, and state-level characteristics. We then use the characteristics of firms in the pre-2000 sample period to calculate two sets of fitted IPO probabilities, one using the estimated coefficients from our pre-2000 regressions and the other using the estimated coefficients from the post-2000 regressions. Since this approach virtually fixes the pool of private firms, the difference between the two sets of IPO probabilities is likely driven by the changing environment rather than changing firm characteristics. We find that the fitted IPO probabilities in the post-2000 period are significantly lower than those in the pre-2000 period. In contrast, there is little change in these firms' fitted acquisition probabilities from the pre-2000 period to the post-2000 period.

To test whether the disappearing IPO phenomenon is caused by the series of regulations (e.g., Reg FD, SOX, and the Global Settlement) during 2001-2003, we conduct similar analyses for the exit decisions during a narrow window around the adoptions of these regulations in early-

2000s, but find no significant drop (in fact, even a slight increase) in the fitted IPO probabilities, which is inconsistent with the *smaller net financial benefits hypothesis*.

Next, we use the multinomial logit model to analyze the determinants of exit choices. Specifically, we interact the firm-, industry-, and state-level characteristics with a *post2000* dummy variable which equals one for the year of 2001 and onwards, and zero otherwise. We find that firms with higher TFP are more likely to go public after year 2000 relative to the pre-2000 period, but they are not more likely to get acquired, which is consistent with the *greater sensitivity to product market competition hypothesis* and the *more abundant private equity financing hypothesis*.[25] Additionally, firms in industries with more venture-capital investments are less likely to go public after year 2000, which provides further evidence supporting the *more abundant private equity financing hypothesis*. Consistent with the *greater sensitivity to product market competition hypothesis*, we find that firms in more competitive industries and those operating in fewer business segments (i.e., having lower economy of scope) are less likely to go public after year 2000. Further, firms in industries with lower analyst coverage (i.e., more information asymmetry and lower stock liquidity) are less likely to go public after year 2000, which supports the *smaller net financial benefits hypothesis.* In stark contrast to our IPO results, none of these interactions are statistically significant in our acquisition regressions.

To more closely examine how various metrics of economic environment (e.g., product market competition or the supply of private equity financing) impact exit choices differently over time, we conduct difference-in-differences (DiD) analyses based on our multinomial logit models. Specifically, we divide firms along two different dimensions based both on time periods (pre- vs.

[25] We also conduct multivariate analysis around the regulatory changes. A similar multinomial logit analysis using data from 2001-2006 reveals that firms with higher TFP are NOT more likely to go public during 2004-2006 relative to 2001-2003. This result is also inconsistent with the *smaller net financial benefits hypothesis,* which suggests that only the higher quality firms choose to go public after the regulatory changes.

post-2000) and on a particular metric of the economic environment (e.g., high- vs. low-venture capital activities in an industry/state), and run multinomial logit regressions on these four sets of firms' exit decisions. Then we calculate IPO probabilities using the fixed firm characteristics of a pre-2000 baseline sample and the four sets of estimated coefficients to calculate fitted IPO probabilities. The results of DiD analyses show that firms in states or industries with higher VC investments and those in high-tech industries experienced a larger decline in IPO propensity than their peers, which supports the *more abundant private equity financing* and the *increased need for confidentiality hypotheses*. Additionally, firms in more competitive industries and those operating exclusively in one business segment experienced a larger decline in IPO propensity compared to their peers, which supports the *greater sensitivity to product market competition hypothesis*. Firms in industries with lower analyst coverage experienced a larger decline in IPO propensity compared to firms in industries with higher analyst coverage, which supports the *smaller net financial benefits hypothesis*.[26]

Last but not least, we examine IPO firms' post-exit long-term TFP relative to matched remaining-private firms. Among VC-backed firms, IPO firms have significantly higher post-exit long-term TFP than matched private firms in the pre-2000 era but this pattern disappears in the post-2000 era. In contrast, among non-VC-backed firms, the difference in post-exit long-term TFP between IPO and matched private firms is statistically insignificant in both eras. These findings suggest that staying private with the help of VC financing, relative to raising public equity via IPOs, is more beneficial (in terms of spurring long-term productivity) in the post-2000 era, which supports the *more abundant private equity financing hypothesis*.

[26] In further multivariate analyses, we find that IPO firms have significantly larger TFP in the post-2000 era, but acquired firms do not, which confirms our univariate results.

In summary, using proprietary datasets from the U.S. Census Bureau on private firms, our results show that, in contrast to some common conjectures, the dramatic reduction in U.S. IPOs is not due to the economy being unable to produce enough private firms that are eligible (strong enough) to go public by pre-2000 standards. In fact, the average TFP of private firms is slightly higher post-2000 compared to pre-2000. Likewise, we do not find evidence supporting the conventional wisdom that the disappearing IPO puzzle mainly manifests in small private firms. Nor do we find a significant change in the characteristics of private firms exiting through acquisitions from pre- to post-2000. Further, the decline in IPO propensity persists even if we account for the changing characteristics of private firms over time, and the difference in TFP between IPO firms and acquired firms (and between IPO firms and firms remaining private) is considerably higher post-2000 compared to pre-2000. Finally, the post-exit long-term TFP of venture-capital-backed (VC-backed) IPO firms, relative to matched VC-backed private firms, is significantly lower in the post-2000 era than in the pre-2000 era, while this pattern is absent among IPO and matched private firms without VC backing. Overall, our results strongly support the *greater sensitivity to product market competition hypothesis* and the *more abundant private equity financing hypothesis*, and only provide mixed evidence regarding the *smaller net financial benefits hypothesis* and the *increased need for confidentiality hypothesis*.

2.2 Theory and Hypothesis Development

In this section, we outline the underlying theories and develop testable hypotheses for our empirical analyses. We describe each hypothesis and its implications for the proportion and quality of private firms undertaking IPOs, being acquired, or remaining private.

2.2.1 The Weaker Economy Hypothesis

The *weaker economy hypothesis* argues that, after the year 2000, the number of private firms eligible to exit successfully through IPOs or acquisitions has gone down significantly compared to the pre-2000 years. Since the proprietary Census data allow us to observe the number of private firms that are able to meet various thresholds for going public or being acquired (measured in terms of TFP, sales, employment, etc.), we are able to directly test this hypothesis.

In particular, we test the following predictions of the *weaker economy hypothesis*:

H1a: The number of private firms that are "eligible" to undertake IPOs or acquisitions, based on the levels of TFP, sales, and employment, is lower post-2000 than pre-2000.

H1b: The average TFP, sales, and employment of private firms in the U.S. economy are lower post-2000 than pre-2000.

2.2.2 The Greater Sensitivity to Product Market Competition Hypothesis

This hypothesis posits that, post-2000, the nature of product market competition may have dramatically changed, threatening the viability of standalone public firms to a greater extent. Consequently, only a smaller fraction of private firms would choose to exit by going public, while a large fraction choose to exit by being acquired by a larger firm. In their theoretical analysis of the exit choices of private firms, Bayar and Chemmanur (2011) argue that only private firms with stronger business models (more viable against product market competition) choose to go public, while weaker firms choose to be acquired, since they can benefit from the help of their acquirers in product market competition.

Under this hypothesis, only stronger firms would be able to meet the higher threshold for being stand-alone public firms post-IPO. We therefore test the following prediction:

H2a: The TFP, sales, and employment of IPO firms at the time of going public are higher *post-2000 than pre-2000.*

On the other hand, we would not expect a significant change in the average TFP, sales, or size of private firms being acquired because even weaker private firms that exit through acquisitions can survive greater product market threat with the help of their acquiring firms. We therefore test the following prediction:

H2b: The TFP, sales, and employment of acquired private firms do not significantly change from pre-2000 to post-2000.

The *greater sensitivity to product market competition hypothesis* also predicts that private firms facing greater competition tend to experience a larger decline in IPO propensity from pre-2000 to post-2000. To examine this prediction, we employ two proxies of the intensity of product market competition that a firm faces: the industry concentration ratio (i.e., the sales-based Herfindahl-Hirschman Index) and the firm's business diversification (i.e., the number of business segments that the firm operates in) because lower industry concentration or a more focused business model indicates greater product market competition to the firm.

H2c: Private firms in less concentrated industries or those operating in fewer business segments experience a larger decline in IPO propensity relative to their peers from pre-2000 to post 2000.

2.2.3 The More Abundant Private Equity Financing Hypothesis

It has been argued that the deregulation of securities laws in the 1990s, and in particular, the passage of the National Securities Markets Improvement Act (NSMIA) in 1996, allowed many private firms abundant access to private equity financing, especially after the year 2000 (see, e.g., Ewens and Farre-Mensa (2020) and de Fontenay (2017)).[27] As Ewens and Farre-Mensa (2020) show, the passage of the NSMIA made it easier for unregistered funds such as venture capital (VC) and private equity funds to raise capital, by exempting these funds from the blue-sky laws in various states and increasing the maximum number of investors that these funds may have without unregistering under the Investment Company Act. Ewens and Farre-Mensa (2020) argue that since VC funds investing in late-stage startups tend to be larger and have more investors, these regulatory changes were particularly effective in increasing the supply of VC financing for late-stage startups, which in turn allowed such firms to remain private longer.

The *more abundant private equity financing hypothesis* thus leads to the following prediction.

H3a: Private firms in states or industries with greater venture capital investments experience a larger decline in IPO propensity relative to their peers from pre-2000 to post-2000.

Additionally, the increased VC or other private financing can also affect the quality threshold of private firms exiting through IPOs. Since private firms can now raise more capital from private equity post-2000 than pre-2000, only the most productive ones among them will further turn to public markets for additional funding when their efficient production scale exceeds the existing amount of capital they own (see theory papers such as Clementi (2002) and Chemmanur and He (2011) for the relationship between firms' productivity and their decision to go public). Therefore, the *more abundant private equity financing hypothesis* yields the following prediction.

H3b: The TFP of IPO firms at the time of their going public is higher post-2000 than pre-

[27] Other regulatory changes that affected firms' access to private financing in the 1990s are the SEC's adoption of Rule 144A in 1990 and several subsequent amendments to Rule 144A, allowing unfettered resale of private shares after a short period (de Fontenay, 2017) and thus potentially reducing the cost of capital of private firms.

2000.

If the more abundant private equity flows only to the highest-quality firms that would have otherwise gone public (but not chosen to be acquired), the TFP of private firms that are acquired would be unaffected. However, if the more abundant VC and other private equity financing applies to all exit-eligible private firms across the board (i.e., those firms that may have gone public or been acquired in the absence of such financing), then we would expect the TFP of private firms being acquired post-2000 to be greater than those exiting pre-2000. Thus, the *more abundant private equity financing hypothesis* is agnostic about the change in TFP for private firms choosing to be acquired from pre-2000 to post-2000.

H3c: The TFP of acquired private firms either becomes higher or remains the same from pre-2000 to post-2000.

Finally, the more abundant private equity financing will make the marginal benefits (in terms of future growth and productivity) of going public (and raising capital from the public market) relative to staying private (and raising capital from PE financing) lower in the post-2000 era, which leads to the following prediction.

H3d: Among firms with actual private equity financing (e.g., those that are VC-backed), the gap in the post-exit long-term TFP between an IPO firm and its remaining-private peer firm is significantly lower in the post-2000 era than in the pre-2000 era. In contrast, this pattern does not exist among non-VC-backed firms.

2.2.4 The Smaller Net Financial Benefits from Becoming a Standalone Public Firm Hypothesis

As discussed by several papers (e.g., Gao, Ritter, and Zhu (2013), Doidge, Karolyi, and Stulz (2013), and Ewens, Xiao, and Xu (2020)), it is commonly believed among practitioners that the changes in the public equity market in the early 2000s, namely, the Regulation Fair Disclosure (Reg FD) in the year 2000, the Sarbanes-Oxley Act (SOX) in the year 2002, and the Global Settlement in the year 2003, have increased the financial costs of being a standalone public firm. At the same time, people have conjectured that the closures of many boutique brokerage firms in the early 2000s reduced analyst coverage and in turn the benefits of being a standalone firm in terms of increased analyst coverage and stock liquidity. In the following, we define the "net benefits" of being a standalone public firm as the liquidity and other financial benefits arising from lower information asymmetry (due to, e.g., higher analyst coverage) associated with being a public firm net of the regulatory costs of being a standalone public firm.

In our context, we hypothesize that the net benefits of being a standalone public firm relative to being acquired by another firm or remaining private declined after the year 2003 (i.e., after the series of regulatory changes took full effect). This hypothesis yields two testable predictions.

H4a: Everything else equal, the propensity for a private firm to go public is significantly lower after 2003, while that for a private firm to be acquired does not significantly change around 2003.

H4b: The differences in the TFP, sales, and employment between private firms going public and those being acquired or remaining private are greater after 2003, while such differences between private firms that are acquired and those remaining private does not significantly change around 2003.

Finally, if the decreased analyst coverage (stock liquidity) of being a standalone public firm post 2000 is an important driving force for the disappearing IPO puzzle post 2000, then we would observe a larger drop in IPO propensity for firms suffering more from information asymmetry because analyst coverage is more valuable for these firms. This leads to the following prediction.

H4c: Private firms in industries with more information asymmetry (i.e., lower analyst coverage) experience a greater decline in IPO propensity post 2000.

2.2.5 The Increased Need for Confidentiality Hypothesis

After the dramatic growth in the use of the internet for business purposes in the 1990s, the number of private firms with intangible assets (e.g., internet, software, or other high-tech firms) went up dramatically. Given that many of these firms have relatively few fixed assets, a large portion of their value is likely to have come from intellectual property, which, in turn, likely led to a greater need for confidentiality in firms exiting after 2000. Several authors have argued theoretically that there is a considerable release of private (confidential) information by firms during the IPO process (see, e.g., Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001)). In addition, Farre-Mensa (2017) provides empirical evidence that public firms face higher costs due to mandatory information disclosure compared to private firms. This means that firms having a need for confidentiality (e.g., high-tech firms) are less likely to go public post-2000 than pre-2000. Hence, we have the following prediction.

H5: Private firms in the technology sector experience a larger decline in IPO propensity relative to their non-tech peers from pre-2000 to post-2000.

2.3 Data, Sample Construction, and Variable Definitions

2.3.1 Data and Sample Construction

Our empirical analyses use two samples from 1990-2014, which is the data period approved for our Census project. The first sample is the Longitudinal Business Database (LBD) maintained by the Center of Economic Studies at the U.S. Census Bureau. The LBD database tracks the births and deaths of all business establishments in the U.S. and provides basic information about each establishment including industry, age, payroll (salaries), and employment (number of employees) on an annual basis. We further obtain name and location (state, city, zip code, and street address) for each establishment by matching LBD to the Standard Statistical Establishment List (SSEL). The latter is the Business Register or the "master" data set of the U.S. Census Bureau which contains names and locations of establishments.[28] We use LBD's firm identifier, "FIRMID", to aggregate the attributes of all establishments that belong to the same firm.

Our second sample is the combination of the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM) databases, which cover establishments in the manufacturing sector. This database is formerly referred to as the Longitudinal Research Database (LRD). Compared to LBD, the second sample contains richer establishment-level information for a comprehensive sample of both private and public firms in the manufacturing sector. The variables include the total value of shipments (sales), payroll for different types of workers (e.g., blue-collar vs. white-collar), and capital expenditures. The CMF covers the entire universe of U.S. manufacturing establishments in the census years (1992, 1997, 2002, 2007, and 2012), and the ASM surveys a large sample of manufacturing establishments in every non-census year, including all establishments with more than 250 employees as well as smaller establishments that are randomly selected every fifth year to complete a rotating five-year panel.[29] It is worth noting that a large fraction of high-tech industries (such as computer hardware), which are important players in the IPO market, are covered by the ASM/CMF database due to the broad definition of

[28] A comprehensive description of the SSEL can be found in Jarmin and Miranda (2002).
[29] Given that a random sample of smaller establishments is continuously present in our sample, our data is not substantially skewed towards large firms. As a result, small firms are well represented in the data. The rotating sample of smaller establishments is sampled by the Census Bureau each year in the non-census years in order to minimize such a bias in the data. Since the coverage of smaller establishments in our data varies over years, we also repeat our analysis by confining only to establishments with more than 250 employees and found similar results.

"manufacturing" by the Census Bureau (see, e.g., Chemmanur, Krishnan, and Nandy (2011) for a more detailed discussion of the industry coverage of the ASM/CMF database).

Following Chemmanur, He, He, and Nandy (2018), we obtain the data of U.S. IPOs and acquisitions during our sample period from the Securities Data Company (SDC) database. For the sample of IPOs, we remove all IPOs related to equity carve-outs, American depositary receipts, American depositary shares, global deposit receipts, global deposit shares, units, trust receipts, or trust units.[30] We also require that the IPO firm is present on Compustat for the fiscal year of the IPO. For the sample of private firms getting acquired, we remove all deals that are reverse takeovers, spin-offs, recapitalizations, self-tenders, exchange offers, repurchases, minority stake purchases, acquisitions of remaining interest, privatizations, divestitures, asset sales, deals whose target and acquirer belong to the same parent company, and deals whose status is defined as "incomplete" by the SDC.[31] We obtain the data of venture-capital-backed firms during our sample period from the Thomson One VentureXpert database. We construct the samples of IPOs, acquired firms, and venture-capital-backed firms by matching the original data to the Census databases using a combination of name-and-address matching algorithms (as commonly used by Census data researchers) and manual checking. The matching rates are very high: over 97% of the IPOs, over 84% of the private-target acquisitions from the SDC, and over 80% of the venture-backed firms in the VentureXpert database can be matched to the LBD. Finally, we obtain the data of analyst coverage from the Institutional Brokers' Estimate System (IBES) database.

2.3.2 Variable Definitions and Summary Statistics

Since our study focuses on the disappearing IPO phenomenon and the greater tendency to exit through acquisitions rather than IPOs in the post-2000 period, we construct a dummy variable,

[30] Our results remain similar if we drop reverse leveraged buyouts (reverse LBOs).
[31] For firms that both have IPOs and are acquired, we only analyze their first exits.

Post2000, which equals one if the year of an observation is 2001 and onwards, and zero otherwise. To test the *smaller net financial benefits hypothesis*, we also construct a dummy variable, *PostReg*, which equals one if the year of an observation is in the three years from 2004 and 2006, and zero if the year of the observation is from 2001 and 2003.

For our analyses involving the ASM/CMF sample, we follow Chemmanur, He, He, and Nandy (2018) and construct a broad set of variables at the firm, industry, and state levels that are associated with entrepreneurial firms' exit choices (i.e., going public, getting acquired, or remaining private). First, we calculate each firm's total factor productivity (TFP) as the weighted average of plant-level TFP, using sales (value of shipments) as the weight. To construct plant-level TFP, we follow the previous literature to estimate a log-linear Cobb-Douglas production function for each six-digit NAICS industry-year, where the dependent variable is the natural logarithm of sales (total value of shipments) and the independent variables are the natural logarithms of capital stock and labor costs. Appendix B provides a detailed description of the construction of TFP, which follows the existing literature (e.g., Schoar (2002), Chemmanur, He, and Nandy (2009), Giroud (2013), Krishnan, Nandy, and Puri (2015)).

We also construct other variables used in our multivariate analysis as follows. *LnSales* is the natural logarithm of the total value of shipments in thousands of 1997 dollars at the firm level. *SalesGrowth* is calculated as the average annual percentage change in sales (total value of shipments) in the past three years. *LnAge* is the natural logarithm of the age (in years) of the oldest plant of a firm. *CapInt* (capital intensity) is capital stock scaled by total employment. *Capex* (capital expenditure) is defined as capital expenditure scaled by capital stock. *MktShr* is the market share in terms of sales at the three-digit NAICS level. *WhiteProp* is defined as the average proportion of total wages that is for white-collar workers in the past three years. *VC* is a dummy variable that equals one if a firm is backed by venture capital, and zero otherwise. We calculate *LnNumSeg* as the natural logarithm of the number of industries (at the six-digit NAICS level) of a firm's establishments to examine the difference in exit choices between conglomerate and single-segment firms. To measure product market competition, we calculate the plant-level Herfindahl Index (*HHI*) in terms of sales at the three-digit NAICS level.[32] Plant-level *TFP*, *CapInt*, *Capex*, *MktShr*, *WhiteProp*, and *HHI* are aggregated to the firm level using sales (total value of shipments) as the weight.

To proxy for alternative financing opportunities from venture capital at the state or industry level, we calculate *VCFracSt* (*VCFracInd*) as the fraction of venture-capital-backed firms at the state (three-digit NAICS) level for a year. To gauge the heterogeneity in exit choices between high-tech and other companies, we construct a dummy variable, *HighTech*, that equals one if a firm belongs to the tech industry.[33,34] To proxy for a private firm's degree of information asymmetry, we calculate the firm's industry-level analyst coverage (*LnNumAna*) as the natural logarithm of one plus the average number of analysts following the public firms in the firm's three-digit NAICS industry. All continuous variables above are winsorized at their 1st and 99th percentiles to control for outliers. The detailed definitions of these variables are contained in Appendix C.

Table 2.1 provides the summary statistics of these variables for the ASM/CMF sample, i.e., private firms in the manufacturing sector. This sample contains about 999,000 non-public

---

[32] We calculate *HHI* for each plant and then aggregate at the firm level because a firm can have multiple plants in different industries.

[33] Tech industries include the following six-digit NAICS codes: 333295, 333315, 334111, 334112, 334113, 334119, 334210, 334220, 334413, 334511, 421430, 421690, 423430, 423690, 443120, 511140, 511210, 514210, 518210, 519130, 541330, 541511, 541512, 541513, 541519, 541710, 541711, and 541712. This definition of high-tech industries follows that specified by the U.S. Census Bureau, which is listed on the following website: https://www.cencus.gov/censusexplorer/naics_codes_used.xls.

[34] In untabulated analysis, we find that high-tech firms are more likely to redact information from their SEC registration filings compared to non-high-tech firms, which indicates that high-tech firms indeed have a higher need for confidentiality. See Boone, Floros, and Johnson (2016) for a detailed discussion of information redaction in registration filings.

manufacturing firm-years during 1990-2014, among which around 500 exit via IPOs and around 950 exit through acquisitions.[35] *IPO* is a dummy variable which equals one if a private firm goes public in a year, and zero otherwise. *ACQ* is a dummy variable which equals one if a private firm is acquired in the year, and zero otherwise. In Table 2.1, the means of *IPO* and *ACQ* are 0.052% and 0.095%, respectively. 55.5% of the firm-year observations in our baseline regression sample are after year 2000. The means of *TFP*, *LnSales*, *LnAge*, *CapInt*, *Capex*, *LnNumSeg*, *LnNumAna*, and *HHI* are -0.050, 8.185, 2.605, 0.073, 0.082, 0.200, 1.160, and 0.013, respectively. The mean of *MktShr* is 0.011%. On average, 38.5% of a firm's wages are paid to white-collar employees. Moreover, 2.9% of the firm-years are backed by venture capital, and 1.1% of the firm-years operate in the high-tech industries. On average, 3.6% (3.5%) of the firms per state (industry) are backed by venture capital.

2.4 Univariate Analyses

In this section, we conduct univariate analyses to revisit the phenomena of disappearing IPOs in the U.S. as well as the growing propensity to exit through acquisitions instead of IPOs. We also examine the characteristics of IPO and acquired firms over time for a preliminary evaluation of the different hypotheses.

2.4.1 Revisiting the Phenomenon of Disappearing IPOs

We first divide the universe of LBD firms in a given year into four categories: those going public in the year, exiting through acquisitions in the year, already being publicly traded (i.e., going public at least one year before), or remaining privately owned. We then plot in Panel A of Figure 2.1 the proportion of IPOs among all LBD firms in each year of our sample period, i.e., 1990-2014. As can be seen, the propensity of IPO drops dramatically from 0.005% in 1999 to 0.001%

[35] We round the sample size following the Census disclosure policy.

in 2001, and remains at a low level afterwards. The overall IPO propensity in the pre-2000 period is also remarkably higher than that in the post-2000 period. Panels B and C of Figure 2.1 further show the proportion of publicly listed firms and the proportion of non-exiting private firms, respectively. There is an obvious downward trend for the proportion of public firms and an upward trend for the proportion of non-exiting private firms from the pre-2000 period to the post-2000 period. These results are consistent with the existing literature that documents the disappearing IPO puzzle and the delisting puzzle in the post-2000 era.

We further plot in Panel D of Figure 2.1 the proportion of acquired private firms among the LBD firms every year. Similar to IPO propensity, the propensity to exit through acquisitions also experiences a sharp decline around the burst of the tech bubble, from 0.017% in 2000 to 0.007% in 2002. However, the decline is reversed quickly after 2002, and the overall level of private-target acquisition propensity from middle 2000s is similar to that before 2000. The sharp contrast between the trends of IPOs and acquisitions is consistent with the general conception that more entrepreneurs choose to exit through acquisitions rather than IPOs in the post-2000 era.

2.4.2 Disappearing IPOs in Subsamples: A Closer Look

In this subsection, we examine the phenomenon of disappearing IPOs across various subsamples.

We first examine IPO propensity across different industries. For each year in our sample, we calculate IPO propensity as the proportion of IPOs among all LBD firms in that year and then average this ratio across years in the two sub-periods of 1990-2000 and 2001-2014. Panels A and B of Figure 2.2 present the change in IPO propensity from the pre-2000 period to the post-2000 period for each two-digit NAICS industry. We present both the raw changes (Panel A) and percentage changes (Panel B) to assess the economic magnitudes from different angles. Panel A shows that while all industries exhibit negative changes in IPO propensity in terms of percentage points, the largest declines occur in the information industry (NAICS code 51) and the management of companies and enterprises industry (NAICS code 55).[36] Moreover, Panel B shows that most industries experience an over 60-percent decline in IPO propensity.[37] These results reveal that the phenomenon of disappearing IPOs is pervasive across industries.

Next, we plot the changes in IPO propensity across geographical regions (U.S. states) in Figure 2.2 Panels C and D. These panels are similar to Panels A and B except that we form subsamples based on states rather than industries. Panel C shows that while all states experience a decline in IPO propensity in terms of percentage points, California and Massachusetts experience the largest declines, possibly because these two states account for the majority of high-tech companies and have the most abundant venture capital financing, which is broadly consistent with the *more abundant private equity financing hypothesis*. Panel D shows that the majority of the U.S. states experience an over 50-percent decline in IPO propensity. Taken together with Panels A and B, these results show that the phenomenon of disappearing IPOs is a relevant issue for most of the U.S. economy.

Using number of employees as the proxy for firm size, Doidge, Karolyi, and Stulz (2017) show that the decline in the U.S. firms' propensity to be listed is greater among small firms. Thus, we test whether a similar pattern holds for the decline in IPO propensity. In Figure 2.2 Panels E and F, we conduct subsample analyses across firm size. We follow Doidge, Karolyi, and Stulz (2017) and classify firms into nine size groups based on their employment: (1) fewer than 20

[36] The information industry comprises firms that produce and distribute information and cultural products, provide the means to transmit or distribute these products as well as data or communications, and process data. The management of companies and enterprises industry contains firms that administer, oversee, and manage establishments of the company or enterprise that normally undertake the strategic or organizational planning and decision making role of the company or enterprises (e.g., offices of holding companies).

[37] Note that we redact certain industries or states from our figures if the information pertaining to them does not pass the disclosure requirements of the Census.

employees; (2) between 20 and 99 employees; (3) between 100 and 249 employees; (4) between 250 and 499 employees; (5) between 500 and 999 employees; (6) between 1,000 and 2,499 employees; (7) between 2,500 and 4,999 employees; (8) between 5,000 and 9,999 employees; and (9) over 10,000 employees. Interestingly, Panel E shows that larger firms experience a bigger decline in IPO propensity than smaller firms in terms of percentage points. Panel F presents the percentage-change in IPO propensity across firm size groups, in which the percentage drop in IPO propensity for small firms is only slightly larger than that for large firms. Therefore, these results using the proprietary private firm data suggest that the decline in IPO propensity is not significantly greater among small firms but rather pervasive across all size groups.

2.4.3 Is the Puzzle of Disappearing IPOs Due to a Weaker U.S. Economy?

In this subsection, we conduct several analyses to test the *weaker economy hypothesis*. We first test *Hypotheses 1a* and *1b* in Section 2.2.1 by examining whether the number of "eligible" private firms and the average quality of private firms decrease post 2000. Panel A of Figure 2.3 plots the total number of U.S. firms in the LBD during our sample period of 1990-2014. As can be seen, there is an upward trend in the number of firms from 1990 to 2007, and this number declines dramatically from 2008 to 2011 (possibly due to the financial crisis) before bouncing back afterwards. Note that these results do not contradict Decker, Haltiwanger, Jarmin, and Miranda's (2016b), who find that the entry rate of U.S. firms declines in recent decades. As shown in their paper, the entry rate remains higher than the exit rate until 2008 despite the decline, indicating that the total number of U.S. firms increases every year until 2008. The results in Figure 2.3A are also consistent with Guzman and Stern (2020), who find no secular decline in start-ups post-2000 after adjusting for startup quality. Overall, the total number of firms post-2000 is higher than that in the pre-2000 period. We also plot the fraction of large firms in the economy, i.e., those with at least

200 employees, in Panel B of Figure 2.3. There is a clear upward trend in the fraction of large firms throughout the sample period. These results provide visual evidence against the *weaker economy hypothesis*.

Despite the evidence in Figure 2.3, it is possible that the number of firms or that of larger firms (in terms of employment) may not accurately reflect the overall quality of U.S. firms. We therefore, in Figure 2.4, directly examine alternative measures of firm quality using the richer firm characteristics of the manufacturing sector (based on our ASM/CMF sample).

Panel A of Figure 2.4 presents the time series of average total factor productivity (TFP) of U.S. manufacturing firms as well as the fraction of manufacturing firms with TFP greater than 0.05 (which is approximately the 75^{th} percentile of this variable across our sample firms). The average TFP decreases from 1990 to 1994, followed by an increase till the end of our sample period. The proportion of high-TFP firms exhibits a similar pattern. These results again do not support the *weaker economy hypothesis*.

We further examine sales and sales growth as proxies for firm quality. Panel B of Figure 2.4 presents the time trend in average sales of manufacturing firms as well as the proportion of firms with sales greater than $10 million. We observe an upward trend in both average sales and high-sales firms during our sample period. Panel C presents the time trends in average sales growth and the fraction of firms with sales growth greater than 15% (similar to the above figures, this cutoff is chosen based on the approximate 75^{th} percentile of the distribution). Although the trends in average sales growth and the fraction of high-growth firms are less clear than the trends based on the first two measures, there is no clear downward trend in sales growth or the fraction of high-growth firms in the 2000s. Overall the results in Figures 2.3 and 2.4 do not support *H1a* and *H1b* under the *weaker economy hypothesis*.

2.4.4 Quality of IPO Firms Relative to Acquired Firms and Private Firms.

In this subsection, we test *Hypotheses 2a* and *2b* under the *greater sensitivity to product market competition hypothesis* and *Hypotheses 3b* and *3c* under the *more abundant private equity financing hypothesis* by examining the characteristics of IPO firms relative to acquired firms and remaining-private firms. Both hypotheses suggest that the quality threshold of going public significantly increases while the threshold of exiting through acquisitions does not necessarily change in the post-2000 era.

We first examine the average number of employees for IPO firms, acquired firms, and private firms using the comprehensive LBD sample. Figure 2.5 plots the annual average number of employees for these three categories of firms during our sample period of 1990-2014. Panel A shows that IPO firms generally have larger numbers of employees in the post-2000 period than in the pre-2000 period. In the meantime, this pattern exists for acquired firms and remaining-private firms as well in Panels B and C. Therefore, the results in Panel A support *Hypothesis 2a* but not *Hypothesis 2b*. The results in Figure 2.5 show that the increase in the number of employees occurs for all subgroups of firms, which suggests that we need to interpret Figure 2.5 with caution because the results can be driven by a general uptrend of firm size for all private firms.

Next, we turn to examining TFP, sales, and sales growth using the sample of manufacturing firms. We calculate the annual averages of TFP, sales, and sales growth in each year for IPO firms, acquired firms, and remaining-private firms. To facilitate comparison, we plot the differences among these three groups in Figure 2.6, with a focus on the difference between IPO firms and acquired firms and that between IPO firms and remaining-private firms.

Panel A of Figure 2.6 presents the results on TFP. The difference between IPO firms and acquired firms and that between IPO firms and private firms are positive in all years of the sample period. Additionally, both differences increase from the pre-2000 period to the post-2000 period. These results support *Hypotheses 2a* and *3b*. Additionally, the difference between acquired firms and private firms remains stable over time, which supports *Hypotheses 2b* and *3c*.

Panels B and C of Figure 2.6 present the corresponding results for sales and sales growth. Panel B shows that the trend in sales is consistent with that in TFP, providing further support for the increased quality threshold of going public. In Panel C, the trend in sales growth is much less clear than that for TFP or sales, but the differences between IPOs and acquired firms and that between IPOs and private firms are generally higher in the post-2000 than in the pre-2000 period. Overall, these results also support *Hypotheses 2a, 2b, 3b,* and *3c*.

In Figure 2.7, we calculate the changes in TFP (Panel A), sales (Panel B), and sales growth (Panel C) from the pre-2000 period to the post-2000 period for IPO firms, acquired firms, and private firms, respectively. Overall, the increases in these three quality measures for IPO firms are much more positive than those for acquired firms and private firms. These results are consistent with Figure 2.6 and support the *Hypotheses 2a* and *2b* under the *greater sensitivity to product market competition hypothesis* and the *Hypotheses 3b* and *3c* under the *more abundant private equity financing hypothesis*.

2.5 Multivariate Analyses

In this section, we conduct multivariate analyses using the rich firm characteristics of our sample of manufacturing firms. Compared to univariate analyses, the multivariate test design has two advantages. First, multivariate analyses control for the confounding changes in firm characteristics over time. Second, the multivariate test design allows us to directly examine the drivers of exit choices in a discrete dependent variable model and therefore test more hypotheses from Section 2.2.

2.5.1 Determinants of Exit Choices: Multinomial Logit Regression Analyses

We construct a model of the determinants of private firms' exit decisions and use it to formally examine the changes in IPO propensity and acquisition propensity over time. Specifically, we estimate the following multinomial logit regressions of exit choices on various firm, state, and industry characteristics:

$$EXIT_{i,j,s,t} = \mathrm{F}\big(\alpha + \beta_1 TFP_{i,t} + \beta_2 LnSales_{i,t} + \beta_3 LnAge_{i,t} + \beta_4 CapInt_{i,t} + \beta_5 Capex_{i,t} + \beta_6 MktShr_{i,t} + \beta_7 WhiteProp_{i,t} + \beta_8 VC_{i,t} + \beta_9 LnNumSeg_{i,t} + \beta_{10} VCFracSt_{s,t} + \beta_{11} VCFracInd_{j,t} + \beta_{12} HighTech_j + \beta_{13} LnNumAna_{j,t} + \beta_{14} HHI_{j,t} + FixedEffects\big) + \varepsilon_{i,j,s,t}, \tag{2.1}$$

where *i* indexes firm, *j* indexes industry, *s* indexes state, and *t* indexes year. The dependent variable, *EXIT*, is a categorical variable that equals zero for a firm-year if the firm remains private in the year (the base category), equals one if the firm is acquired in the year, and equals two if the firm goes public in the year. Hence, each multinomial logit model in our context contains two columns, one comparing going public vs. remaining private and the other comparing getting acquired vs. remaining private. We include year fixed effects in all the regressions and cluster the standard errors by three-digit NAICS industry.

Table 2.2 presents the results. Columns (1) to (4) include all independent variables except *HHI*, and Columns (5) to (8) include all independent variables except *LnNumAna*.[38] Columns (1), (2), (5), and (6) report the multinomial logit model for the sample in the pre-2000 period (1990-2000). Columns (1) and (5) show that larger firms, younger firms, firms with more capital

[38] We include *HHI* and *LnNumAna* in separate regressions as these two industry-level variables are highly correlated and including both into the same model induces severe multi-collinearity problems.

expenditures, firms with higher proportions of white-collar salary, VC-backed firms, firms in industries with more VC investments, and high-tech firms are more likely to go public than to remain private in the pre-2000 period. Columns (2) and (6) show that such firms are also more likely to be acquired than to remain private in the pre-2000 period. Moreover, firms that operate in more business segments and in states with more VC investments are more likely to be acquired than to remain private in the pre-2000 period. Columns (3), (4), (7), and (8) present the multinomial logit model for the post-2000 period (2001-2014). Compared to the results from the pre-2000 sample, *TFP*, industry-level analyst coverage, and product market concentration now significantly predict IPO propensity but capital expenditures and industry-level VC investments no longer significantly predict IPO propensity. Additionally, capital intensity, capital expenditures, and state-level VC investments do not significantly predict the exit by acquisition relative to remaining private.

These preliminary results, especially the ones about TFP and industry-level VC investments, have implications for our hypotheses. First, TFP does not positively predict IPO decision in the pre-2000 period but does in the post-2000 period. Second, TFP does not predict acquisition in both pre-2000 and post-2000 periods. These results support *H2a* and *H2b* under the *greater sensitivity to product market competition hypothesis* and *H3b* and *H3c* under the *more abundant private equity financing hypothesis*. Additionally, industry-level VC investments positively predict IPOs in pre-2000 but not in post-2000, which also supports the *more abundant private equity financing hypothesis*

Next, we use the multinomial logit model as analyzed in Columns (1) to (4) to construct the predicted (i.e., fitted) IPO and acquisition probabilities for the pre-2000 and post-2000 periods using characteristics of private firms in the pre-2000 sample.[39] Specifically, for the pre-2000 period, we calculate the predicted IPO and acquisition probabilities by applying the estimated coefficients in Columns (1) and (2), respectively. For the post-2000 period, we calculate the predicted IPO and acquisition probabilities by applying the estimated coefficients in Columns (3) and (4), respectively. This approach virtually "fixes the pool" of the same set of entrepreneurial firms and compare their IPO and acquisition propensities based on the changing institutional features of the U.S. economy from pre-2000 to post-2000.

Panel B of Table 2.2 reports the results of this analysis. In addition to the estimated probabilities, we also report the t-tests on the differences between the pre-2000 probabilities and the post-2000 probabilities. The estimated IPO probability is 0.0092% in the pre-2000 period but only 0.0004% in the post-2000 period. The difference is about 96 percent of the starting level (i.e., 0.0092%) and also statistically significant at the 1% level. In sharp contrast, the probability of exiting through acquisitions is 0.0100% in the pre-2000 period and 0.0095% in the post-2000 period. Although the decline in acquisition probability is statistically significant, it is only about five percent of the starting level (i.e., 0.0099%) and therefore economically small. These results together show that IPO probability in the post-2000 period is significantly lower than that of the pre-2000 period even when we consider an observably "identical" set of entrepreneurial firms preparing to exit in the two time periods.

[39] Results using the multinomial logit model as analyzed in Columns (5) to (8) are very similar.

2.5.2 Determinants of Exit Decisions: An Interaction Analysis that Compares the Pre-2000 and the Post-2000 Periods.

In this subsection, we formally examine the changes in the determinants of exit decisions from the pre-2000 period to the post-2000 period using an interaction analysis based on the multinomial logit model. This exercise helps us test the predictions of various hypotheses.

Specifically, we estimate the following multinomial logit regressions of exit choices on the interactions of the *Post2000* dummy with firm, industry, and state characteristics:

$$
\begin{aligned}
EXIT_{i,j,s,t} = \mathrm{F}\big(&\alpha + \beta_1 TFP_{i,t} \times Post2000_t + \beta_2 LnSales_{i,t} \times Post2000_t + \beta_3 LnAge_{i,t} \times \\
&Post2000_t + \beta_4 CapInt_{i,t} \times Post2000_t + \beta_5 Capex_{i,t} \times Post2000_t + \beta_6 MktShr_{i,t} \times \\
&Post2000_t + \beta_7 WhiteProp_{i,t} \times Post2000_t + \beta_8 VC_{i,t} \times Post2000_t + \beta_9 LnNumSeg_{i,t} \times \\
&Post2000_t + \beta_{10} VCFracSt_{s,t} \times Post2000_t + \beta_{11} VCFracInd_{j,t} \times Post2000_t + \beta_{12} HighTech_j \times \\
&Post2000_t + \beta_{13} LnNumAna_{j,t} \times Post2000_t + \beta_{14} HHI_{j,t} \times Post2000_t + \gamma_1 TFP_{i,t} + \\
&\gamma_2 LnSales_{i,t} + \gamma_3 LnAge_{i,t} + \gamma_4 CapInt_{i,t} + \gamma_5 Capex_{i,t} + \gamma_6 MktShr_{i,t} + \gamma_7 WhiteProp_{i,t} + \\
&\gamma_8 VC_{i,t} + \gamma_9 LnNumSeg_{i,t} + \gamma_{10} VCFracSt_{s,t} + \gamma_{11} VCFracInd_{j,t} + \gamma_{12} HighTech_j + \\
&\gamma_{13} LnNumAna_{j,t} + \gamma_{14} HHI_{j,t} + FixedEffects\big) + \varepsilon_{i,j,s,t}, \qquad (2.2)
\end{aligned}
$$

where the variables are similarly defined as in Equation (2.1). We include year fixed effects in all the regressions and cluster the standard errors by three-digit NAICS industry.

Table 2.3 reports the results. Similar to Panel A of Table 2.2, Columns (1) and (2) include all independent variables except *HHI* and its interaction, and Columns (3) and (4) include all independent variables except *LnNumAna* and its interaction. In both IPO columns (Columns (1) and (3)), the interactions of *TFP*, *VC, LnNumSeg, LnNumAna*, and *HHI* are significantly positive, and that of *Capex* is significantly negative. Additionally, the interaction of *VcFracInd* is significantly negative in Column (1) and marginally significant in Column (3). In contrast, none of the independent variables are significant in the two columns regarding acquisition decisions (Columns (2) and (4)).

The results in Table 2.3 provide rich evidence for our hypotheses. First, when we compare the post-2000 period to the pre-2000 period, we find that the positive effect of TFP on going public relative to remaining private becomes significantly larger, while its effect on exiting through acquisitions does not significantly change. These findings support *H2a* and *H2b* under the *greater sensitivity to product market competition hypothesis* and *H3b* and *H3c* under the *more abundant private equity financing hypothesis*.

Second, firms in industries with less VC investment are more likely to go public during the post-2000 era, which is consistent with *H3a* under the *more abundant private equity financing hypothesis*.[40] Third, firms operating in more business segments (industries) and those in less competitive industries (i.e., with higher *HHI*) are more likely to go public in the post-2000 period than in the pre-2000 period, but the likelihood of these firms exiting through acquisitions does not significantly change between the two eras. These findings support *H2c* under the *greater sensitivity to product market competition hypothesis*. Fourth, firms operating in industries with less analyst coverage are less likely to go public but not less likely to be acquired after 2000 than before 2000, which is consistent with *H4c* under the *smaller net financial benefits hypothesis*. Finally, firms in high-tech industries are more likely to go public in the post-2000 period than in the pre-2000 period, but these firms' propensity to exit through acquisitions does not change much. This result does not support *H5* under the *increased need for confidentiality hypothesis*, although it could be explained by the possibility that high-tech firms might have higher unobservable quality and thus

[40] Interestingly, VC-backed firms are more likely to go public post-2000, probably due to venture capital funds tend to invest in high-quality start-ups with higher IPO probability. In untabulated analyses, we find evidence consistent with this conjecture: VC-backed firms exhibit higher future TFP and sales growth than otherwise-similar firms.

be able to meet the higher threshold quality of going public post-2000 (predicted by both the *greater sensitivity to product market competition hypothesis* and the *more abundant private equity financing hypothesis*).

2.5.3 Determinants of Exit Decisions: Before and After the Early-2000s Regulatory Changes

Our analyses so far follow the existing literature and divide our sample period by the year 2000. To precisely test *H4a* and *H4b* under the *smaller net financial benefits hypothesis*, we separately estimate the multinomial logit regressions for two narrow windows, namely, three-year periods surrounding the year 2003.

Panel A of Table 2.4 presents the multinomial logit regression of exit choices on various firm, state, and industry characteristics for the pre-regulation window (i.e., 2001-2003, in Columns (1), (2), (5), and (6)) and the post-regulation window (i.e., 2004-2006, in Columns (3), (4), (7), and (8)), respectively. The test design is similar to Table 2.2 except for the different time periods we examine. Panel B of Table 2.4 reports the predicted/fitted IPO and acquisition probabilities for the pre-regulation and post-regulation eras using characteristics of firms in the pre-regulation sample (i.e., the "base group") and regression coefficients from Columns (1) to (4). We find that the predicted post-regulation IPO probability is actually significantly higher than the predicted pre-regulation probability, even when we calculate these fitted probabilities using a common set of firm characteristics. Additionally, the post-regulation acquisition probability is also significantly higher than that pre-regulation. These results do not support *H4a* and *H4b* under the *smaller net financial benefits hypothesis*.

In Table 2.5, we test *H4c* under the *smaller net financial benefits hypothesis* by estimating multinomial logit regressions that include the interactions of the exiting determinants with the post-regulation dummy, which equals one for 2004-2006, and zero for 2001-2003. The regression design is similar to that of Table 2.3 except for the different time periods that we examine. The *smaller net financial benefits hypothesis* (*H4c*) predicts the interaction between post-regulation dummy and TFP in the IPO columns to be significantly positive. However, the TFP interaction is only marginally significant in Column (1) and becomes insignificant in Column (3). We also examine the sales interaction as an alternative measure of IPO quality, and the coefficient is insignificant in either of the models. These results do not support *H4c* under the *smaller net financial benefits hypothesis*.

2.5.4 Difference-in-Differences (DiD) Analysis on Predicted Exiting Probabilities

In this subsection, we adopt an alternative test design, namely, the difference-in-differences (DiD) analysis of predicted exiting probabilities from multinomial logit models, to further analyze how economic and institutional environments (i.e., industry or geographical attributes) impact IPO and acquisition probabilities differently in the pre-2000 and post-2000 eras. Specifically, for each variable of interest (to test certain hypotheses), we sort the full regression sample into four subsamples based on whether the value of the variable is above or below the median and whether the year of the observation is before (including) or after 2000. We then estimate the multinomial logit regressions specified in Equation (2.1) for each of the four subsamples separately and obtain four sets of estimated coefficients. After that, we choose one of the two subsamples in the pre-2000 era as the "base group" and calculate four predicted probabilities (each for IPOs and acquisitions) by applying the estimated regression coefficients to the characteristics of firms in this base group. By doing so, we "fix" the firm characteristics and explicitly test the impact of changing economic environments on firms' exiting probabilities. This DiD design is more flexible than our baseline multinomial logit regressions with interactions in that it allows the coefficients for all covariates in our model to be different in the four subgroups (i.e., not requiring that a given industry or state characteristic affects all the four subgroups of firms in an identical fashion).

Panel A of Table 2.6 presents the results using *HHI* (industry-level product market concentration) as the sorting variable. The top half presents the four predicted/fitted IPO probabilities, the differences between the post-2000 and the pre-2000 fitted probabilities (with t-statistics in parentheses), and the DiD estimators calculated as the differences between the two differences (with t-statistics in parentheses). We find that the IPO propensity for firms in industries with stronger product market competition (i.e., lower *HHI*) drops more after 2000. This result, on the contrary, does not hold for the propensity of exiting through acquisitions. Panel B of Table 2.6 shows that the IPO propensity for single-segment firms drops more after 2000. The findings in both Panel A and Panel B are consistent with the *H2c* under the *greater sensitivity to product market competition hypothesis*.

Panel C presents the results using *VCFracst* (the fraction of firms backed by venture capital investment in a state-year) as the sorting variable. The results show that the IPO propensity for firms in states with higher VC investments drops more after 2000, which supports *H3a* under the *more abundant private equity financing hypothesis*. The bottom half of Panel A further shows that firms in the states with higher VC investment also experience a greater decline in probabilities of getting acquired after 2000. Panel D reports the results on *VCFracInd* (the fraction of firms in a three-digit NAICS industry that are backed by venture capital investment), which offer similar inferences as those in Panel C.

Panel E shows that the IPO propensity for firms in industries with higher information asymmetry (i.e., lower analyst coverage) and thus lower stock liquidity drops more in the post-2000 era, which is consistent with *H4c* under the *smaller net financial benefits hypothesis*.

Finally, the results in Panel F show that the IPO propensity for high-tech firms drops more after 2000, which is consistent with *H5* under the *increased need for confidentiality hypothesis*. Since we find mixed results regarding firms operating in high-tech industries (i.e., in Table 2.3 and Table 2.6), we acknowledge that either our evidence does not offer consistent support for the *increased need for confidentiality hypothesis* or that our industry-measure for the need of confidentiality is imprecise (or correlated with other firm attributes).

2.5.5 Further Analyses of the Greater Sensitivity to Product Market Competition Hypothesis and the More Abundant Private Equity Financing Hypothesis

Our results so far provide the strongest support for the *greater sensitivity to product market competition hypothesis* and the *more abundant private equity financing hypothesis*. In this subsection, we adopt two new test designs to further examine these two hypotheses.

2.5.5.1 OLS Analysis of TFP before and after 2000

Our first analysis focuses on TFP because it is a key metric to test the unique prediction on exiting quality threshold from the above two hypotheses. Table 2.7 reports the following ordinary least squares (OLS) regressions:

$$TFP_{i,j,s,t} = \alpha + \beta_1 IPO_{i,t} \times Post2000_t + \beta_2 IPO_{i,t} + \beta_3 ACQ_{i,t} \times Post2000_t + \beta_4 ACQ_{i,t} + \beta_5 LnSales_{i,t} + \beta_6 LnAge_{i,t} + \beta_7 CapInt_{i,t} + \beta_8 Capex_{i,t} + \beta_9 MktShr_{i,t} + \beta_{10} WhiteProp_{i,t} + \beta_{11} VC_{i,t} + \beta_{12} LnNumSeg_{i,t} + \beta_{13} VCFracSt_{s,t} + \beta_{14} VCFracInd_{j,t} + \beta_{15} HighTech_j + \beta_{16} LnNumAna_{j,t} + \beta_{17} HHI_{j,t} + FixedEffects + \varepsilon_{i,j,s,t}, \quad (2.3)$$

where we examine the association between TFP and a private firm's exit choices in a given year. $IPO_{i,t}$ ($ACQ_{i,t}$) is a dummy variable that equals one if firm *i* goes public (gets acquired) in year *t*. *Post2000* is a dummy variable that equals one if the year of observation is after 2000. We include the same set of control variables at the firm, industry, and state levels as in Table 2.2. We include year fixed effects in all models, and industry or industry×year fixed effects in some models. Standard errors are clustered by three-digit NAICS industry.

Columns (1) and (2) present the baseline OLS regressions including year fixed effects. Similar to our multinomial logit analysis, we include *HHI* and *LnNumAna* separately in these two models due to concerns for multi-collinearity. We find that the interaction between *IPO* and *Post2000* is significantly associated with TFP in all specifications, indicating that the IPO firms in the post-2000 era have significantly higher TFP compared to the remaining-private firms. The interaction between *ACQ* and *Post2000*, however, is significantly associated with TFP only in Column (1) with no fixed effects. Moreover, we report the F-tests and the corresponding p-values for the differences between the coefficients of *IPO*×*Post2000* and *ACQ*×*Post2000*. We find that the differences are statistically significant in all specifications. Hence, the IPO firms in the post-2000 era have significantly higher TFP than private firms exiting through acquisitions.

For robustness, we include both year fixed effects and industry fixed effects in Columns (3) and (4), and industry×year fixed effects in Column (5).[41] In all these robustness tests, the IPO interactions remain significant and the ACQ interactions remain insignificant, and the differences between the two are significant. These results confirm our previous findings that private firms with higher TFP are more likely to go public in post-2000 period relative to pre-2000 period, but they are not more likely to be acquired. Thus, the results are consistent with both the *greater sensitivity to product market competition hypothesis* (*H2a* and *H2b*) and the *more abundant private equity financing hypothesis* (*H3b* and *H3c*).

[41] This is actually an advantage of using OLS models because discrete-choice models like the multinomial logit do not allow us to include many layers of fixed effects to control for unobservable time-varying characteristics such as industry conditions.

2.5.5.2 Post-exit Long-term TFP for IPO and Matched Remaining-private Firms

Our second analysis specifically tests *H3d* under the *more abundant private equity financing hypothesis* by comparing the post-exit long-term TFP for IPO and matched remaining-private firms pre- and post-2000. For each firm that goes public in a given year during our sample period, we first find remaining-private firms that operate in the same state and the same industry (at the three-digit NAICS level), as well as have the same VC-backing status as the IPO firm in that year. Further, we require the size (in terms of sales) of the matched firms to be within 0.5 and 2 times of the size of the IPO firm. Finally, among the above set of matched firms, we choose the one with the closest TFP to the IPO firm. We calculate the two-year and three-year average TFP for both the IPO firms and the matched remaining-private firms from the year after the IPO, and then regress the post-IPO TFP on the IPO dummy and the interaction between the IPO dummy and the post-2000 dummy.

Table 2.8 reports the following OLS regressions:

$$TFP3yr_{i,t}\ (TFP2yr_{i,t}) = \beta_1 IPO_{i,t} \times Post2000_t + \beta_2 IPO_{i,t} + \beta_3 LnSales_{i,t} + \beta_4 LnAge_{i,t} + \beta_5 CapInt_{i,t} + \beta_6 Capex_{i,t} + \beta_7 MktShr_{i,t} + \beta_8 WhiteProp_{i,t} + \beta_9 LnNumSeg_{i,t} + FixedEffects + \varepsilon_{i,t}, \tag{2.4}$$

where we examine the relation between three-year (two-year) average post-exit TFP and the IPO decisions for VC-backed firms (Columns (1) and (3)) and non-VC-backed firms (Columns (2) and (4)) separately. We include year fixed effects and the fixed effects for each matched pair of firms, so this analysis effectively compares an IPO firm's post-exit TFP with that of the matched remaining-private firm over two or three years after the IPO. Standard errors are clustered by three-digit NAICS industry.

We find that the coefficient estimate of the interaction term is significantly negative for the VC-backed sample but insignificant for the non-VC-backed sample. This result suggests that the gap in post-exit TFP between an IPO firm and an ex-ante similar remaining-private firm is significantly lower in the post-2000 era than the pre-2000 era *only* for VC-backed firms (i.e., those with available private equity financing).[42] In contrast, for non-VC-backed firms, the post-exit TFP gap between an IPO firm and the matched private firm is not significantly different in both the pre-2000 and the post-2000 eras. Taken together, these results suggest that the marginal benefit of going public (and raising capital from the public market) relative to staying private (and raising capital from PE financing) is lower in the post-2000 era, which is consistent with *H3d* under the *more abundant private equity financing hypothesis*.

2.6 Conclusion

The U.S. equity markets have experienced a remarkable decline in IPOs since 2000, both in terms of IPO volume and entrepreneurial firms' relative tendency to exit through acquisitions. Existing literature has provided several explanations, but many of these analyses to date focus on firms that have already gone public. Differing from previous studies, we use proprietary U.S. Census data to conduct a comprehensive analysis of the above two notable trends from the perspective of private firms' exiting choices between IPOs or acquisitions, and thus provide new evidence on the disappearing-IPO puzzle. Specifically, we test five different hypotheses motivated by the theoretical literature or common beliefs, namely, the *weaker economy hypothesis*, the *greater sensitivity to product market competition hypothesis*, the *more abundant private equity*

[42] Table 2.8 shows that the coefficient on the *IPO* dummy itself is significantly positive for the VC-backed sample, which is consistent with Maksimovic, Phillips, and Yang (2019) who find that VC-sponsored IPO firms outperform their matched remaining-private firms after the IPOs. Our results on the interaction between the *IPO* and *post-2000* dummies reveal that the positive gap in performance between VC-backed IPO firms and their remaining-private peers significantly shrinks in the post-2000 period than in the pre-2000 period.

financing hypothesis, the *smaller net financial benefits from being a standalone public firm hypothesis*, and the *increased need for confidentiality hypothesis*, using micro-level private firm data during 1990-2014.

We first revisit the phenomenon of disappearing IPOs. Consistent with the existing literature, we observe a significant decrease in IPO propensity after the year 2000, even after controlling for the changing characteristics of private firm in the U.S. economy. Interestingly, we find that small firms do not experience a larger decline in IPO propensity than large firms. Thus, the evidence using private firms finds little support for the conjecture that the puzzle of disappearing IPOs is mainly attributable to the decline in IPO propensity among small firms.

Next, we conduct both univariate and multivariate analyses to test the above five hypotheses. We find that the number of private firms, the fraction of high-quality (i.e., "eligible to exit") private firms, and the average quality (in terms of TFP, sales, or employment) of private firms increase from the pre-2000 period to the post-2000 period. These results do not support the *weaker economy hypothesis*.

Our results strongly support the *greater sensitivity to product market competition hypothesis*. Specifically, we find that the differences in quality (in terms of TFP and sales) between IPO firms and acquired private firms and those between IPO firms and remaining-private firms have increased after the year 2000. Additionally, several multivariate analyses based on different test designs show that firms with higher TFP are more likely to go public relative to remaining private in the post-2000 period than in the pre-2000 period, but they are not more likely to get acquired after the year 2000. These results suggest that the quality threshold of going public (but not being acquired) has been raised in the post-2000 era, which is consistent with the heightened product market threat for standalone public firms. Furthermore, firms in more competitive industries and those with fewer business segments are less likely to go public after the year 2000.

We also find evidence in support of the *more abundant private equity financing hypothesis*. Other than the TFP analysis discussed above, which is consistent with this hypothesis, we also find that firms in states or industries with higher venture capital investments experienced a larger decline in IPO propensity than their peers. Moreover, the IPO firms backed by venture capital have significantly lower post-exit long-term TFP than matched (i.e. similar) private firms that are also VC-backed in the post-2000 era relative to the pre-2000 era, while this pattern is absent among IPO and matched private firms without VC backing. This evidence suggests that the marginal benefit of going public (and raising capital from the public market) relative to staying private (and raising capital from private equity financing) is lower in the post-2000 era. These results indicate that several recent regulatory changes, such as the JOBS Act 3.0 and the guidance from the Department of Labor that allows companies to include private equity funds in their 401(k) plans, despite their potential benefits, might exacerbate the already-depleted IPO market by increasing the supply of private equity investment.[43]

We find mixed evidence for the other two hypotheses. Regarding the *smaller net financial benefits hypothesis*, we find that firms in industries with lower analyst coverage (and thus smaller financial benefits of becoming liquidly traded public firms) are less likely to go public after the year 2000, which is consistent with this hypothesis. However, there does not seem to be a significant change in IPO propensity around early-2000s' regulatory changes that substantially increase the financial costs of standalone public firms, which runs against this hypothesis. Finally, by examining the exit choices of high-tech industry firms, which might be more concerned about

[43] See, for example, Hensarling (2018) and Maxey (2020) for detailed information on the JOBS Act 3.0 and the guidance from the Department of Labor to allow 401(k) plans to invest in private equity.

confidentiality, we fail to find consistent evidence for the *increased need for confidentiality hypothesis*.

Our findings shed new light on the puzzle of disappearing IPOs as well as the growing propensity of entrepreneurial firms to exit through acquisitions. Using proprietary micro-level data on private firms, we provide a comprehensive picture of the disappearing IPOs in the post-2000 period, and show that this puzzle is a complicated phenomenon driven by factors in multiple dimensions, especially the evolving product market dynamics and the increased supply of private equity financing. As long as these economic factors continue to be in force, we probably would not see a rebound of the IPO volume to its pre-2000 level even after several recent legislative moves in the U.S. aiming to revive the IPO market such as the Jumpstart Our Business Startups Act (JOBS Act) in 2012.

Table 2.1: Summary Statistics for the Sample of Regression Analyses

This table reports the summary statistics of the variables used in the regression analyses. The sample for regression analyses contains private manufacturing firms from the ASM/CMF databases between 1990 and 2014, including a total of about 999,000 firm-years (rounded to thousand following Census disclosure requirement). The definitions of all variables are provided in Appendix C.

	Mean	Std	N
Variables	(1)	(2)	(3)
IPO (in %)	0.052	2.285	999,000
ACQ (in %)	0.095	3.080	999,000
Post2000	0.555	0.497	999,000
TFP	-0.050	0.469	999,000
LnSales	8.185	1.762	999,000
LnAge	2.605	0.868	999,000
CapInt	0.073	0.094	999,000
Capex	0.082	0.139	999,000
MktShr (in %)	0.011	0.033	999,000
WhiteProp	0.385	0.189	999,000
VC	0.029	0.168	999,000
LnNumSeg	0.200	0.493	999,000
VCFracSt	0.036	0.024	999,000
VCFracInd	0.035	0.039	999,000
HighTech	0.011	0.102	999,000
LnNumAna	1.160	0.270	999,000
HHI	0.013	0.018	999,000

Table 2.2: Determinants of Exit Decisions through IPOs vs. Acquisitions: Multinomial Logit Regressions

This table presents the analyses on the determinants of private firms' exit decisions through IPOs or acquisitions (ACQ). Panel A presents the multinomial logit regressions of exit choices on firm, industry, and state characteristics. The dependent variable is a categorical variable that equals zero if a firm remains private in year *t* (the base category), equals one if a firm gets acquired in year *t*, and equals two if a firm goes public in year *t*. Each set of regressions consists of two columns, one that compares the exit decision of IPO to remaining private, and the other that compares the exit decision of getting acquired to remaining private. Columns (1), (2), (5), and (6) use the pre-2000 period of 1990-2000, and Columns (3), (4), (7), and (8) use the post-2000 period of 2001-2014. All the independent variables are defined in Appendix C. All regressions include year fixed effects. Robust z-statistics, clustered by three-digit NAICS industry, are reported in parentheses. *, **, and *** represent statistical significance from the omitted category (remaining private) at the 10%, 5%, and 1% levels, respectively. Panel B reports the predicted IPO and ACQ probabilities for the pre-2000 and post-2000 periods using the characteristics of firms from the pre-2000 sample and the regression coefficients from Columns (1) to (4). The reported probabilities are multiplied by 10^4 to ease reading.

Panel A: Multinomial Logit Regressions

Sample	Pre-2000		Post-2000		Pre-2000		Post-2000	
	IPO	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP	-0.161	-0.183	0.266	-0.118	-0.165	-0.179	0.302*	-0.115
	(-0.861)	(-1.374)	(1.477)	(-1.020)	(-0.875)	(-1.348)	(1.724)	(-0.961)
LnSales	0.867***	0.456***	0.765***	0.404***	0.861***	0.453***	0.770***	0.402***
	(7.515)	(8.417)	(6.004)	(8.064)	(7.425)	(7.671)	(6.141)	(8.140)
LnAge	-0.413***	-0.229**	-0.598***	-0.288***	-0.411***	-0.228**	-0.594***	-0.285***
	(-3.742)	(-2.357)	(-4.506)	(-7.136)	(-3.729)	(-2.324)	(-4.450)	(-7.173)
CapInt	-0.434	-1.198	0.414	-0.463	-0.589	-1.256*	0.404	-0.466
	(-0.484)	(-1.596)	(0.884)	(-1.624)	(-0.670)	(-1.716)	(0.875)	(-1.609)
Capex	2.315***	0.671***	0.511	0.417	2.301***	0.671***	0.480	0.416
	(11.900)	(2.755)	(1.368)	(1.291)	(11.89)	(2.767)	(1.308)	(1.287)
MktShr	-0.119	-0.026	-0.176	-0.034	-0.094	-0.022	-0.223	-0.033
	(-0.862)	(-0.397)	(-1.192)	(-0.414)	(-0.679)	(-0.331)	(-1.476)	(-0.395)
WhiteProp	1.554***	0.635***	1.281*	1.018***	1.567***	0.639***	1.391*	1.006***
	(3.267)	(3.383)	(1.763)	(4.563)	(3.296)	(3.396)	(1.921)	(4.743)
VC	1.937***	1.479***	2.775***	1.639***	1.944***	1.482***	2.778***	1.642***
	(11.690)	(10.720)	(8.429)	(13.760)	(11.550)	(10.650)	(8.391)	(13.710)
LnNumSeg	-0.102	0.549***	0.299	0.620***	-0.105	0.550***	0.298	0.619***
	(-0.394)	(3.782)	(0.978)	(6.963)	(-0.404)	(3.775)	(0.966)	(6.968)
VCFracSt	3.309	4.263**	4.520	3.549	3.411	4.240**	4.220	3.522
	(1.396)	(2.098)	(1.645)	(1.455)	(1.382)	(2.095)	(1.599)	(1.439)
VCFracInd	6.113***	4.384***	2.652	2.967**	6.394***	4.369***	3.135	2.833*

	(5.188)	(3.746)	(1.148)	(1.966)	(6.068)	(3.824)	(1.305)	(1.842)
HighTech	0.502***	0.407**	0.853***	0.338*	0.486***	0.413**	0.971***	0.325**
	(2.599)	(2.533)	(4.217)	(1.886)	(2.579)	(2.574)	(3.728)	(2.025)
LnNumAna	-0.308	-0.097	0.659**	-0.100				
	(-0.894)	(-0.484)	(2.136)	(-0.486)				
HHI					-2.782	0.271	9.476**	0.428
					(-1.054)	(0.113)	(2.054)	(0.161)
Constant	-17.200***	-12.620***	-18.920***	-11.070***	-17.480***	-12.700***	-18.320***	-11.160***
	(-16.600)	(-20.330)	(-12.530)	(-18.330)	(-16.730)	(-22.790)	(-12.040)	(-18.930)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	445,000	445,000	554,000	554,000	445,000	445,000	554,000	554,000

Panel B: Predicted IPO and ACQ Probabilities for Pre-2000 and Post-2000 Eras

	Pre-2000 Probability	Post-2000 Probability	T-test
IPO	9.243	0.373	-100.500
ACQ	9.963	9.504	-19.850

Table 2.3: The Changing Impact of Exit Decision Determinants from Pre- to Post-2000
This table presents the multinomial logit regressions of exit choices on the interactions of firm, industry, and state characteristics with *Post2000*, a dummy variable that equals one if the year of an observation is 2001 or later. The dependent variable is a categorical variable that equals zero if a firm remains private in year *t*, equals one if a firm gets acquired in year *t*, and equals two if a firm goes public in year *t*. Columns (1) and (3) compare the exit decision of IPO to remaining private, and Columns (2) and (4) compare the exit decision of getting acquired (ACQ) to remaining private. All the independent variables are defined in Appendix C. All regressions include year fixed effects. Robust z-statistics, clustered by three-digit NAICS industry, are reported in parentheses. *, **, and *** represent statistical significance from the omitted category (remaining private) at the 10%, 5%, and 1% levels, respectively.

	IPO	*ACQ*	*IPO*	*ACQ*
	(1)	(2)	(3)	(4)
TFP×Post2000	0.432**	0.069	0.473***	0.069
	(2.517)	(0.439)	(2.717)	(0.430)
LnSales×Post2000	-0.100	-0.051	-0.092	-0.050
	(-0.846)	(-0.804)	(-0.735)	(-0.756)
LnAge×Post2000	-0.187	-0.059	-0.182	-0.059
	(-1.170)	(-0.649)	(-1.151)	(-0.638)
CapInt×Post2000	0.856	0.744	0.974	0.796
	(1.071)	(0.904)	(1.202)	(0.991)
Capex×Post2000	-1.805***	-0.254	-1.827***	-0.256
	(-3.807)	(-0.746)	(-3.882)	(-0.755)
MktShr×Post2000	-0.057	-0.008	-0.125	-0.012
	(-0.502)	(-0.080)	(-1.159)	(-0.115)
WhiteProp×Post2000	-0.240	0.419	-0.155	0.405
	(-0.413)	(1.349)	(-0.277)	(1.350)
VC×Post2000	0.839**	0.161	0.833**	0.160
	(1.998)	(0.819)	(1.968)	(0.816)
LnNumSeg×Post2000	0.399**	0.069	0.403**	0.068
	(2.168)	(0.498)	(2.130)	(0.486)
VCFracSt×Post2000	2.897	0.491	3.422	0.426
	(0.499)	(0.112)	(0.590)	(0.097)
VCFracInd×Post2000	-4.219*	-1.990	-3.768	-2.163
	(-1.719)	(-1.295)	(-1.606)	(-1.359)
HighTech×Post2000	0.386**	-0.017	0.506**	-0.035
	(2.099)	(-0.123)	(2.436)	(-0.265)
LnNumAna×Post2000	0.954**	-0.015		
	(2.171)	(-0.050)		
HHI×Post2000			12.720***	0.299
			(3.368)	(0.078)
TFP	-0.165	-0.187	-0.169	-0.184
	(-0.884)	(-1.419)	(-0.903)	(-1.396)

LnSales	0.864***	0.454***	0.858***	0.450***
	(7.531)	(8.431)	(7.441)	(7.712)
LnAge	-0.410***	-0.227**	-0.408***	-0.226**
	(-3.680)	(-2.353)	(-3.672)	(-2.320)
CapInt	-0.456	-1.217	-0.602	-1.272*
	(-0.502)	(-1.629)	(-0.671)	(-1.742)
Capex	2.307***	0.664***	2.293***	0.664***
	(11.870)	(2.703)	(11.860)	(2.715)
MktShr	-0.118	-0.023	-0.092	-0.020
	(-0.859)	(-0.363)	(-0.672)	(-0.302)
WhiteProp	1.507***	0.593***	1.518***	0.596***
	(3.207)	(3.218)	(3.236)	(3.226)
VC	1.927***	1.471***	1.934***	1.474***
	(11.800)	(10.560)	(11.660)	(10.490)
LnNumSeg	-0.100	0.551***	-0.104	0.552***
	(-0.386)	(3.809)	(-0.398)	(3.802)
VCFracSt	5.886	6.784**	5.766	6.828**
	(1.273)	(2.086)	(1.252)	(2.110)
VCFracInd	6.994***	5.125***	7.347***	5.109***
	(4.804)	(3.873)	(5.713)	(3.979)
HighTech	0.478**	0.368**	0.459**	0.374**
	(2.410)	(2.218)	(2.370)	(2.255)
LnNumAna	-0.291	-0.091		
	(-0.838)	(-0.459)		
HHI			-2.913	0.269
			(-1.098)	(0.114)
Constant	-17.290***	-12.720***	-17.540***	-12.800***
	(-18.550)	(-21.050)	(-18.740)	(-23.670)
Year FE	Yes	Yes	Yes	Yes
Observations	999,000	999,000	999,000	999,000

Table 2.4: Determinants of Exit Decisions through IPOs versus Acquisitions: Periods around the Early-2000s regulations

This table presents the analyses on the determinants of private firms' exit decisions through IPOs or acquisitions during the three-year windows before and after the series of regulations in early 2000s, including the Regulation Fair Disclosure, the Sarbanes Oxley Act, and the Global Settlement. Panel A presents the multinomial logit regressions of exit choices on firm, industry, and state characteristics. The dependent variable is a categorical variable that equals zero if a firm remains private in year *t*, equals one if a firm gets acquired in year *t*, and equals two if a firm goes public in year *t*. Each set of regressions consists of two columns, one that compares the exit decision of IPO to remaining private, and the other that compares the exit decision of getting acquired (ACQ) to remaining private. Columns (1), (2), (5), and (6) use the sub-period 2001-2003, and Columns (3), (4), (7), and (8) use the sub-period 2004-2006. All the independent variables are defined in Appendix C. All regressions include year fixed effects. Robust z-statistics, clustered by three-digit NAICS industry, are reported in parentheses. *, **, and *** represent statistical significance from the omitted category (remaining private) at the 10%, 5%, and 1% levels, respectively. "N/A" denotes coefficients that cannot be reported due to the disclosure rules of the Census. Panel B reports the predicted IPO and ACQ probabilities for the pre-regulation (2001-2003) and post-regulation (2004-2006) eras using the characteristics of firms in the pre-regulation sample and the regression coefficients from Columns (1) to (4). The reported probabilities are multiplied by 10^4 to ease reading.

Panel A: Multinomial Logit Regressions

Sample	Pre-regulation		Post-regulation		Pre-regulation		Post-regulation	
	IPO	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP	0.160	-0.134	0.897*	-0.334**	0.160	-0.156	0.925*	-0.326**
	(0.671)	(-0.381)	(1.846)	(-2.053)	(-0.383)	(-0.377)	(1.841)	(-2.055)
LnSales	0.744*	0.303**	0.611***	0.402***	0.725*	0.300**	0.627***	0.381***
	(1.886)	(2.073)	(3.750)	(5.461)	(1.860)	(2.081)	(3.783)	(5.632)
LnAge	-1.041***	-0.475***	-0.252	-0.131	-1.044***	-0.470***	-0.255	-0.108
	(-5.103)	(-2.876)	(-1.081)	(-0.922)	(-5.089)	(-2.798)	(-0.992)	(-0.946)
CapInt	-2.481*	-1.516*	0.713	-0.439	-2.552*	-1.524*	0.801	-0.406
	(-1.665)	(-1.727)	(0.704)	(-0.526)	-(1.660)	(-1.717)	(0.754)	(-0.403)
Capex	0.212	0.514	-1.260	0.767	0.213	0.515	-1.253	0.770
	(0.370)	(0.814)	(-1.255)	(1.388)	(0.391)	(0.803)	(-1.291)	(1.492)
MktShr	0.203	-0.140	-0.240	-0.031	0.204	-0.144	-0.234	-0.031
	(0.398)	(-0.607)	(-1.023)	(-0.255)	(0.414)	(-0.633)	(-1.189)	(-0.227)
WhiteProp	2.395**	1.514***	0.599	-0.030	2.403**	1.525***	0.624	-0.034
	(2.116)	(3.424)	(0.663)	(-0.063)	(2.099)	(3.467)	(0.650)	(-0.071)
VC	N/A	1.182***	N/A	1.679***	N/A	1.190***	N/A	1.692***
	N/A	(2.964)	N/A	(6.960)	N/A	(3.035)	N/A	(7.025)
LnNumSeg	0.629	1.163***	0.082	0.442***	0.660	1.168***	0.075	0.446***
	(0.833)	(3.661)	(0.235)	(5.597)	(1.003)	(3.992)	(0.228)	(5.600)
VCFracSt	-2.607	6.900***	-2.752	8.651**	-2.615	6.853***	-2.797	8.726**

	(-0.551)	(2.985)	(-0.404)	(2.303)	(-0.497)	(3.045)	(-0.388)	(2.337)
VCFracInd	-2.740	3.795**	3.273	6.019***	-2.755	3.989**	3.152	6.028***
	(-0.495)	(2.242)	(1.128)	(2.662)	(-0.513)	(2.201)	(1.209)	(3.236)
HighTech	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
LnNumAna	0.708	-0.573	0.401	0.035				
	(0.922)	(-1.639)	(0.668)	(0.092)				
HHI					16.580**	1.890	7.926	1.244
					(2.144)	(0.382)	(0.996)	(0.218)
Constant	-17.500***	-10.750***	-14.420***	-11.880***	-17.500***	-10.770***	-14.580***	-12.040***
	(-4.646)	(-7.601)	(-7.800)	(-18.640)	(-4.625)	(-7.600)	(-7.413)	(-18.550)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	154,000	154,000	62,000	62,000	154,000	154,000	62,000	62,000

Panel B: Predicted IPO and ACQ Probabilities for Pre- and Post-regulation Eras

	Pre-regulation Probability	Post-regulation Probability	T-test
IPO	1.367	3.509	42.82
ACQ	1.458	7.083	48.96

Table 2.5: The Changing Impact of Exit Decision Determinants from Pre- to Post-regulation periods

This table presents the multinomial logit regressions of exit choices on the interactions of firm, industry, and state characteristics with the *PostReg*, a dummy variable that equals one if the year of an observation is between 2004 and 2006, and equals zero if the year of the observation is between 2001 and 2003. The dependent variable is a categorical variable that equals zero if a firm remains private in year *t*, equals one if a firm gets acquired in year *t*, and equals two if a firm goes public in year *t*. Columns (1) and (3) compare the exit decision of IPO to remaining private, and Columns (2) and (4) compare the exit decision of getting acquired to remaining private. All the independent variables are defined in Appendix C. All columns include year fixed effects. Robust z-statistics, clustered by three-digit NAICS industry, are reported in parentheses. *, **, and *** represent statistical significance from the omitted category (remaining private) at the 10%, 5%, and 1% levels, respectively. "N/A" denotes coefficients that cannot be reported due to the disclosure rules of the Census.

	IPO	*ACQ*	*IPO*	*ACQ*
	(1)	(2)	(3)	(4)
TFP×PostReg	0.769*	-0.191	0.791	-0.196
	(1.659)	(-0.499)	(1.645)	(-0.511)
LnSales×PostReg	-0.118	0.089	-0.125	0.101
	(-0.315)	(0.508)	(-0.334)	(0.576)
LnAge×PostReg	0.777**	0.355	0.793**	0.346
	(2.353)	(1.362)	(2.434)	(1.334)
CapInt×PostReg	3.081	1.096	2.777	1.189
	(1.487)	(0.732)	(1.474)	(0.806)
Capex×PostReg	-1.482	0.264	-1.566	0.252
	(-1.136)	(0.362)	(-1.298)	(0.348)
MktShr×PostReg	-0.504	0.115	-0.426	0.092
	(-1.492)	(0.455)	(-1.263)	(0.348)
WhiteProp×PostReg	-1.956**	-1.542**	-1.901**	-1.477**
	(-2.016)	(-2.482)	(-2.020)	(-2.399)
VC×PostReg	N/A	0.507	N/A	0.495
	N/A	(1.308)	N/A	(1.281)
LnNumSeg×PostReg	-0.449	-0.707**	-0.448	-0.707**
	(-0.886)	(-2.134)	(-0.867)	(-2.145)
VCFracSt×PostReg	-0.587	1.767	-0.480	1.619
	(-0.049)	(0.497)	(-0.044)	(0.447)
VCFracInd×PostReg	6.915	2.194	6.500	3.668*
	(1.263)	(0.857)	(1.069)	(1.854)
HighTech×PostReg	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A
LnNumAna×PostReg	-0.397	0.654		
	(-0.516)	(1.141)		
HHI			-7.084	1.821

			(-0.977)	(0.170)
TFP	0.128	-0.134	0.146	-0.124
	(0.573)	(-0.381)	(0.621)	(-0.348)
LnSales	0.741*	0.303**	0.744*	0.290**
	(1.919)	(2.074)	(1.906)	(1.987)
LnAge	-1.046***	-0.475***	-1.046***	-0.465***
	(-4.786)	(-2.878)	(-4.982)	(-2.826)
CapInt	-2.345	-1.516*	-2.033	-1.617*
	(-1.564)	(-1.727)	(-1.460)	(-1.832)
Capex	0.210	0.514	0.283	0.522
	(0.340)	(0.842)	(0.488)	(0.857)
MktShr	0.290	-0.140	0.193	-0.123
	(0.865)	(-0.608)	(0.576)	(-0.534)
WhiteProp	2.462*	1.514***	2.513**	1.459***
	(1.930)	(3.425)	(2.216)	(3.195)
VC	3.193***	1.182***	3.232***	1.193***
	(6.378)	(2.965)	(6.376)	(2.984)
LnNumSeg	0.532	1.163***	0.531	1.164***
	(0.929)	(3.663)	(0.900)	(3.678)
VCFracSt	-2.019	6.900***	-2.417	7.009***
	(-0.244)	(2.987)	(-0.322)	(3.031)
VCFracInd	-4.012	3.795**	-2.700	2.423
	(-0.718)	(2.243)	(-0.461)	(1.480)
HighTech	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A
LnNumAna	1.118	-0.573		
	(1.394)	(-1.640)		
HHI			16.330**	-0.316
			(2.247)	(-0.039)
Constant	-17.470***	-10.750***	-16.930***	-11.130***
	(-4.620)	(-7.605)	(-4.359)	(-7.951)
Year FE	Yes	Yes	Yes	Yes
Observations	216,000	216,000	216,000	216,000

Table 2.6: Difference-in-differences Tests on the Predicted IPO and Acquisition Probabilities from Multinomial Logit Regressions

This table reports the difference-in-differences (DiD) tests on the predicted IPO and acquisition probabilities from multinomial logit regressions estimated on various subsamples and time periods (i.e., pre-2000 or post-2000 eras). The full sample period is 1990-2014. For each variable of interest, we sort the full regression sample into four subsamples based on whether the value of the variable is above or below the median and whether the year of the observation is before or after 2000 (1990-2000 vs. 2001-2014). After that, we estimate the multinomial logit regression specified by Equation (2.1) for each of the four subsamples separately and obtain four sets of regression coefficients. We then choose one of the two subsamples in the pre-2000 era as the "base group" and calculate four predicted probabilities (each for IPOs and acquisitions) by applying the four sets of estimated regression coefficients to the characteristics of firms in this base group. For Panels A to F, we use the firms in the industries with more competition (low *HHI*), single-segment firms, firms in the states with high VC coverage, firms in the industries with high VC coverage, firms in the industries with more information asymmetry (low analyst coverage), and high-tech firms as the base group, respectively. In each panel, we present the four calculated probabilities, the differences between the post-2000 and the pre-2000 probabilities (with t-statistics in parentheses), and the DiD estimators calculated as the differences between the two differences (with t-statistics in parentheses). All the numbers (except for t-statistics) are multiplied by 10^4 to ease reading.

Panel A: Predicted IPO/ACQ Probabilities by Industry Concentration

		IPO Probabilities		
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *HHI*	4.180	0.166	-4.014 (-109.000)	-0.475 (-9.454)
Low *HHI*	4.489	<0.001	-4.489 (-69.830)	
		ACQ Probabilities		
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *HHI*	6.316	5.194	-1.122 (-67.410)	2.174 (47.650)
Low *HHI*	6.361	7.413	1.052 (23.280)	

Panel B: Predicted IPO/ACQ Probabilities by Number of Business Segments

		IPO Probabilities		
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
Single-segment	7.039	0.153	-6.886 (-80.930)	2.538 (31.000)
Multi-segment	6.054	1.706	-4.438 (-142.400)	
		ACQ Probabilities		
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
Single-segment	7.811	6.364	-1.447 (-72.110)	0.477 (15.200)
Multi-segment	10.980	10.010	-0.970 (-43.760)	

Panel C: Predicted IPO/ACQ Probabilities by State-level VC Investments

		IPO Probabilities		
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *VCFracSt*	11.200	0.679	-10.521 (-75.270)	2.030 (25.950)

Low *VCFracSt*	8.491	<0.001	-8.491 (-61.82)	

ACQ Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *VCFracSt*	11.880	6.419	-5.461 (-104.900)	14.904 (93.840)
Low *VCFracSt*	8.977	18.420	9.443 (76.490)	

Panel D: Predicted IPO/ACQ Probabilities by Industry-level VC Investments

IPO Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *VCFracInd*	12.680	0.546	-12.134 (-89.940)	5.359 (37.680)
Low *VCFracInd*	6.775	<0.001	-6.775 (-57.770)	
ACQ Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *VCFracInd*	12.570	10.730	-1.840 (-56.290)	8.423 (58.770)
Low *VCFracInd*	5.857	12.440	6.583 (46.420)	

Panel E: Predicted IPO/ACQ Probabilities by Industry-level Analyst Coverage

IPO Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *NumAna*	6.220	<0.001	-6.220 (-64.530)	-0.932 (-12.480)
Low *NumAna*	7.720	0.568	-7.152 (-51.860)	
ACQ Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
High *NumAna*	7.976	6.624	-1.352 (-51.590)	1.934 (36.380)
Low *NumAna*	8.538	9.120	0.582 (9.739)	

Panel F: Predicted IPO/ACQ Probabilities by Whether Industry is High Tech

IPO Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
HighTech	123.800	<0.001	-123.800 (-29.080)	42.288 (12.940)
Non-*HighTech*	85.190	3.678	-81.512 (-23.790)	
ACQ Probabilities				
	Pre-2000	Post-2000	Diff (Post-Pre)	DiD
HighTech	65.330	<0.001	-65.330 (-40.880)	65.160 (37.720)
Non-*HighTech*	49.000	48.830	-0.170 (-0.255)	

Table 2.7: TFP of IPO, Acquired, and Private Firms: Multivariate Analyses

This table presents the OLS regressions of *TFP* on a private firm's exit choices in a given year (i.e., goes public, gets acquired, or remains private), the interactions between exit choices and the *Post2000* dummy variable, and control variables at the firm, industry, and state levels. The dependent variable, *TFP*, is a firm's total factor productivity in year *t*. *IPO* (*ACQ*) is a dummy variable that equals one if the firm goes public (gets acquired) in year *t*. *Post2000* is a dummy variable that equals one if the year of an observation is equal to or later than 2000, and zero otherwise. All other variables are defined in Appendix C. Columns (1) and (2) include year fixed effects; Columns (3) and (4) include year fixed effects and industry fixed effects; Column (5) includes industry×year fixed effects. We report the F-tests and the corresponding p-values for the differences between the coefficients of *IPO×Post2000* and *ACQ×Post2000* in each regression. Robust t-statistics, clustered by three-digit NAICS industry, are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: TFP				
	(1)	(2)	(3)	(4)	(5)
IPO×Post2000	0.122***	0.117**	0.125***	0.121***	0.128***
	(2.693)	(2.668)	(2.841)	(2.724)	(3.011)
IPO	-0.025	-0.023	-0.041	-0.038	-0.041
	(-0.636)	(-0.557)	(-1.049)	(-0.961)	(-1.145)
ACQ×Post2000	0.037	0.034	0.037	0.035	0.035
	(1.196)	(1.081)	(1.184)	(1.123)	(1.191)
ACQ	-0.038	-0.037	-0.044*	-0.043*	-0.043**
	(-1.624)	(-1.532)	(-1.935)	(-1.857)	(-2.029)
LnSales	0.100***	0.100***	0.109***	0.109***	0.111***
	(13.040)	(12.380)	(13.960)	(13.860)	(15.240)
LnAge	-0.072***	-0.072***	-0.075***	-0.075***	-0.076***
	(-39.440)	(-35.850)	(-36.710)	(-37.130)	(-35.420)
CapInt	-0.339***	-0.330***	-0.280***	-0.278***	-0.287***
	(-6.119)	(-5.919)	(-4.982)	(-4.968)	(-5.097)
Capex	0.462***	0.463***	0.455***	0.456***	0.459***
	(19.130)	(19.140)	(19.470)	(19.400)	(19.400)
MktShr	0.037**	0.044**	0.031*	0.032*	0.029*
	(2.116)	(2.479)	(1.738)	(1.744)	(1.737)
WhiteProp	-0.225***	-0.223***	-0.245***	-0.244***	-0.248***
	(-13.560)	(-14.220)	(-16.870)	(-16.860)	(-17.890)
VC	-0.027***	-0.027***	-0.035***	-0.035***	-0.036***
	(-3.281)	(-3.165)	(-4.028)	(-4.015)	(-4.436)
LnNumSeg	-0.013*	-0.013**	-0.010	-0.010	-0.012*
	(-1.963)	(-2.045)	(-1.465)	(-1.461)	(-1.760)
VCFracSt	0.474***	0.472***	0.430***	0.428***	0.438***
	(3.002)	(3.138)	(3.468)	(3.481)	(3.827)
VCFracInd	-0.612*	-0.618*	-0.073	-0.049	
	(-1.778)	(-2.005)	(-0.369)	(-0.235)	

HighTech	0.061	0.056			
	(1.578)	(1.574)			
LnNumAna	-0.059		-0.035**		
	(-1.315)		(-2.310)		
HHI		-0.913***		0.083	
		(-3.064)		(0.312)	
Constant	-0.539***	-0.592***	-0.638***	-0.681***	-0.698***
	(-6.194)	(-9.462)	(-8.991)	(-11.090)	(-12.030)
F-test	5.060	5.409	6.328	6.067	7.072
P-value	0.029	0.024	0.015	0.017	0.010
Year FE	Yes	Yes	Yes	Yes	No
Industry FE	No	No	Yes	Yes	No
Industry×Year FE	No	No	No	No	Yes
Observations	999,000	999,000	999,000	999,000	999,000
R-squared	0.125	0.126	0.136	0.136	0.139

Table 2.8: Post-exit Long-term TFP for IPO and Matched Private Firms

This table presents the OLS regressions of firms' post-exit long-term total factor productivity (*TFP*) on *IPO*, the interaction between *IPO* and the *Post2000* dummy variable, and other control variables. The sample includes IPO firms and matched private firms with non-missing TFP data within three years after the IPO. For each firm that goes public in a given year during our sample period, we first find remaining-private firms that operate in the same state and the same industry (at the three-digit NAICS level), as well as have the same VC-backing status as the IPO firm in that year. Further, we require the size (in terms of sales) of the matched firms to be within 0.5 and 2 times of the size of the IPO firm. Finally, among the above set of matched firms, we choose the one with the closest TFP to the IPO firm. We run the regressions separately for VC-backed firms and non-VC-backed firms. The dependent variable of Columns (1) and (2) is the three-year average TFP after the IPO. The dependent variable of Columns (3) and (4) is the two-year average TFP after the IPO. *IPO* is a dummy variable that equals one if the firm goes public in year *t*, and zero if the firm remains private. *Post2000* is a dummy variable that equals one if the year of an observation is later than 2000. All other variables are defined in Appendix C. All regressions include year fixed effects and matched-pair fixed effects. Robust t-statistics, clustered by three-digit NAICS industry, are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dep. Var.: *TFP3yr*		Dep. Var.: *TFP2yr*	
Subsamples	*VC*	*Non-VC*	*VC*	*Non-VC*
	(1)	(2)	(3)	(4)
IPO×Post2000	-0.184**	-0.059	-0.244**	-0.069
	(-2.188)	(-0.522)	(-2.836)	(-0.580)
IPO	0.140***	-0.003	0.165***	0.006
	(3.069)	(-0.046)	(3.295)	(0.104)
LnSales	0.086	0.039	0.094	0.045
	(1.339)	(0.591)	(1.652)	(0.637)
LnAge	-0.119***	-0.099***	-0.115***	-0.096***
	(-8.643)	(-3.165)	(-6.804)	(-2.898)
CapInt	-0.091	0.281	-0.149	0.273
	(-0.339)	(1.455)	(-0.463)	(1.125)
Capex	0.049	-0.389**	0.020	-0.432***
	(0.204)	(-2.837)	(0.079)	(-3.243)
MktShr	0.132	-0.026	0.136	-0.028
	(1.631)	(-0.560)	(1.587)	(-0.653)
WhiteProp	-0.250	-0.092	-0.215	-0.136**
	(-1.402)	(-1.463)	(-1.105)	(-2.103)
LnNumSeg	0.071**	0.015	0.063**	0.019
	(2.775)	(0.514)	(2.303)	(0.629)
Constant	-0.517	0.002	-0.617	-0.037
	(-0.786)	(0.003)	(-0.997)	(-0.049)
Year FE	Yes	Yes	Yes	Yes
Matched Pair FE	Yes	Yes	Yes	Yes

Observations	450	600	450	600
R-squared	0.470	0.499	0.456	0.499

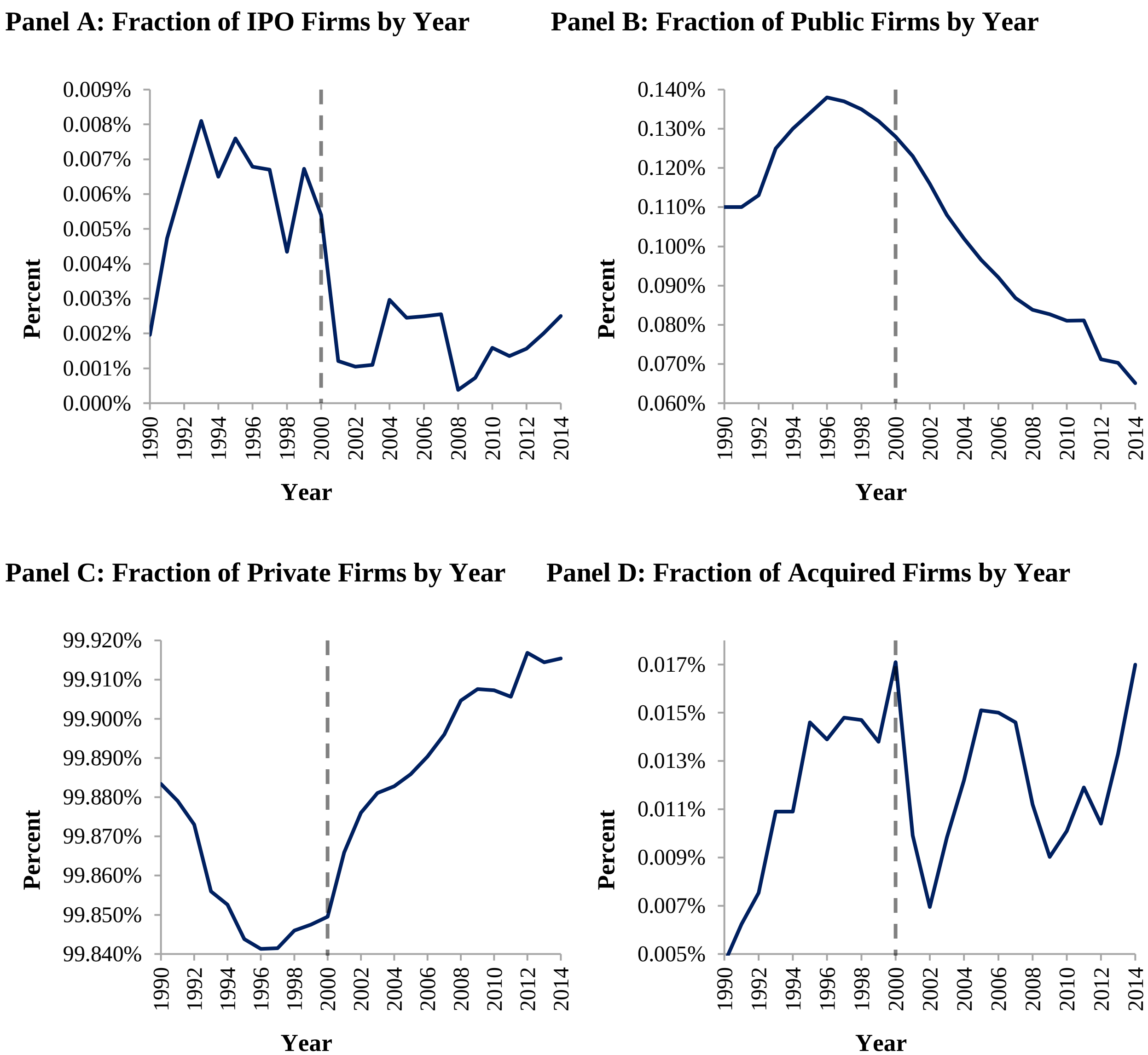
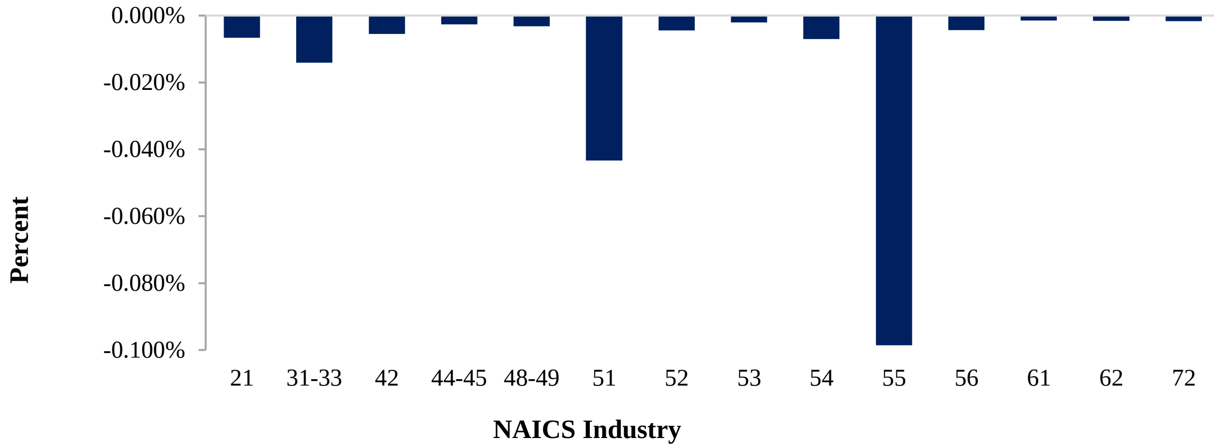
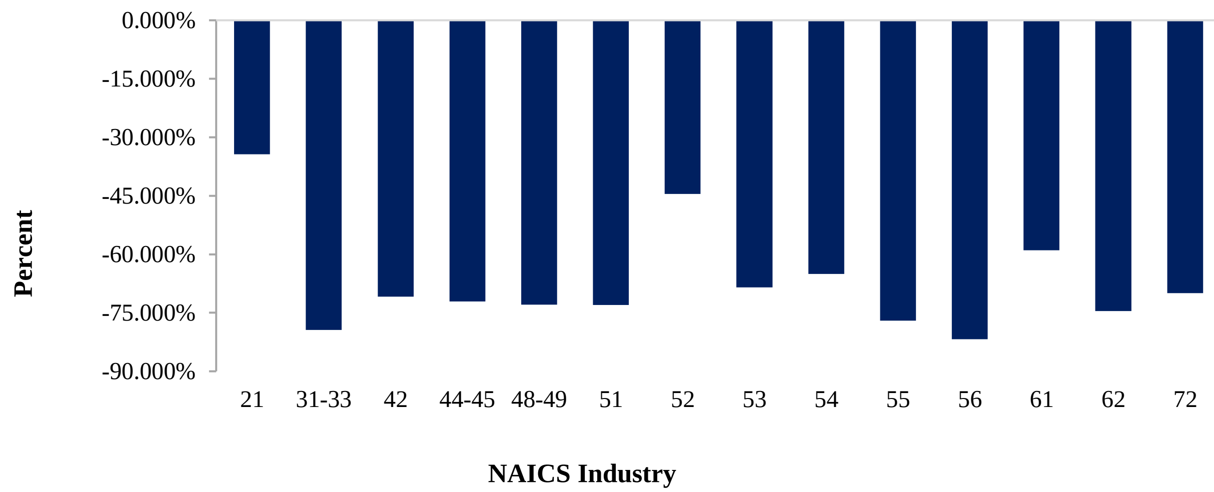


Figure 2.1: Fraction of IPO/Acquired/Public/Private Firms by Year
This figure shows the fraction of IPO/acquired/public/private firms in the LBD sample from 1990 to 2014. IPO/acquired/public firms are identified by matching LBD data to SDC and Compustat data. The remaining firms are treated as private firms.

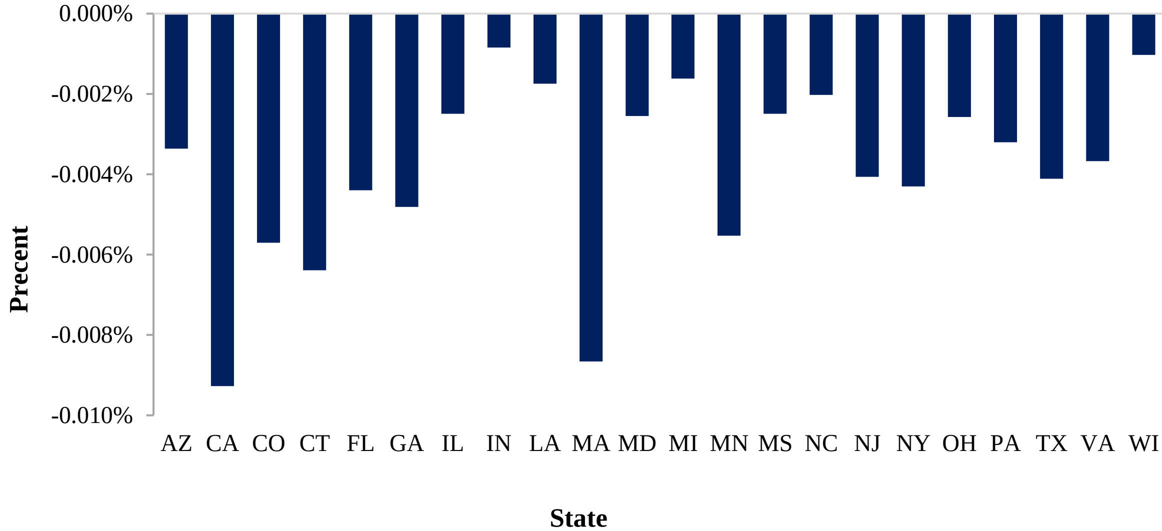
Panel A: Change in IPO Propensity from Pre-2000 to Post-2000 Era by NAICS Industry



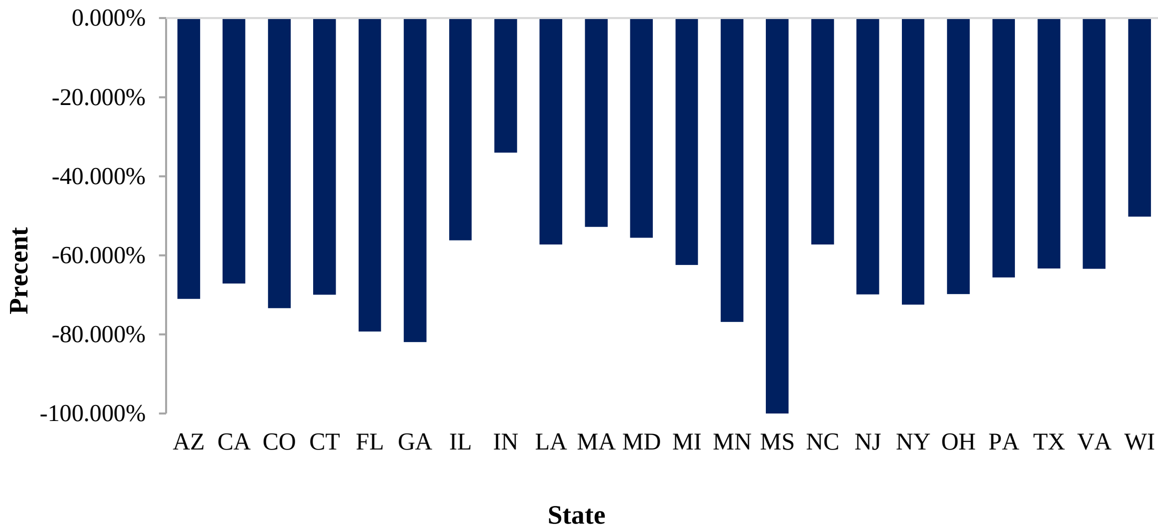
Panel B: Percentage Change in IPO Propensity from Pre-2000 to Post-2000 Era by NAICS Industry



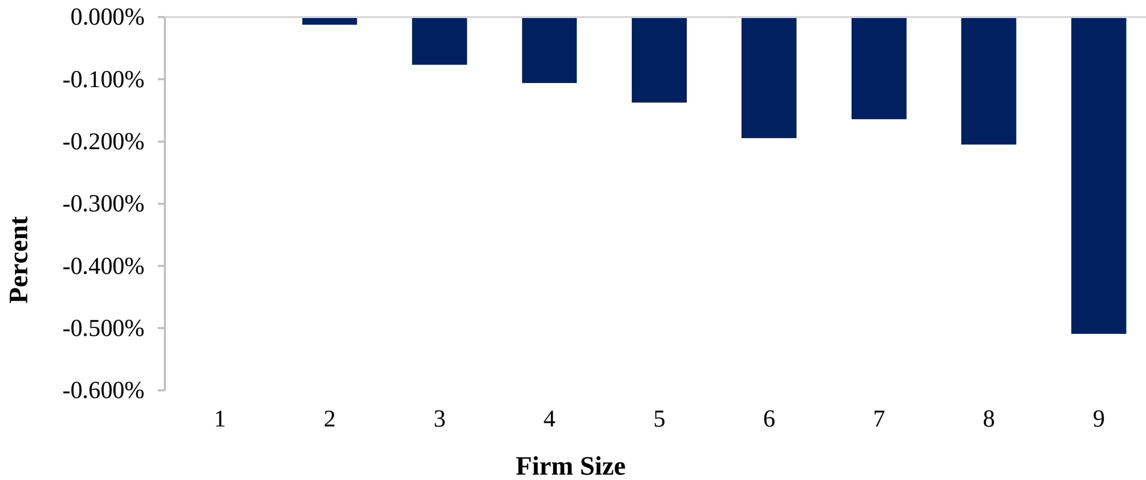
Panel C: Change in IPO Propensity from Pre-2000 to Post-2000 Era by State



Panel D: Percentage Change in IPO Propensity from Pre-2000 to Post-2000 Era by State



Panel E: Change in IPO Propensity from Pre-2000 to Post-2000 Era by Firm Size



Panel F: Percentage Change in IPO Propensity from Pre-2000 to Post-2000 Era by Firm Size

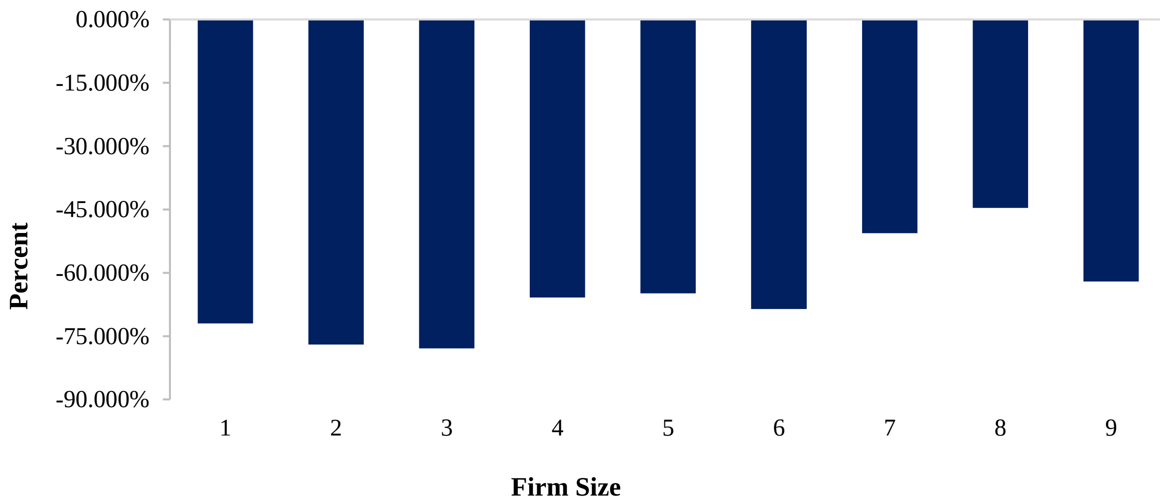
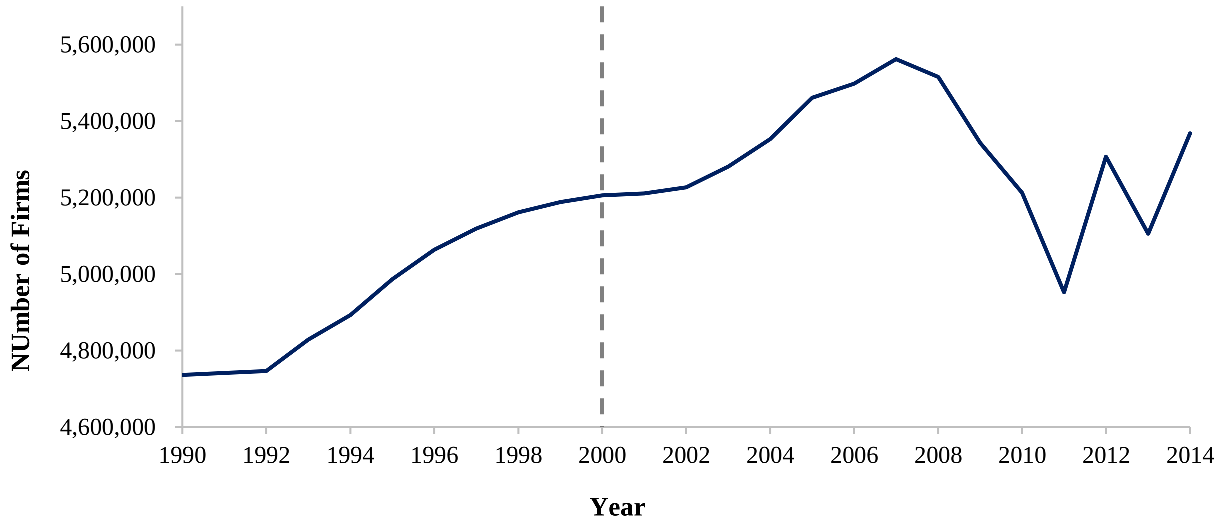


Figure 2.2: Raw and Percentage Changes in IPO Propensity from Pre-2000 to Post-2000 Era

This figure shows the raw and percentage changes in IPO propensity in the sample of LBD firms from pre-2000 to post-2000 era by various groups of firms. Panels A and B show the raw and percentage changes in IPO propensity by industry (at the two-digit NAICS level). Panels C and D show the raw and percentage changes in IPO propensity by state. The statistics for certain industries and states from LBD data are omitted due to the disclosure requirements of the Census. Panels E and F show the raw and percentage changes in IPO propensity by firms with different size (number of employees).

Panel A: Number of LBD Firms by Year



Panel B: Fraction of LBD Firms with at Least 200 Employees by Year

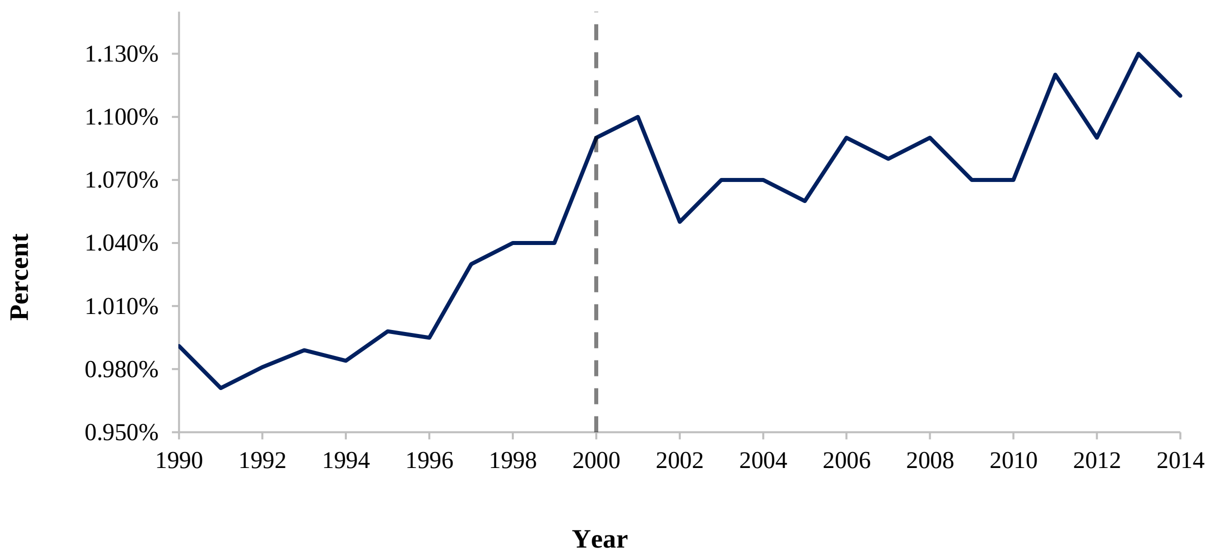
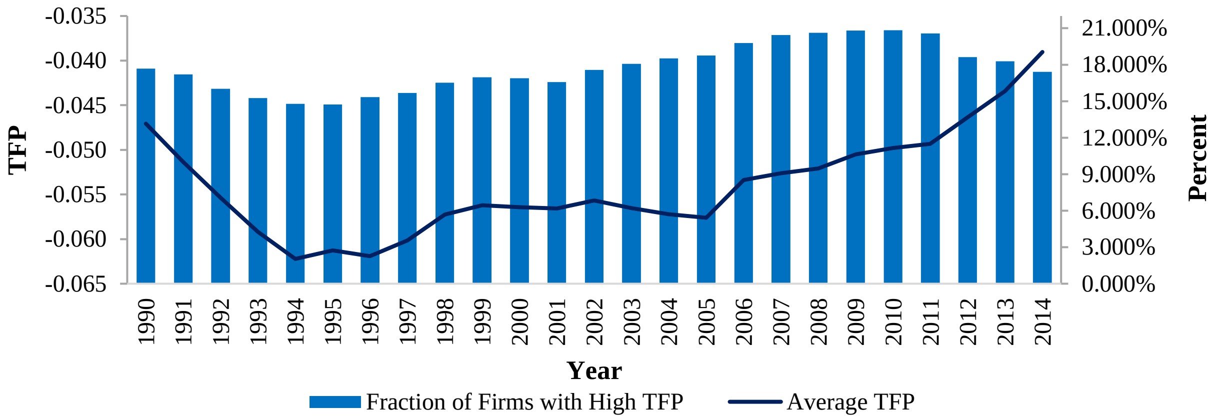


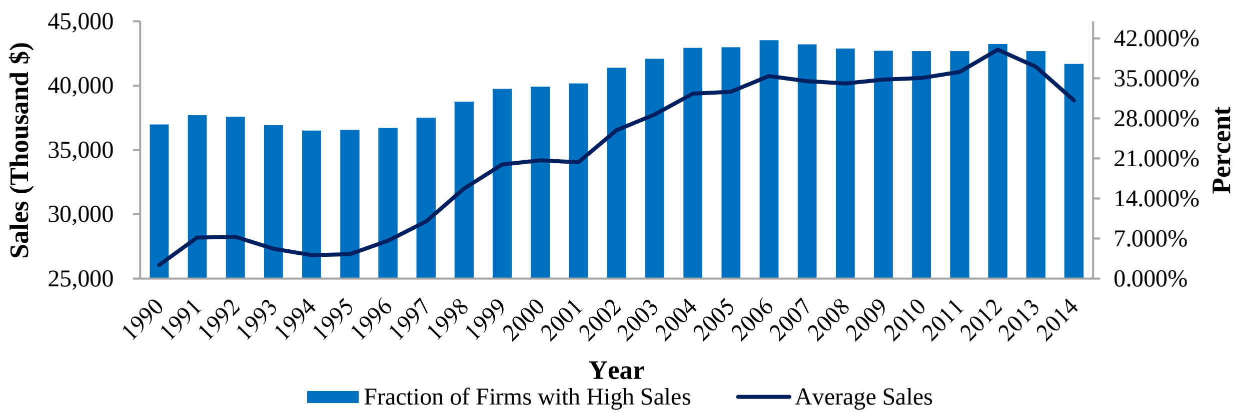
Figure 2.3: Number of Firms and Fraction of Firms with at Least 200 Employees in the LBD Sample by Year

This figure shows the number of firms and the fraction of firms with at least 200 employees in the LBD sample from 1990 to 2014.

Panel A: Average TFP and Fraction of Manufacturing Firms with High TFP by Year



Panel B: Average Sales and Fraction of Manufacturing Firms with High Sales by Year



Panel C: Average Sales Growth and Fraction of Manufacturing Firms with High Sales Growth by Year

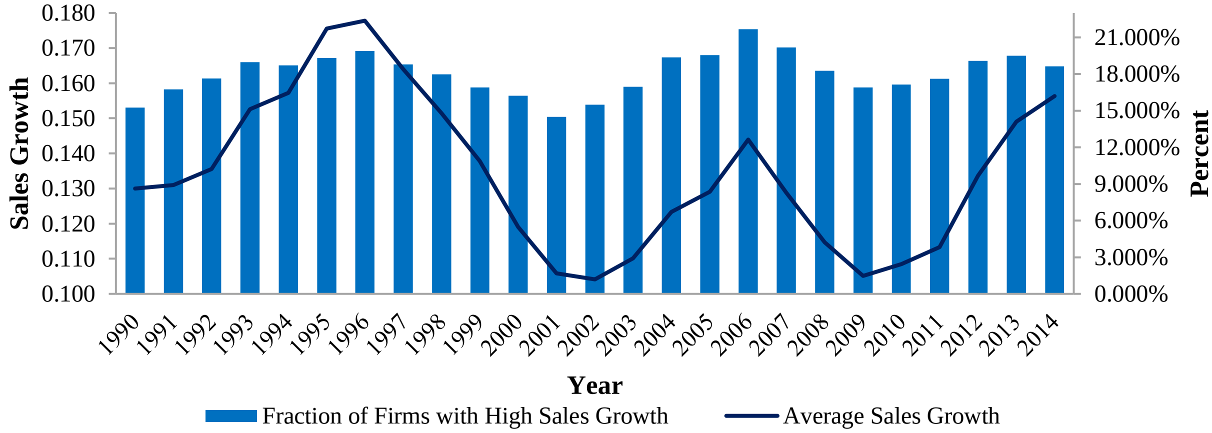
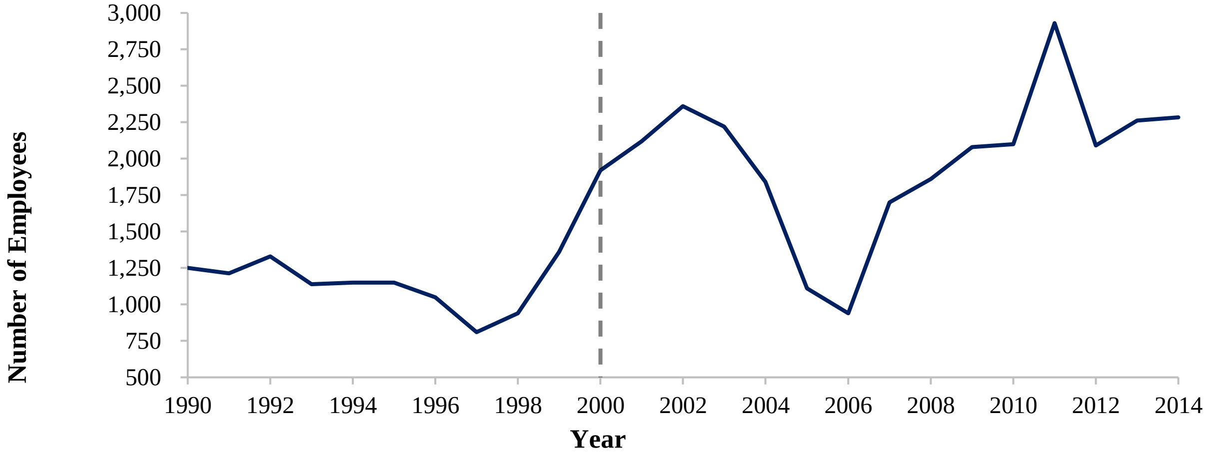


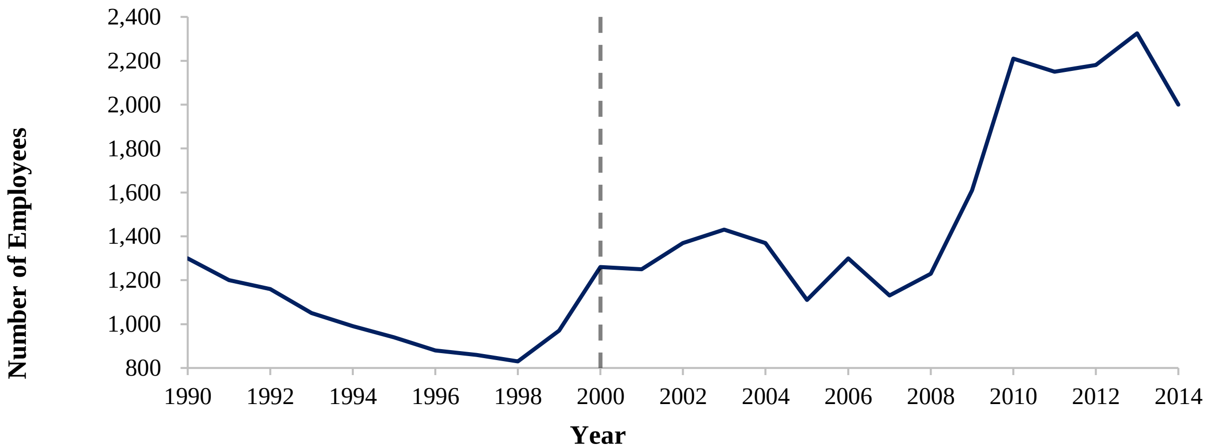
Figure 2.4: Average TFP/Sales/Sales Growth and Fraction of Manufacturing Firms with High TFP/Sales/Sales Growth by Year

This figure shows the five-year rolling average TFP/sales/sales growth by year (the left vertical axis) as well as the time trend in the fraction of manufacturing firms with TFP greater than 0.05, sales greater than $10 million, or sales growth greater than 15% (the right vertical axis). Definitions of annual TFP, sales, and sales growth are provided in Appendix C.

Panel A: Average Number of Employees of IPO Firms by Year



Panel B: Average Number of Employees of Acquired Firms by Year



Panel C: Average Number of Employees of Private Firms by Year

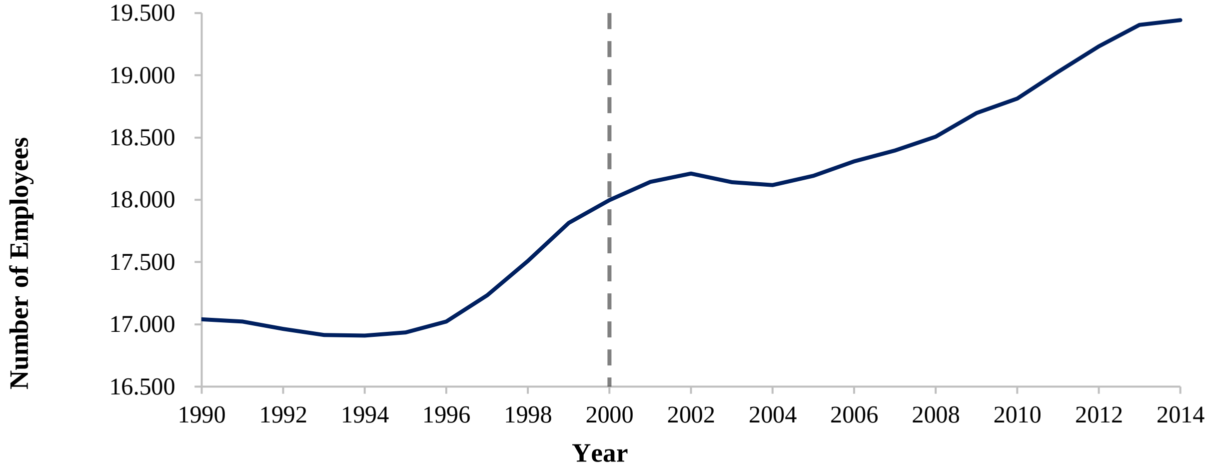
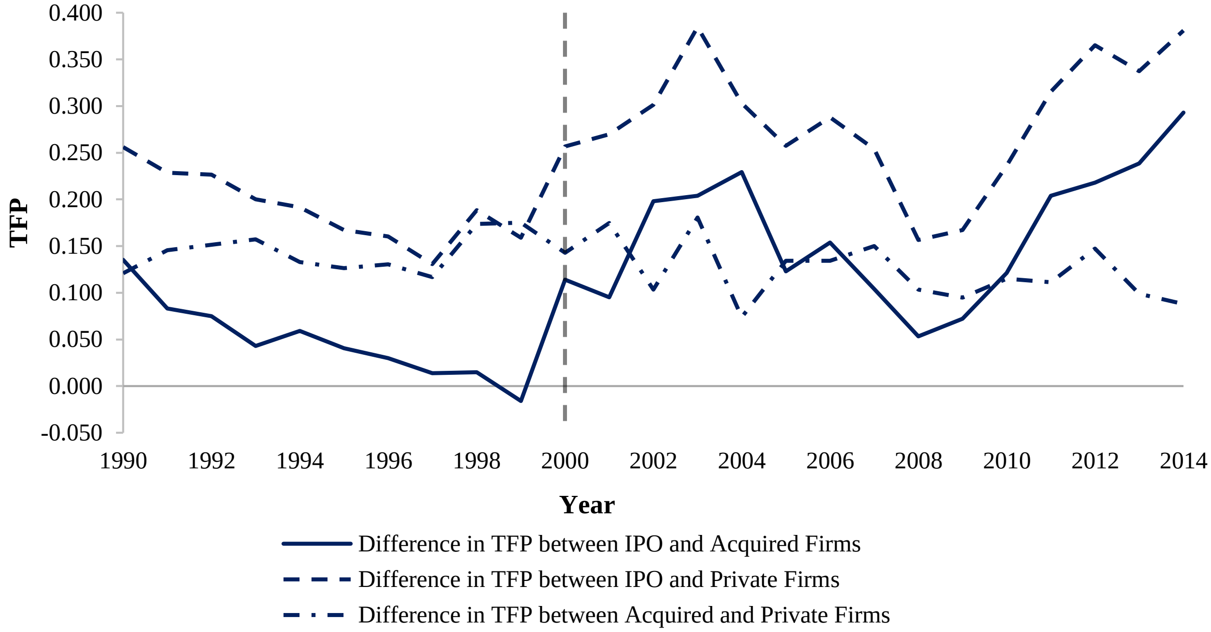


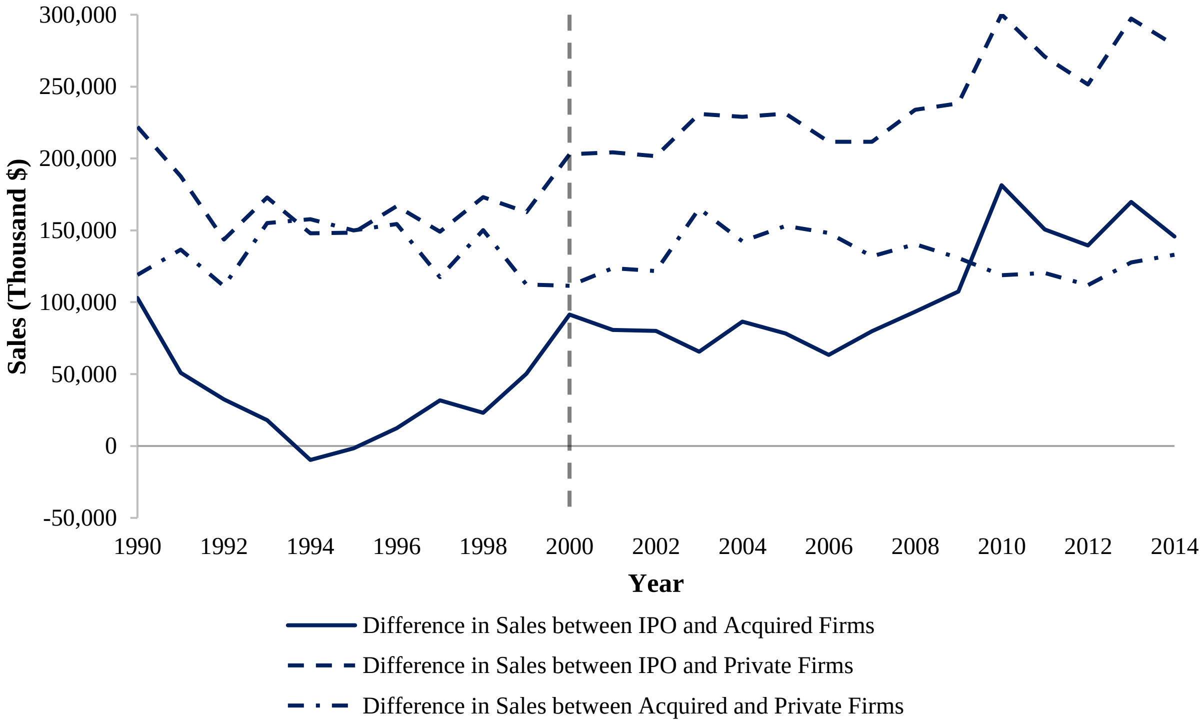
Figure 2.5: Average Number of Employees of IPO/Acquired/Public/Private Firms in the LBD Sample by Year

This figure shows the five-year rolling average number of employees of IPO/acquired/private firms in the LBD sample from 1990 to 2014. IPO/acquired firms are identified by matching LBD data to SDC and Compustat data. The remaining firms are treated as private firms.

Panel A: Difference in TFP between IPO/Acquired/Private Manufacturing Firms by Year



Panel B: Difference in Sales between IPO/Acquired/Private Manufacturing Firms by Year



Panel C: Difference in Sales Growth between IPO/Acquired/Private Manufacturing Firms by Year

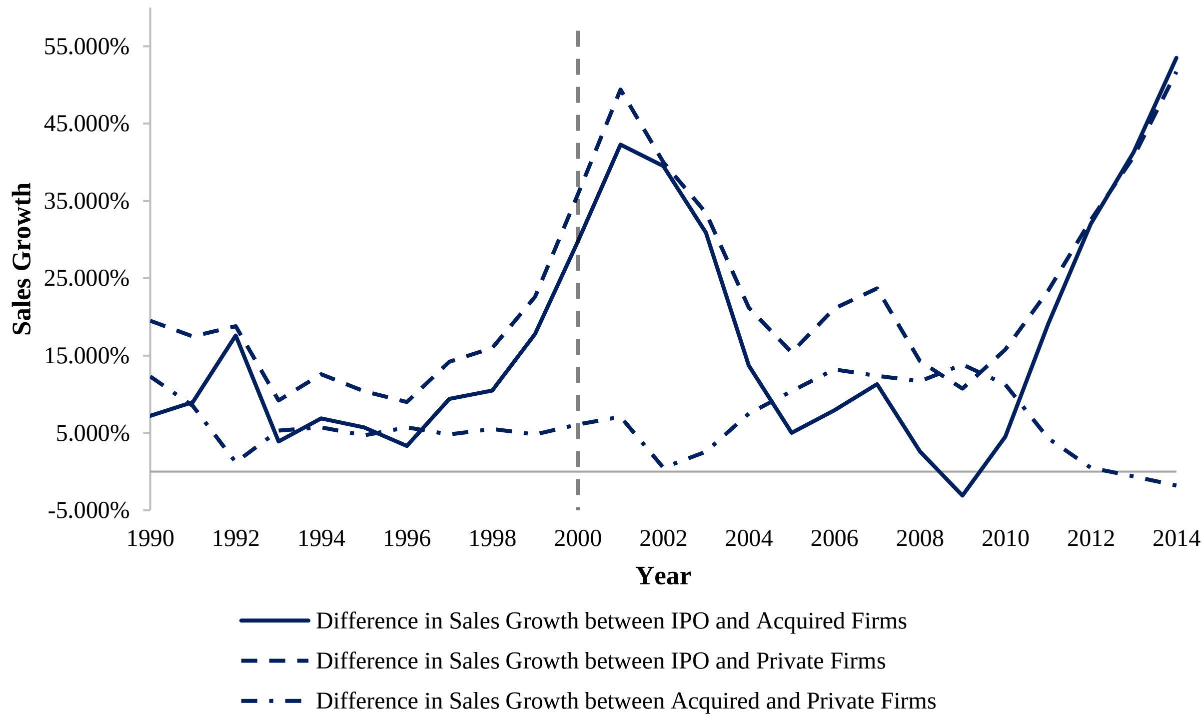
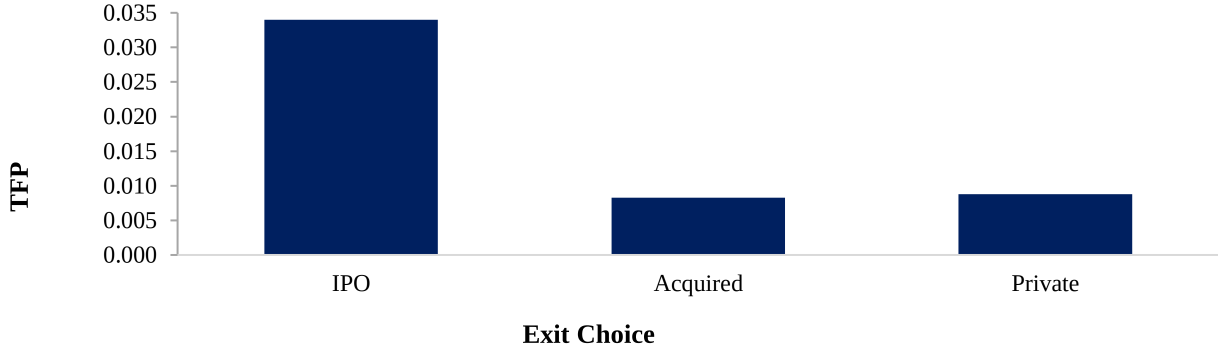


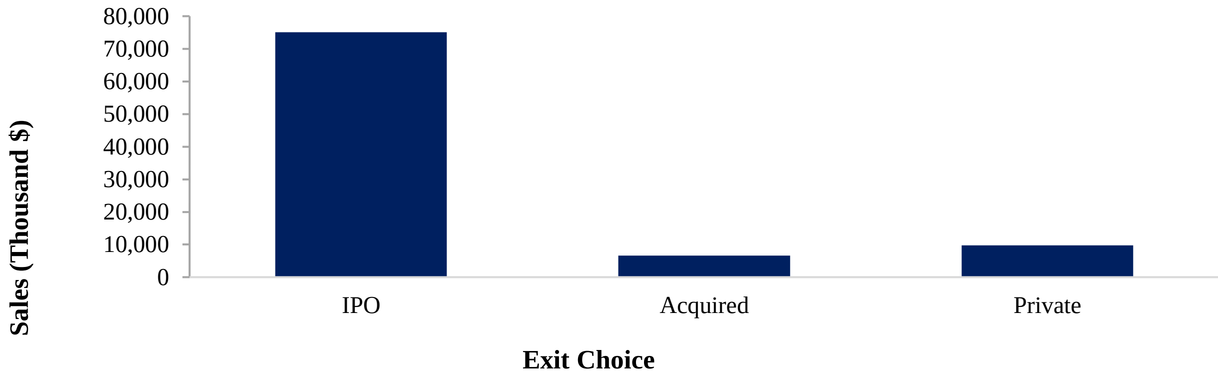
Figure 2.6: Difference in TFP/Sales/Sales Growth among IPO/Acquired/Private Manufacturing Firms by Year

This figure shows the difference in TFP/sales/sales growth among IPO/acquired/private manufacturing firms from 1990 to 2014. Definitions of annual TFP, sales, and sales growth are provided in Appendix C.

Panel A: Change in TFP from Pre-2000 to Post-2000 Era by Exit Choice



Panel B: Change in Sales from Pre-2000 to Post-2000 Era by Exit Choice



Panel C: Change in Sales Growth from Pre-2000 to Post-2000 Era by Exit Choice

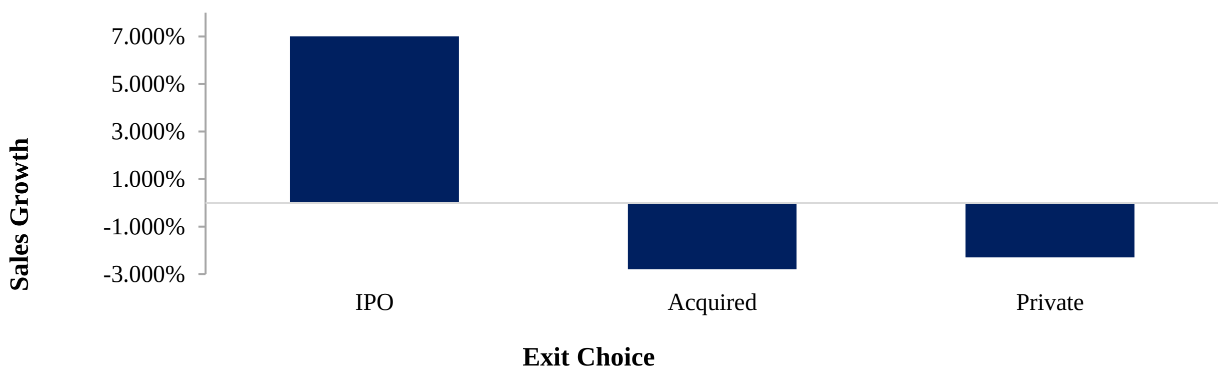


Figure 2.7: Changes in TFP/Sales/Sales Growth from Pre-2000 to Post-2000 Era by Exit Choices

This figure shows the changes in TFP/sales/sales growth for IPO/acquired/private manufacturing firms from pre-2000 to post-2000 era. Definitions of annual TFP, sales, and sales growth are provided in Appendix C.

CHAPTER 3

Diffusers of Entrepreneurship[44]

[44] Xiao Ren, Sean Cao, Jie He, and Zhilu Lin. To be submitted to *Journal of Accounting and Economics*. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1091. All results have been reviewed to ensure that no confidential information is disclosed. CBDRB-FY20-147.

Abstract

We examine an emerging phenomenon that talented employees leave successful entrepreneurial firms to join less mature ones. Using a unique person-level dataset and a comprehensive sample of private firms from the U.S. Census Bureau, we find that these “entrepreneurial diffusers”, by potentially passing on entrepreneurial knowledge and institutional wisdom, can enhance their new colleagues’ innovation productivity and help their new employers successfully exit. We further find that these diffusers are motivated by an entrepreneurial culture that prizes risk-taking rather than by the prospect of monetary gain. Finally, the departure of entrepreneurial diffusers contributes to the well-documented long-run IPO underperformance in accounting and stock returns. Our paper offers new insights into a labor market channel of the cross-firm diffusion of entrepreneurship, which is critical to the sustainability of a vibrant entrepreneurial ecosystem.

3.1 Introduction

Entrepreneurship is a crucial engine for long-term growth. Decades of Silicon Valley success stories, from Google to Facebook to recent “unicorns” such as Uber and Airbnb, have captivated the news media and pop culture, inspired young talents to join new ventures, and motivated researchers to explore the underlying economic forces that are conducive to a sustainable and vibrant entrepreneurial ecosystem. While much of the existing research focuses on the operations and financing of start-up companies on a standalone basis, an equally important question is how the entrepreneurial spirit, culture of innovation, institutional wisdom, and technological knowledge are passed on from successful start-ups to less mature ones. Understanding the nature and mechanisms of such entrepreneurship “diffusion” is important because the collective success of a country’s entrepreneurial ventures is critical to its economic growth and wealth creation. As yet, however, the channels through which entrepreneurship diffuses in an economy are largely underexplored in the literature.

In this paper, we aim to fill in the gap by examining the flow of human capital from mature entrepreneurial firms that have just successfully "exited" (in the form of initial public offerings (IPOs) or sell-outs) to less mature private start-ups.[45] We also explore the motives for and consequences of such labor movement. The post-"exit" exodus of key employees from successful entrepreneurial firms is a well-documented phenomenon in Silicon Valley. For instance, shortly after Google went public in August 2004, 100 of the first 300 employees that were hired left the company, taking with them the institutional wisdom, entrepreneurial culture, and mentorship techniques developed during their time there. Many opted to continue their entrepreneurial pursuits by either starting their own businesses or joining other young start-ups, rather than enjoying early retirement or moving to another public corporation for the sake of job stability and promotion. The same pattern of human capital flow also occurred at other successful entrepreneurial ventures such as Intel, PayPal, Facebook, and Uber, and has thus become a part of Silicon Valley's culture. For example, Elon Musk left PayPal to join the newly established Tesla in 2004. Contrary to the popular belief that Musk was the founder of Tesla, he initially worked as Tesla's senior engineer (more specifically, product architect) and became its CEO in 2008. In this paper, we provide a detailed look into this culture of labor movement and examine whether it facilitates the diffusion of entrepreneurship throughout the economy. Specifically, we focus on the group of employees who leave newly public or recently acquired entrepreneurial ventures to join other private firms

[45] Although there might be other ways to gauge the success of an entrepreneurial firm—such as its growth rate or the ability to obtain venture capital investments—we use its exit event (i.e., an IPO or sell-out) to determine whether it is mature or not because such events are generally viewed as the clearest signals of entrepreneurial success. See previous literature such as Poulsen and Stegemoller (2008), Bayar and Chemmanur (2012), Chemmanur et al. (2018), and Bowen, Fresard, and Hoberg (2020) for a more detailed discussion on why and when private entrepreneurial firms choose to "exit," i.e., to change ownership structures to allow early equity investors such as entrepreneurs and venture capitalists to cash out.

that have not reached the point of exiting. As these people help "diffuse" the entrepreneurial knowledge and technological know-how to new start-ups (e.g., by serving as team-leaders or mentors), we call them "entrepreneurial diffusers."

Our paper mainly aims to answer four related research questions. First, who are these entrepreneurial diffusers, and do they exhibit stronger "entrepreneurial qualities" (i.e., the essential characteristics required for entrepreneurial success) than those employees who choose to stay with current employers or leave for other publicly traded companies after their firm's exit? As entrepreneurial qualities are hard to measure in practice, we will mainly examine an employee's past innovation behavior to gauge the degree of her creativity and risk-taking spirit, which are both required for achieving entrepreneurial success. Second, we examine whether these entrepreneurial diffusers add value to the new start-ups they join by increasing the latter's innovation potential and likelihood of a successful exit. If the diffusion of entrepreneurship bolsters the sustainability and growth of an entrepreneurial ecosystem, this has important implications for the long-term health and welfare of the economy.[46] Third, we investigate the motives of entrepreneurial diffusers who change jobs amid early career success. In particular, we will examine two mutually non-exclusive incentives, namely, the desire to accumulate wealth by having their wages or other earnings increased over the long term (i.e., the monetary incentive), and the preference for adventurous and exploratory working environments as opposed to the staid workplace culture of mature and mundane public firms (i.e., the entrepreneurial spirit incentive).[47] Finally, we examine the

---

[46] The value of working for successful entrepreneurial ventures has been widely recognized by business practitioners. For example, Carolyn Betts-Fleming, the chief executive of Betts Recruiting, a leading recruiting firm based in San Francisco, argued in 2019 that "the track record of riding a wave at a company from nothing to IPO in a short period is a very valuable asset to have."
[47] It is worth noting that entrepreneurial diffusers could also be driven by other motivations. We focus on the two major incentives that are widely discussed among practitioners and in the literature (to be discussed later).

consequences that the departure of entrepreneurial diffusers has on their original employers in terms of accounting performance and shareholder returns.

To answer these questions, we need to overcome several empirical hurdles, most of which arise from data limitations. First, to examine whether entrepreneurial diffusers contribute to the success of the new start-ups that they join, we need to observe not only those start-ups that end up successfully exiting but also those that do not. This is difficult to achieve because most commercial databases, such as Compustat and CRSP, focus primarily on publicly traded firms, and thus account solely for firms that have successfully exited. Those databases that include some private firms only cover a small subset of the population without providing sufficient information.[48] To tackle this problem, we make use of the Longitudinal Business Database (LBD) maintained by the U.S. Census Bureau, which covers the entire universe of business establishments in the U.S., both public and private.

Second, we need person-level data on entrepreneurial diffusers, including their employment history and basic demographic characteristics that may influence their risk attitudes (e.g., age, gender, and ethnicity). However, most commercial databases of person-level data only cover top executives or board directors. To overcome this difficulty, we exploit another dataset from the U.S. Census Bureau, namely, the Longitudinal Employer-Household Dynamics (LEHD) dataset, which contains individual employees' entire job histories and demographic information for over 95% of the private sector in all U.S. states. By matching the LEHD to the LBD, we are able to identify entrepreneurial diffusers, as well as the firms they leave and the firms that they

[48] For example, VentureXpert only covers private firms that are backed by venture capital (i.e., the cream of the crop in the vast population of entrepreneurial ventures) and Capital IQ mostly covers large private firms that are mandated by the U.S. Securities and Exchange Commission (SEC) to disclose financial information (see, e.g., Gao, Hsu, and Li (2018)). Similarly, SDC contains transaction-level information only for those private firms that are ready to exit in the form of IPOs or sell-outs, but not for those that do not successfully reach the exiting stage.

subsequently join. Further, the LEHD database contains information on employees' earnings, including base salary as well as other forms of compensation that are taxed as ordinary income, such as bonuses, stocks, stock options, and profit distributions (see, e.g., Tate and Yang (2015), and Aldatmaz, Ouimet, and Van Wesep (2018)), which allows us to effectively capture all types of labor income gains in order to discern the diffusers' incentives.

Third, to study the entrepreneurial quality of the diffusers, we need information on their past innovation activities. Since neither the LBD nor the LEHD provide such information, we make use of the individual inventor data from the Harvard Business School (HBS) Patenting Database, which contains information about each inventor's patenting activities as well as where the inventor was employed when a given patent was filed.

While both of our main data sources (i.e., the census data and the inventor data) have their own limitations, they perform complementary functions in our analysis. Although the entrepreneurial diffusers identified from the census data do not necessarily engage in innovation at the same level that inventors do, they may possess other talents such as technical, marketing, mentoring/advising, or management skills that could benefit the new start-ups they join. At the same time, although using inventors' patenting activities to track their employment history is imperfect, it allows us to gauge the entrepreneurial quality of a subset of important, technologically savvy diffusers. Hence, integrating these two datasets in our analysis allows us to provide unique insights on the phenomenon of entrepreneurship diffusion.[49]

Using the inventor data, we first find that the innovation productivity of entrepreneurial diffusers—as measured by the number of patents they generate, the average number of citations

[49] Our empirical design thus reflects the complementarity of the two data sources. Where helpful, we show parallel results to demonstrate that our findings are robust to using either data source. For questions that only one data source can help answer, we rely on the unique information from that particular source.

received by each of those patents, the average originality of the patents, and the number of exploratory patents they generate—is higher than that of "stayers" (i.e., those inventors who choose to stay with newly exited firms), "leavers to public firms" (i.e., those who leave newly exited firms for other public firms), or even new hires. Thus, entrepreneurial diffusers seem to have the best talent among all types of employees at newly exited firms. The loss of their talents cannot be easily replaced by hiring new employees. These results suggest that entrepreneurial diffusers possess the creativity and the risk-taking spirit required for entrepreneurial success.

We next turn to the census data, and examine whether and how these entrepreneurial diffusers add value to the new start-ups they join. If such employees possess valuable human capital and pass on their skills, vision, and entrepreneurial spirit to their new employers, then the latter's likelihood of successfully exiting, in the form of either an IPO or a sell-out, should increase in the fraction of entrepreneurial diffusers among the firm's workforce. To fully address endogeneity issues, we would ideally want to observe exogenous shocks to a start-up's fraction of diffusers but not other types of employees, but such shocks are hard to come by. Further, compared to analyses of public firms, studies on private firms are more often hamstrung by the limitations of available data, which makes a clean identification strategy even more challenging. Therefore, we try our best to mitigate endogeneity concerns by matching exiting firms to non-exiting ones on the basis of key observable characteristics available for the private firms in our sample that are likely to be associated with firm quality, such as VC-backing status, which is commonly used as a comprehensive proxy for unobservable firm quality (see, e.g., Hochberg, Ljungqvist, and Lu (2007), Kerr, Lerner, and Schoar (2011), and Dimmock, Huang, and Weisbenner (2019)). Specifically, we match non-exiting private firms to exiting ones based on year, industry, size, age, VC-backing status, and whether they operate multiple establishments, and then compare the respective likelihoods of a subsequent exit. Using the matched sample, we find that a one percentage point increase in the fraction of a start-up's employees who are entrepreneurial diffusers (i.e., those who at some point left newly exited firms and moved to private firms) is associated with a 3.2 percentage point increase in the probability that the firm will successfully exit. This result suggests that entrepreneurial diffusers are likely to add value to the new start-ups they join.

We then explore one specific channel of entrepreneurial diffusion's value creation, namely, the mentoring and nurturing of new colleagues, which improves firm productivity. Using the inventor data, we find that, in the five years after entrepreneurial diffusers join these start-ups, they significantly outperform matched firms (with similar ex-ante characteristics but without such labor inflows) in terms of innovation output, quality, originality, and exploration. More importantly, upon the hiring of entrepreneurial diffusers, the *non-diffuser* inventors at these start-ups begin to exhibit greater innovation productivity than ex-ante similar inventors at the matched firms. These results suggest that entrepreneurial diffusers enhance the innovation potential of the start-ups they join by playing a mentoring role.

We acknowledge that our matching procedures in these two tests are imperfect. It is possible that the above results related to the likelihood of a successful exit or changes in innovation productivity are driven by entrepreneurial diffusers' ability to identify and join firms with high potentials to succeed. However, such selection-driven human capital flow can be viewed as a useful *signal* of private firms' quality to other entrepreneurial market participants and thus represents another form of "diffusion" that is currently unexplored in the literature. Given the limitations in available data (i.e., the lack of hard information) on private firms, the soft information possessed by entrepreneurial diffusers, which is reflected in their job-hopping decisions, can be useful for private equity investors and other important stakeholders such as suppliers, customers, and employees, who seek to identify the quality and potential of private firms. In this sense, entrepreneurial diffusers pass their private information about the start-ups they join to the entire entrepreneurial market, which, like the diffusion of their skills and knowledge, enhances the welfare of the new venture ecosystem.

Next, we investigate the motives of entrepreneurial diffusers to leave the newly exited firms and join other start-ups. To test the monetary incentive, we use census data to examine the change in labor income of entrepreneurial diffusers after they move to private firms. We find that, compared to stayers and leavers to public firms, entrepreneurial diffusers do not experience a significantly higher labor income growth in either the short- or long-term. These results suggest that entrepreneurial diffusers do not jump to private firms to grow their personal wealth, which is inconsistent with the monetary incentive hypothesis.[50] This finding echoes anecdotal evidence that young start-ups cannot compete on salary with the likes of Google and Facebook.[51,52]

To test the entrepreneurial spirit incentive, we perform two analyses. First, we use the inventor data to examine the post-exit innovation activities of entrepreneurial diffusers relative to stayers and leavers to public firms. We find that, in the five years after their original employers' exits, entrepreneurial diffusers file more patents and receive more citations per patent than their matched stayers and leavers to public firms. The patents filed by entrepreneurial diffusers are also more original and more exploratory in nature. These results suggest that, by moving to private

[50] On the other hand, leavers to public firms experience significantly higher labor income growth compared to stayers, in both the short and the long run, suggesting that those who leave the exited firms and join other public firms do so to pursue monetary benefits.

[51] For example, when one start-up in Silicon Valley tried to tempt a Google programmer with a $500,000 salary, the programmer turned down the offer because he could make $3 million annually in cash and restricted stock units (see "Silicon Valley tech workers living the start-up dream again," *CIO*, March 7, 2014).

[52] These results are also consistent with the previous literature showing that people pursue entrepreneurship for nonpecuniary reasons such as the desire for autonomy and the tolerance for risk (see, e.g., Hamilton (2000), Hvide and Panos (2014), Ouimet and Zarutskie (2014), Roach and Sauermann (2015), and Cassar and Meier (2018)).

firms, entrepreneurial diffusers can keep engaging in innovation activities, which are explorative and risky in nature. Second, we use census data to examine whether an employee's ex-ante job risk tolerance is associated with the likelihood that she will become an entrepreneurial diffuser. Following He, Shu, and Yang (2020), we use an employee's household labor income diversification to measure her job risk tolerance. Intuitively, if an employee's household labor income is more diversified, the employee will be more tolerant of labor income risk arising from an entrepreneurial job, and thus be more willing to move to a new start-up. Consistent with this prediction, we find a significantly positive association between an employee's household labor income diversification and her tendency to become an entrepreneurial diffuser. Taken together, our results are consistent with the entrepreneurial spirit hypothesis.

In the final part of our paper, we examine how the departure of entrepreneurial diffusers affects newly public firms' post-IPO accounting performance and stock returns.[53] Using both an ordinary least squares (OLS) estimation and a two-stage least squares (2SLS) analysis motivated by Gao, Hsu, and Li (2018), we find that the fraction of employees/inventors who leave a newly public firm after the IPO to join other private firms is negatively associated with the firm's post-IPO operating performance and stock returns. These results illustrate the valuable human capital possessed by entrepreneurial diffusers, and more importantly, suggest that the loss of talented employees with entrepreneurial experience might be one underexplored explanation for the well-known IPO long-run underperformance puzzle (e.g., Ritter (1991), Jain and Kini (1994), Teoh, Welch, and Wong (1998), and Chemmanur and Paeglis (2005)).

[53] For this analysis, we do not examine the post-exit performance for acquired start-up firms because after the sell-out, these exited firms will be integrated into the acquirers, which are typically much larger. Thus, their combined performance after the acquisition will be largely determined by the acquirers rather than the acquired start-ups that lose entrepreneurial diffusers.

While previous literature on the importance of human capital shows that skilled employees can significantly enhance the value and performance of their *current* employers, our paper focuses on how such employees can benefit their *next* employers by diffusing the contributing factors of entrepreneurial success from their current workplaces to new start-ups in the economy. Our study also extends the entrepreneurship literature by focusing on a human capital flow channel through which entrepreneurship is diffused. In our setting, the transfer of entrepreneurial knowledge from one start-up to another is achieved via inter-firm labor flow rather than family inheritance or business advice from common financiers such as venture capitalists.

3.2 Related Literature

Our paper is related to several strands of literature. First, it contributes to the literature on the importance of human capital for firms. For example, Eiling (2013), Donangelo (2014), Israelsen and Yonker (2017), Kuehn, Simutin, and Wang (2017), and Shen (2018) document that human capital as well as labor mobility add critical value to publicly traded firms and thus influence asset prices.[54] Focusing on newly public firms, Chemmanur and Paeglis (2005) show that firms' post-IPO performance is positively associated with the quality of their management. Furthermore, Bernstein (2015) documents that the post-IPO departure of inventors partly contributes to the decline in innovation among newly public firms, and Babina, Ouimet, and Zarutskie (2020) find that the departure of high-wage employees to start-ups after a successful IPO triggers the industrial diversification of the IPO firm. In addition, recent studies have also started to explore the value of human capital for private entrepreneurial firms both theoretically (e.g., Bayar and Chemmanur (2011) and He and Li (2016)) and empirically (e.g., Bayar and Chemmanur (2012), Chemmanur et al. (2018), Dimmock, Huang, and Weisbenner (2019), Chen, Hshieh, and

[54] Similarly, Chemmanur et al. (2019) and Liu, Mao, and Tian (2017) show that human capital is a key driving force of public firms' innovation productivity.

Zhang (2020), and Gu et al. (2020)). While the above literature shows that skilled employees can significantly enhance the value and performance of their *current* employers, our paper focuses on how such employees can benefit their *next* employers by diffusing the entrepreneurial knowledge and technological know-how from their current workplace to new start-ups in the economy. Meanwhile, we also find that the departure of such entrepreneurial diffusers negatively impacts a firm's future performance.

Second, our paper is related to the broader body of literature on why and how entrepreneurs start their own businesses (see the comprehensive reviews by Agarwal and Shah (2014) and Parker (2018)). In particular, this line of research finds that founders of young start-ups can obtain their entrepreneurial knowledge from venture capitalists (e.g., Hellmann and Puri (2002), Samila and Sorenson (2011), Chemmanur, Krishnan, and Nandy (2011), Tian (2011), Chemmanur, Loutskina, and Tian (2014)), social contacts (e.g., Lerner and Malmendier (2013), and Guiso, Pistaferri, and Schivardi (2020)), or family members (e.g., Lindquist, Sol, and Van Praag (2015), Laspita et al. (2012), Hvide and Oyer (2019), Vladasel et al. (2020)), who motivate them to start their own businesses and contribute to the start-ups' subsequent growth. Unlike these studies, we analyze how entrepreneurs, gaining knowledge and experience from their time at successful entrepreneurial firms, pass on their skills and experience to new start-ups in the economy. As such, we focus on an inter-firm channel of human capital flow through which entrepreneurship is diffused.[55]

[55] Our paper is also broadly related to the literature on the performance of serial entrepreneurs, i.e., those who repeatedly start new businesses (e.g., Gompers et al. (2010), Zhang (2011), Parker (2013), Lafontaine and Shaw (2016), and Nahata (2019)). We contribute to this literature in two dimensions. First, we study not only those who repeatedly found new ventures, but also those who repeatedly work for entrepreneurial firms as rank-and-file employees. Second, unlike previous literature that focuses solely on start-up performance, we also study the incentives of entrepreneurial diffusers as well as the effect of their departure on their original employers.

Further, our paper contributes to the recent literature on the economic interaction between mature firms and younger firms. For example, Matray (2020) explores a geographical channel through which the innovation productivity of public firms can spillover to local private firms. In another related paper, Ma, Murfin, and Pratt (2020) document a tangible asset channel through which younger firms benefit from older firms located in the same geographic area by purchasing vintage physical capital from the latter. We contribute to this line of query by showing that the flow of intangible assets (specifically, human capital) can act as a new channel to facilitate the interaction between mature and younger firms without requiring geographical proximity. Furthermore, our paper examines a broader spectrum of corporate outcomes than those studied in the aforementioned papers, and documents the characteristics and incentives of individual entrepreneurial diffusers.

Finally, our paper contributes to the literature on IPO performance. For example, two seminal studies, Ritter (1991) and Jain and Kini (1994), show that firms underperform in the long run after their IPOs. Follow-up literature further advances our understanding of IPO performance by exploring different aspects of the IPO issuers such as their pre-IPO disclosure (Teoh, Welch, and Wong (1998)), management quality (Chemmanur and Paeglis (2005)), and managerial ownership (Mikkelson, Partch, and Shah (1997)). We contribute to this line of research by proposing and documenting a new attribute of IPO issuers, which advances our understanding of the post-IPO underperformance puzzle.

3.3 Data and Sample Construction

We obtain the data on U.S. IPOs and private-target acquisitions (i.e., sell-outs) from the Securities Data Company (SDC) database. Following previous IPO literature (e.g., Chemmanur and He (2011); Chemmanur et al. (2018)), we remove all IPOs related to equity carve-outs, American depositary receipts, American depositary shares, global deposit receipts, global deposit shares, units, trust receipts, and trust units. For the sample of private-target acquisitions, we remove all deals that are reverse takeovers, spin-offs, recapitalizations, self-tenders, exchange offers, repurchases, minority stake purchases, acquisitions of remaining interest, privatizations, divestitures, asset sales, deals whose target and acquirer belong to the same parent company, and deals whose status is defined as "incomplete" by the SDC. We restrict our sample to IPOs and acquisitions completed between 1990 and 2007 because our data on individual employees (i.e., the Longitudinal Employer-Household Dynamics (LEHD) program from the U.S. Census Bureau) cover the period of 1990-2008, and we need at least one year to track the employees' job status after the deals' completion.

We obtain individual employee job history and demographic information from the LEHD program, which covers over 95% of those employed in the private sector in all 50 U.S. states.[56] Employees' quarterly earnings and employment information are obtained from the Employment History File (EHF). Individual characteristics, including age, gender, ethnicity, and education, are obtained from the Individual Characteristics File (ICF). In addition, Title 26 data from the LEHD program identify each person's household through tax return information (primarily from Form 1040), which allows us to calculate the separate contribution of each family member towards household labor income and thus assess household-level income diversification. Our LEHD sample includes 26 participating states that have agreed to share their data with us as external (i.e., non-census) researchers under the Local Employment Dynamics federal-state partnership.[57]

[56] See Abowd et al. (2009) for a comprehensive overview of the LEHD data.
[57] The 26 LEHD states in our sample are Arizona, California, Colorado, Delaware, Georgia, Hawaii, Idaho, Illinois, Indiana, Louisiana, Maryland, Maine, New Jersey, New Mexico, Nevada, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Utah, Vermont, Washington, and Wisconsin.

Following a three-step process, we match employers in the LEHD data to IPO and acquired private firms from the SDC data. First, we match the IPO and acquired firms to the Longitudinal Business Database (LBD) maintained by the U.S. Census Bureau, which contains establishment-level data for virtually the entire universe of U.S. firms. This step is achieved via a combination of name-and-address matching and manual checking, following Chemmanur et al. (2020). In the second step, we match employers in the LEHD database to LBD establishments by Employer Identification Number (EIN), industry, state, and county, using the Business Register Bridge (BRB) file maintained by the U.S. Census Bureau. We then aggregate employees of all establishments that belong to the same firm using LBD's firm identifier, "FIRMID." In the third step, we match the LEHD data to the SDC data using the link files created in the first step. The matched sample contains about 289,000 employees from 1,200 IPO firms and about 642,000 employees from 3,300 acquired private firms.[58]

Following He, Shu, and Yang (2020), for empirical tests using the LEHD sample with firm-level dependent variables, we further require that at least 90 percent of a firm's workforce (measured by either the number of employees or total payroll in LBD) is covered by its establishments in the 26 states for which we have LEHD data. This restriction reduces the sample size to about 550 IPOs and 1,250 sell-outs.

Data on inventors, including their employers, patents, and citations, are obtained from the Harvard Business School (HBS) Patenting Database constructed by Li et al. (2014). Following standard practice in the literature, we treat the assignee of an inventor's patent as her employer. We then adopt a two-step procedure to match IPO firms from the SDC database to assignees in the HBS patenting database. First, we match an IPO firm's Committee on Uniform Securities

[58] These numbers are rounded according to the disclosure requirement by the U.S. Census Bureau.

Identification Procedures (CUSIP) number from the SDC database to the permanent identification numbers (PERMNO) using the link file provided by the Center for Research in Security Prices (CRSP). We then match the IPO firm's PERMNO to patent assignees using the link file provided by Kogan et al. (2017). To match acquired private firms from the SDC database to patent assignees, we use a combination of name-matching algorithms and manual checking. We further require an IPO (acquired) firm to have at least one patent filed in the year before the IPO date (deal completion date). In addition, we drop the inventors whose employment records cannot be tracked after their employers' exit dates, including those who do not file any patents or only file patents for non-corporate assignees (i.e., governments, universities, and individuals) after the exit dates.[59] The matched inventor sample consists of 4,357 inventors from 814 IPO firms and 2,209 inventors from 524 acquired private firms.

Finally, we obtain post-IPO stock return data from CRSP. Information on IPO firms' post-issuance operating performance and financial conditions is obtained from Compustat. Data used to calculate stock options granted to rank-and-file employees are obtained from Execucomp.

3.4 Variable Definitions

3.4.1 Identifying Entrepreneurial Diffusers

To identify entrepreneurial diffusers in the LEHD sample, we begin by identifying all full-time employees of private firms that had recently exited through IPOs or sell-outs during the period of interest. Following the literature (e.g., Babina, et al. (2020)), we define an employee *i* as a full-time employee of firm *j* in quarter *t* if the employee's wage from firm *i* in quarter *t* is above or equal to the federal minimum wage in that quarter and the employee also receives non-zero wages from firm *i* in quarter *t-1* and *t+1*. Using this method, we identify, for a private firm exiting in

[59] We supplement the HBS Patenting Database with the PatentsView database (available at https://www.patentsview.org/download/), which contains additional information on the assignees' identities.

quarter *t*, all of its full-time employees in quarter *t-1*. We then divide the pool of full-time employees into several categories based on their employment status after quarter *t* (i.e., the exiting quarter). For IPO firms, if an employee starts to work full-time for another private (public) firm in any quarter between *t+1* and *t+4*, we define her as an "entrepreneurial diffuser" ("leaver to public firm"), meaning that she quits the job in the newly exited firm and moves to another private (public) firm during the one-year period after the exit.[60] If the employee still works for the IPO firm in quarter *t+4*, we define her as a "stayer." For acquired firms, we define an employee as an entrepreneurial diffuser (leaver to public firm) if she starts to work full-time for another private (public) firm other than the merged firm in any quarter between *t+1* and *t+4*. If the employee still works for the merged firm in quarter *t+4,* she is identified as a stayer. Additionally, we identify an employee as a "new hire" of an IPO firm (merged firm) if she does not have any wage records from the IPO firm (either the acquired firm or acquiring firm) before the IPO date (takeover completion date) and starts to work full-time for the IPO firm (merged firm) in any quarter between quarters *t+1* and *t+4*.

To study how entrepreneurial diffusers affect private firms' likelihood of successfully exiting, we construct a sample of exited firms and matched remaining private firms.[61] For each firm in quarter -1 (i.e., the quarter immediately before the exiting quarter), we calculate *LnDiffuser* as the natural logarithm of one plus the number of entrepreneurial diffusers in the firm, *PctDiffuser* as the fraction of entrepreneurial diffusers in the firm's workforce, and *PctEarnDiffuser* as the fraction of the firm's total payroll earned by the entrepreneurial diffusers. We similarly calculate the variables *LnEmpLeaveToPubExp*, *PctEmpLeaveToPubExp*, and *PctEarnLeaveToPubExp* to

[60] Following Chemmanur et al. (2020), we identify public firms in the census data by matching it to Compustat data and IPO data. Firms that are neither public nor exiting in a given year are treated as private firms.
[61] We describe the matching procedure in Section 3.5.3.

control for the presence of employees with the experience of leaving newly-exited firms but moving to public firms instead of private firms before joining the firms in this sample.

To study how the departure of entrepreneurial diffusers affects newly public firms' post-IPO performance, we calculate the fraction of these firms' pre-IPO full-time employees (at quarter -1) who move to private firms within one year post-IPO (*PctDiffuserLeft*). For this test, we also calculate and control for the fraction of pre-IPO employees who move to public firms within one year after the IPO (*PctLeaverToPub*) as well as the ratio of the number of new employees hired during the same post-IPO window to the number of pre-IPO employees at quarter -1 (*PctNewHire*).

To identify entrepreneurial diffusers in the inventor sample, we first find all the inventors who file at least one patent for an exited firm during the year prior to its exit date (i.e., the IPO date or the deal completion date for sell-outs). These inventors can be assumed to work for the exited firm prior to the exit. Then, for an IPO firm, we follow Bernstein (2015) to define such inventors as entrepreneurial diffusers (leavers to public firms) if they file at least one patent for another private (public) firm in the year after the IPO date.[62] For an acquired firm, we define its pre-exit inventors as entrepreneurial diffusers (leavers to public firms) if they file at least one patent for another private (public) firm other than the merged firm in the year after the deal completion date. Stayers are defined as those inventors who are neither diffusers nor leavers to public firms, and who have not filed any patents for other firms before filing at least one patent for the exited firms after the exit date.[63] In addition, we identify an inventor as a new hire of an IPO firm if she has never filed a patent for the firm before the IPO date and files at least one patent for the IPO firm in the year after the IPO date. Similarly, we identify an inventor as a new hire of the

[62] If the assignee of a patent has a valid PERMNO in the linking file provided by Kogan et al. (2017), we treat it as a public firm. Otherwise it is treated as a private firm.
[63] Our results are robust to treating all inventors who are neither diffusers nor leavers to public firms as stayers.

merged firm after an acquisition if she has never filed a patent for the target or the acquirer before the deal completion date and files at least one patent for the merged firm in the year after the deal completion date.

In the post-IPO performance tests using the inventor sample, we calculate for each IPO firm the fraction of pre-exit inventors who move to private firms within one year after the IPO (*PctDiffuserLeft*), the fraction of inventors who move to public firms within one year after the IPO (*PctLeaverToPub*), and the ratio of the number of new inventors hired within one year after the IPO to the number of pre-exit inventors (*PctNewHire*).

3.4.2 Control Variables in the LEHD Sample

For the employee-level tests using the LEHD sample, we construct several control variables using employee characteristics. *LnTenure* is defined as the natural logarithm of an employee's tenure (in terms of quarters) in the exited firm. *LnAge* is defined as the natural logarithm of an employee's age (in years). *LnEdu* is defined as the natural logarithm of an employee's education level (in years). *LnEarn* is defined as the natural logarithm of an employee's quarterly earnings (in 2007 dollars) from the exited firm.[64] We also control for employees' gender and ethnicity in regression analyses as fixed effects. All of the above variables are measured at quarter -1 (i.e., the quarter immediately before the firm's exit date).

For the firm-level tests using the LEHD sample, we aggregate employees' demographic characteristics to the firm level. *LnAvgTenure*, *LnAvgAge*, *LnAvgEdu*, *LnAvgEarn* are defined as the natural logarithm of average tenure, age, education, and quarterly earnings of a firm's employees, respectively. *Gender* (*Ethnicity*) is defined as the fraction of male (white) employees

[64] Employee earnings reported in the LEHD data include all forms of monetary compensation that are taxed as ordinary income, such as gross wages and salaries, bonuses, stocks, stock options, tips and other gratuities, and meals and lodging (see, e.g., Tate and Yang (2015), Aldatmaz, Ouimet, and Van Wesep (2018), and He, Shu, and Yang (2020)).

in a firm. In addition, we control for the natural logarithm of the total number of employees (*LnEmp*) and the natural logarithm of firm age (*LnFirmAge*), measured as one plus the difference between a given year and the year when a firm's first establishment was founded.

3.4.3 Post-IPO Accounting Performance and Stock Returns

We use two measures, post-IPO buy-and-hold abnormal returns (*BHAR*) and returns on assets (*ROA*), to capture the newly public firms' post-IPO performance. Following Ritter (1991) and Ritter and Welch (2002), we calculate buy-and-hold abnormal returns from the IPO date to one, three, and five years after (*AR1yr*, *AR3yr*, and *AR5yr*, respectively) using the following equation:

$$AR_{0,T}^{i} = \prod_{t=1}^{T\times 12}(1 + r_t^i) - \prod_{t=1}^{T\times 12}(1 + r_t^{vw}), \tag{3.1}$$

where $AR_{0,T}^{i}$ is the post-IPO *BHAR* for firm *i* over the *T*-year period after the IPO date; r_t^i is the stock return of firm *i* in month *t* after the IPO date; and r_t^{vw} is the return of CRSP value-weighted index in month *t* after the IPO date.[65] To measure the IPO firms' post-IPO operating performance, we first calculate *ROA* for each IPO firm in year *T* (*T=1*, *3*, or *5*) after the IPO date as its net income in year *T* divided by its average total assets over years *T-1* and *T*. Then we calculate the average *ROA* for the one, three, and five years (*ROA1yr*, *ROA3yr*, and *ROA5yr*, respectively) after the IPO date for each firm.[66]

Following the literature, we construct a set of firm-level control variables that might be correlated with post-IPO performance. *LnProceeds* is the natural logarithm of IPO proceeds (in terms of million dollars). IPO initial return (*IR*), i.e., underpricing, is calculated as the percentage change from the offer price to the closing price of the first trading day after the IPO. *VC* is a dummy

[65] Our results are robust to using CRSP equal-weighted index returns as the benchmark to calculate abnormal returns.
[66] Our results are qualitatively similar if we use operating income before depreciation as the numerator or if we use total assets in year *T-1* or year *T* as the denominator when calculating ROA.

variable that equals one if a firm is backed by venture capital at the time of the IPO, and zero otherwise. Tobin's Q (*TobinQ*) is calculated as the market value of assets divided by the book value of assets at the first fiscal year-end post-IPO. *LnMV* is the natural logarithm of the market value of equity at the first fiscal year-end post-IPO. Industry-adjusted research and development ratio (*RDadj*) is the IPO firm's R&D expenses scaled by total assets in the first fiscal year post-IPO minus the mean R&D-to-assets ratio in the firm's three-digit North American Industry Classification System (NAICS) industry over the same window. *IndVCPct* is the fraction of firms in the IPO firm's three-digit NAICS industry that are backed by venture capital. *LnIndIPOVol* is the natural logarithm of total IPO volume in the IPO firm's three-digit NAICS industry in its IPO year. In addition, we control for stock options granted to rank-and-file employees, which might be correlated with both post-IPO performance and the employees' willingness to leave the firms. Following Call, Kedia, and Rajgopal (2016) and Aldatmaz, Ouimet, and Van Wesep (2018), we calculate *IndRFOption* as the number of shares in options granted to rank-and-file employees scaled by total number of shares outstanding of a firm, averaged to the three-digit NAICS industry level.

3.5 Empirical Tests

3.5.1 Summary Statistics

We first report the summary statistics for our LEHD sample. To minimize the effect of outliers on our regression analysis, we winsorize all continuous variables at their 1st and 99th percentiles. Panel A of Table 3.1 presents the summary statistics at the individual-employee level. Among the 931,000 pre-exit full-time employees from IPO or acquired private firms in our sample, 11.1 percent move to private firms within one year following the exits and thus become entrepreneurial diffusers. Meanwhile, 4.8 percent of these employees move to public firms during the same window, and those left over (84.1 percent) stay with their original employers (i.e., the exited firms). On average, the pre-exit employees in our sample have been working in the exited firms for 9.4 quarters. The average age, education level, and quarterly earnings of these employees are 39.7 years, 14.6 years, and $11,015 dollars, respectively.

Panel B of Table 3.1 presents the summary statistics at the firm level for the LEHD sample, which consists of about 11,000 exited firms and matched remaining private firms. Among these firms, 16.4 percent exit through IPOs or sell-outs. The measures for the presence of entrepreneurial diffusers in these firms prior to the exits, *LnDiffuser*, *PctDiffuser*, and *PctEarnDiffuser*, have averages of 0.054, 0.001, and 0.001, respectively.[67] The presence of employees with the previous experience of leaving exited firms to join public firms is smaller than that of the entrepreneurial diffusers, as the averages of *LnEmpLeaveToPubExp*, *PctEmpLeaveToPubExp*, and *PctEarnLeaveToPubExp* are 0.013, <0.001, and <0.001, respectively. Firms in this sample have an average of about 21.2 employees immediately before they exit. The average age of the firms is about 9.7 years in the year prior to the exits. The average age and education level of the employees are 40.4 years and 14.7 years, respectively. On average, 54.4 percent of a firm's employees are male, and 70.7 percent of a firm's employees are white.

3.5.2 Innovation Quality of Entrepreneurial Diffusers

Although the LEHD sample allows us to track the employment status of individual employees in newly exited firms and gauge the demographic characteristics of these employees, it is hard to infer the entrepreneurial qualities (i.e., the essential characteristics required for entrepreneurial successes) of these employees based on the LEHD data alone. The inventor data,

---

[67] The small mean fraction of entrepreneurial diffusers is mostly driven by the large fraction of start-ups without any such employees, which is similar to the right-skewed distribution of innovation activities in the economy due to the large population of zero-patenting firms.

on the other hand, track the number of patents filed and citations received by individual inventors. Such information can be used to infer their innovative behavior and thus their creativity and risk-taking spirit, which are both required qualities for achieving entrepreneurial successes (see, e.g., Chemmanur et al. (2019) and Islam and Zein (2020)). Therefore, we turn to the inventor sample to examine the difference in quality between entrepreneurial diffusers and other employees in the exited firms.

To measure an inventor's innovation quantity and quality, we calculate the average number of patents filed per year (*Patents*), the average number of citations received per patent (*CitePat*), the average originality score of the patents (*Originality*), and the average number of exploratory patents filed per year (*Exploratory*) by the inventor in the five years before the exit date of her employer. Following Hirshleifer, Hsu, and Li (2018), we calculate *Originality* as the average number of unique technological classes cited by an inventor's patents. A higher *Originality* score indicates that an inventor's patents deviate more from the current technology trajectories. Following Gao, Hsu, and Li (2018), Brav et al. (2018), and Lin, Liu, and Manso (2020), we define a patent as an "exploratory" patent if 80% or more of its citations are not based on the existing knowledge of the firm, i.e., all the patents filed by the firm and the patents that were cited by the firms' patents filed over the past five years. A larger number of exploratory patents filed by an inventor indicates that she is more capable of acquiring new knowledge. Both *Originality* and *Exploratory* capture an inventor's willingness and capacity to explore beyond her existing base of knowledge, which partially reflects her entrepreneurial ability and spirit.

Table 3.2 compares the innovation behaviors of entrepreneurial diffusers (*EntreDiffuser*) to those of employees in other categories.[68] On average, an entrepreneurial diffuser files 1.68 patents per year before the exit date, which is significantly greater than those filed by leavers to public firms (*LeaverToPub*) or by stayers (*Stayer*), reflecting the higher innovation productivity of diffusers. Similarly, the average number of citations received by the patents of entrepreneurial diffusers (27.3) is also significantly larger than those received by the patents of stayers (22.2), which indicates that diffusers generate higher quality patents than those inventors who stay with exited firms. Further, the patents by entrepreneurial diffusers have significantly higher *Originality* (9.01) and are more exploratory (0.66) than those by leavers to public firms or stayers, suggesting that diffusers are more adventurous in nature and more capable than other inventors in exploring new technological domains. More importantly, although the newly exited firms hire a large number of inventors post-exit, the newly hired inventors (*NewHire*) have significantly worse track records in terms of innovation (i.e., fewer patents and fewer citations per patent) and innovative originality (i.e., patents with lower originality scores and fewer exploratory patents) than entrepreneurial diffusers, further suggesting that the loss in exited firms' key human capital due to the departure of entrepreneurial diffusers is hard to replace.

Taken together, the results in this section indicate that entrepreneurial diffusers are among the more talented employees of the exited firms (in terms of creativity and risk-taking spirit), and that the loss of these talents cannot be easily replaced by hiring new employees.

[68] Among the 6,566 pre-exit inventors, 11.9 percent move to private firms and thus are defined as entrepreneurial diffusers, 5.6 percent move to public firms, and 82.5 percent stay with the exited firms. This distribution is generally comparable to that of the LEHD sample.

3.5.3 Entrepreneurial Diffusers and Start-up Firms' Likelihood to Successfully Exit

As entrepreneurial diffusers possess valuable human capital and pass on their skills, vision, and entrepreneurial spirit to the start-ups they join, we hypothesize that private firms' likelihood of successfully exiting through IPOs or sell-outs is positively associated with the presence of entrepreneurial diffusers among their workforces. To mitigate the concern of a selection effect, i.e., that entrepreneurial diffusers are capable of identifying and joining firms with higher likelihoods of exiting to begin with, we match a sample of non-exiting private firms to the exiting ones along several important dimensions. Specifically, for each firm *i* exiting in year *t*, we find all the private firms that remain private in year *t-1* and are in the same three-digit NAICS industry, state, size group, and age group as the exiting firm.[69] We further require the matched non-exiting firms to have the same VC-backing status and multi-unit status (i.e., whether the firm is a single-establishment or multi-establishment firm) as the exiting firm.[70] Finally, for each exiting firm *i*, we retain five eligible matched non-exiting firms that are the closest to firm *i* in terms of size (measured by the total number of employees). Then we estimate the following linear probability model using the final matched sample:

$$EntrepreneurialExit_i = \alpha + \beta_1 Diffuser_i + \beta_2 LeavePubExp_i + \beta_3 LnEmp_i + \beta_4 LnFirmAge_i + \beta_5 LnAvgAge_i + \beta_6 LnAvgEdu_i + \beta_7 PctMale_i + \beta_8 PctWhite_i + MatchedPair + \varepsilon_i, \quad (3.2)$$

[69] Following Davis et al. (2014), we classify firms into 12 size groups based on their employment: (1) 1-4 employees, (2) 5-9 employees, (3) 10-19 employees, (4) 20-49 employees, (5) 50-99 employees, (6) 100-249 employees, (7) 250-499 employees, (8) 500-999 employees, (9) 1,000-2,499 employees, (10) 2,500-4,999 employees, (11) 5,000-9,999 employees, and (12) 10,000 or more employees. We classify firms into five age groups: (1) 0-5 years, (2) 6-10 years, (3) 11-15 years, (4) 16-20 years, and (5) 21 or more years.

[70] Ideally, we want to control for firm quality measures, such as sales growth and profitability, which are key determinants of private firms' exit choices. However, such information is missing in most databases covering private firms including the LBD. Therefore, we make our best effort by matching on VC-backing status, which is commonly used as a comprehensive proxy for unobservable firm quality (see, e.g., Hochberg, Ljungqvist, and Lu (2007), Kerr, Lerner, and Schoar (2011), and Dimmock, Huang, and Weisbenner (2019)).

where *EntrepreneurialExit* is a dummy variable that equals one if a private firm *i* exits through IPO or sell-out in year *t*, and zero otherwise. *Diffuser* captures the presence of entrepreneurial diffusers working for firm *i* in quarter *t-1* (i.e., the pre-exit quarter), and can be one of the three measures discussed earlier: *LnDiffuser*, *PctDiffuser*, or *PctEarnDiffuser*. We control for the presence of employees with experience of leaving to public firms, *LeavePubExp*, in similar ways. All other control variables, defined in Section 3.4.2, are measured either at year *t-1* (for firm characteristics) or quarter *t-1* (for employee characteristics). We include matched-pair fixed effects, which fully absorb industry, year, and state fixed effects as well as their multiplicative combinations as the matching is done at the industry-state-year level. These fixed effects also control for the effects of VC-backing status, age, size, and multi-unit status on the likelihood of a successful exit. To account for possible within-industry correlations in errors, we cluster standard errors at the three-digit NAICS industry level.

Table 3.3 presents the results of estimating Equation (3.2). We find that private firms with more entrepreneurial diffusers are more likely to successfully exit through IPOs or sell-outs, consistent with the hypothesis that entrepreneurial diffusers help their new employers (i.e., the less mature start-ups) to achieve entrepreneurial success. The coefficient on *PctDiffuser* in Column (2) indicates that a one standard deviation increase in the fraction of entrepreneurial diffusers in a firm's workforce is associated with a 1.9 percentage point (about 12% of the mean exiting likelihood) increase in the firm's likelihood to successfully exit, which is economically significant. The regression results also show that the presence of employees with previous experience of leaving newly exited firms to public firms is positively associated with firms' exit likelihood as well, but such correlations are statistically insignificant.

Overall, results in this section suggest that entrepreneurial diffusers add value to the new start-ups they join by increasing the firms' likelihood of successfully exiting.

3.5.4 Innovation Quality of the Firms Joined by Entrepreneurial Diffusers

In this section, we explore one specific channel of entrepreneurial diffusion's value creation by examining the innovation quality of the start-ups joined by diffusers.

To mitigate selection concerns, we again adopt a matching approach by constructing a matched sample of firms with similar innovation productivity but without an influx of entrepreneurial diffusers joining the firm. Specifically, for each treatment firm *i* (i.e., each private firm *i* with at least one entrepreneurial diffuser joining the firm on date *t*), we find all the private firms who share the same major patent class with firm *i* (i.e., the technology class in which a firm files the largest number of patents) and whose total number of patents filed in the five-year period before year *t* is between 0.8 and 1.2 times of that of firm *i*. For each treatment firm *i* and its matched firms, we calculate the average number of patents filed per year (*FirmPatentsPostJoin*), the average number of citations received per patent (*FirmCitePatPostJoin*), the patents' average originality score (*FirmOriginalityPostJoin*), and the average number of exploratory patents filed per year (*FirmExploratoryPostJoin*) in the five-year period after *t*. Then, for each treatment firm *i*, we calculate the differences between its four innovation activity measures and the median values of these measures of its matched firms.

Panel A of Table 3.4 reports the average of the above differences after the entrepreneurial diffusers join the firm. As can be seen, treatment firms file 4.21 more patents annually than matched firms that did not bring on diffusers. The patents filed by treatment firms are also higher quality, as their average number of citations per patent is 6.51 higher than that of the matched firms. In addition, patents filed by treatment firms are more original (with 6.44 higher originality score) and more exploratory (with 1.45 more exploratory patents filed annually) compared to matched firms. All these differences are significant at the 1% level.

We further explore how entrepreneurial diffusers improve the innovation productivity of the firms they join. We hypothesize that entrepreneurial diffusers can play a mentoring/advising role in these start-ups and improve their new colleagues' innovation productivity by passing on their technological knowledge and innovative spirit. To test this prediction, we compare the innovation productivity of entrepreneurial diffusers' new colleagues in the treatment firms and ex-ante similar inventors in the matched firms. Specifically, for each non-diffuser inventor *j* who works for treatment firm *i* (with at least one entrepreneurial diffuser joining the firm on date *t*), we find all the inventors who work for firm *i*'s matched firms on date *t*, and whose average annual number of patents filed in the five-year period before *t* is no more than one from that of inventor *j*. We then compare the innovation productivity of inventor *j* and the median of her matched inventors in the five-year period after *t*.

Consistent with our prediction, Panel B of Table 3.4 shows that in the five years after entrepreneurial diffusers join a firm, their new colleagues produce more patents and patents with higher quality and originality than matched inventors at other firms. These results suggest that the hiring of entrepreneurial diffusers has a positive spillover effect that helps improve the innovation productivity of inventors who already work at the start-ups that the diffusers join.

We should, however, add the caveat that despite our efforts to mitigate endogeneity concerns, it is still possible that the positive association between start-up success (as judged by either the likelihood of a successful exit or the innovation productivity) and the presence of entrepreneurial diffusers can be explained by the diffusers' ability to pick and join firms with greater unobservable potential. If that is the case, given the data limitation on private firms (i.e., the lack of hard information about their quality), the human capital flow of entrepreneurial diffusers could serve as a signal (i.e., soft information) about private firms' quality, which could be useful to investors and other stakeholders. Future research could further develop this line of inquiry by exploring whether participants in the entrepreneurial market (e.g., venture capital investors) observe and make use of such information.

3.5.5 Incentives of Entrepreneurial Diffusers

In this section, we explore what motivates entrepreneurial diffusers to quit their firms after a successful exit and move to other private firms. We focus on two potential motivations: the monetary incentive hypothesis (i.e., that diffusers are driven by personal financial gain), and the entrepreneurial spirit hypothesis (i.e., that diffusers are driven by their own preference to work in an entrepreneurial environment). To test the monetary incentive hypothesis, we use the LEHD sample to study the association between an employee's decision to leave her exited firm and her post-exit short-term and long-term monetary gains. To test the entrepreneurial spirit hypothesis, we first use the inventor sample to study the association between the inventors' decisions to leave the exited firms and their post-exit innovation activities. Second, we use the LEHD sample to study whether and how employees' income risk tolerance is associated with their choice between private and public firms conditional on leaving the exited firms.

3.5.5.1 The Monetary Incentive

The monetary incentive hypothesis suggests that, after a private firm exits, either by going public or by being acquired, entrepreneurial diffusers move to other private firms to pursue monetary benefits in the form of either higher wages or greater value appreciation of employee stocks/options. To test this hypothesis, we use the LEHD sample, which covers all pre-exit employees of exited firms (i.e., entrepreneurial diffusers, leavers to public firms, and stayers) to study these employees' post-exit monetary gains. As noted before, these employee earnings include all types of labor income from a particular employer, such as base salary, bonuses, stocks, stock options, and profit distributions. We estimate the following OLS regression using the LEHD sample:

$$CareerOutcome_i = \alpha + \beta_1 EntreDiffuser_i + \beta_2 LeaverToPub_i + \beta_3 LnTenure_i + \beta_4 LnAge_i + \beta_5 LnEdu_i + \beta_6 LnEarn_i + Deal + Male + White + \varepsilon_i, \qquad (3.3)$$

where *CareerOutcome* measures the post-exit career outcomes in terms of monetary gains for employee *i* whose employer exits in year *t*. These outcomes are captured by two empirical measures. The first measure, *EarnGap*, is the difference between an employee's post-exit quarterly earnings and her pre-exit quarterly earnings (in thousands, 2007 dollars). The pre-exit quarterly earnings are an employee's earnings from the exited firm in quarter -1 (i.e., the quarter immediately before the exit date). The post-exit quarterly earnings of an entrepreneurial diffuser or a leaver to public firm are her full-time quarterly earnings from her new employer. A stayer's post-exit quarterly earnings are her earnings from the exited firm in the fourth quarter after the exit. The second measure, *LnEarnPost*, captures the long-run wealth effect of employees' career decisions. For an entrepreneurial diffuser or a leaver to public firm, *LnEarnPost* is defined as the natural logarithm of her average quarterly earnings (in thousands, 2007 dollars) in the five years after leaving the exited firm. For a stayer, this variable is defined as the natural logarithm of her average quarterly earnings over the five years starting from the fourth quarter after her employer's exit date. *EntreDiffuser* (*LeaverToPub*) is a dummy variable that equals one if an employee moves to a private (public) firm within one year after her original employer's exit, and zero otherwise. The coefficient of *EntreDiffuser* (*LeaverToPub*) thus compares the career outcomes (monetary gains) of entrepreneurial diffusers (leavers to public firms) to those of stayers, which comprise the omitted (base) group in the regressions. The control variables are defined in Section 3.4.2 and measured at quarter -1. We include deal (IPO or sell-out) fixed effects, which fully absorb all firm-level characteristics as well as any trends in labor income at the macro (time or industry) level. We also include indicator variables for an employee's gender and ethnicity in the regressions, but do not report the coefficients to comply with the U.S. Census Bureau's disclosure rule. Standard errors are clustered at the deal level.

Table 3.5 presents the results of estimating Equation (3.3). Column (1) uses *EarnGap* as the dependent variable, while Column (2) uses *LnEarnPost* as the dependent variable. As can be seen, entrepreneurial diffusers do not have a significant increase in earnings compared to stayers, in either the short or long run, whereas leavers to public firms have a significant increase in earnings compared to stayers. The F-tests for the difference between the coefficients of *EntreDiffuser* and *LeaverToPub* are significant at the 1% level in both columns. Taken together, the two columns show that entrepreneurial diffusers do not experience a large gain in labor income in either the short or long term, compared to employees who make other career decisions. These results suggest that the pursuit of monetary gains is probably not the primary reason for entrepreneurial diffusers to move to private firms after their original employers' successful exits.

3.5.5.2 The Entrepreneurial Spirit Incentive

Literature shows that, after a private firm goes public or is acquired, it exhibits a decrease in creative activities such as innovation (see, e.g., Aggarwal and Hsu (2014), Bernstein (2015), Cunningham, Ederer, and Ma (2020), Gao, Hsu, and Li (2018), and Dambra and Gustafson (2020)), which might trigger the departure of talented employees who desire autonomy and an entrepreneurial environment. Hence, the entrepreneurial spirit hypothesis postulates that entrepreneurial diffusers—who are more explorative, risk tolerant, and adventurous in nature—

might move to private firms in the pursuit of an environment that better nurtures these qualities, since their original employers come to focus more on routine businesses after successfully exiting.

To test the entrepreneurial spirit hypothesis, we first compare the post-exit innovation activities of entrepreneurial diffusers and those of other inventors. Given that, as shown earlier, entrepreneurial diffusers have higher pre-exit innovation quality, we conduct a matched-sample analysis to control for their pre-exit innovation activities. Specifically, for each entrepreneurial diffuser whose employer exits in year *t*, we find all the leavers to public firms and all the stayers whose employers also exit in year *t*, and whose average annual patent output in the five years before the exit is comparable (i.e., has a difference no greater than 1) to that of the diffuser. By doing so, we compare entrepreneurial diffusers to inventors in other categories with similar levels of pre-exit innovation productivity. For those matched entrepreneurial diffusers and other inventors, we first calculate each individual's average number of patents filed per year (*PatentsPostExit*), average number of citations received per patent (*CitePatPostExit*), average originality score per patent (*OriginalityPostExit*), and average number of exploratory patents filed per year (*ExploratoryPostExit*) in the five years post-exit. Then, for each entrepreneurial diffuser, we calculate the differences between her four innovation activity measures (mentioned above) and the median values of these measures amongst her matched inventors.

Table 3.6 reports the results, which show that entrepreneurial diffusers file 0.63 more patents annually than their matched leavers to public firms in the five years post-exit. The patents filed by entrepreneurial diffusers have higher quality (measured as citations per patent) and are more original and more exploratory as well. All these four differences are significant at the 1% level. In addition, entrepreneurial diffusers exhibit greater long-term innovation productivity than their matched stayers.

While these results suggest that entrepreneurial diffusers are motivated to move to private firms by their entrepreneurial spirit, the results in Table 3.5 show that doing so does not yield them a large increase in wealth. Thus, whether and how entrepreneurial diffusers consider the tradeoffs between nonpecuniary benefits (entrepreneurial spirit) and pecuniary benefits is a question worth exploring. In other words, if entrepreneurial diffusers can anticipate a potential reduction in their future labor income if they move to private firms to pursue entrepreneurship and innovation, what makes them willing to do so? To provide a partial answer to this question, we study the association between an employee's job risk tolerance and their decision to move to a private firm after their original employer has exited.

Previous literature has shown that entrepreneurial activities are associated with certain attitudes toward risk. For example, Weller and Wenger (2015) find that people with more diversified household incomes are more likely to be entrepreneurs. He, Shu, and Yang (2020) argue that an employee is more risk tolerant towards her job if her household labor income is more diversified (i.e., the weight of the employee's labor income in her total household labor income is lower). In our context, if an employee's household labor income is more diversified, her household will have more income sources beyond what she gains from her job. In that case, the potential loss in future labor income from the employee if she moves to a private firm will have a smaller negative effect on her household's expected total wealth, which better enables the employee to pursue entrepreneurial spirit. Hence, we use household labor income diversification to proxy for an individual employee's job risk tolerance, predicting that household labor income diversification is positively associated with the likelihood of the employee moving to a private firm (rather than a mature public firm). To test this prediction, we estimate the following linear probability model using the LEHD sample of employees from both IPO firms and acquired private firms:

$$EntreDiffuser_i = \alpha + \beta_1 EntreRiskTaking_i + \beta_2 LnTenure_i + \beta_3 LnAge_i + \beta_4 LnEdu_i + \beta_5 LnEarn_i + Male + White + Year + Industry + Deal + \varepsilon_i, \quad (3.4)$$

where *EntreDiffuser* is a dummy variable that equals one if an employee is an entrepreneurial diffuser, and zero if the employee is a leaver to public firm. We exclude stayers in this analysis as we want to study the association between employees' ex-ante job risk tolerance and their choices (i.e., moving to private firms or public firms) conditional on the decision to leave the exited firms. Following He, Shu, and Yang (2020), for each entrepreneurial diffuser or leaver to public firm, we calculate *JobRiskTolerance* as the difference between her household's total labor income and her earnings from the exited firm scaled by her household's total labor income.[71] Higher *JobRiskTolerance* means the employee's household labor income is more diversified, which makes the employee more tolerant to her labor income risk.[72] The control variables are defined in Section 3.4.2, and similar to *JobRiskTolerance*, are all measured at quarter -1 (i.e., the quarter immediately before the exit dates). As in previous tables, we control for each employee's gender and ethnicity using untabulated dummies. We also include various combinations of fixed effects (such as year, three-digit NAICS industry, and exit-deal fixed effects) in our regressions. Standard errors are clustered by exit deals (i.e., IPOs or sell-outs).

Table 3.7 reports the results. In all model specifications, including the most stringent model of Column (4) that includes deal fixed effects, *JobRiskTolerance* has a significantly positive coefficient, suggesting that employees who are more tolerant to labor income risk are more likely

[71] Household identification information, which largely comes from the 1040 tax return data, is available from year 2000 onwards in the LEHD data, which reduces our sample size in this analysis.

[72] It is worth noting that *JobRiskTolerance* is not a measure of employees' innate (i.e., genetically determined) risk attitudes which impact their general behaviors, but rather a measure of resource-based risk attitudes (i.e., employees and their households' abilities to maintain their level of consumption when facing negative labor income shocks from a focal job).

to move to private firms rather than public firms after their original employers' exits, which is consistent with the entrepreneurial spirit hypothesis.

3.5.6 Entrepreneurial Diffusers and Their Original Employers' Post-IPO Performance

In this section, we investigate the association between the departure of entrepreneurial diffusers and their original employers' post-IPO performance.[73] Using the LEHD sample, we estimate the following OLS regression:

$$PostIPOPerformance_i = \alpha + \beta_1 PctDiffuserLeft_i + \beta_2 PctLeaverToPub_i + \beta_3 PctNewHire_i + \beta_4 LnProceeds_i + \beta_5 IR_i + \beta_6 VC_i + \beta_7 TobinQ_i + \beta_8 LnMV_i + \beta_9 RDadj_i + \beta_{10} IndVCPct_i + \beta_{11} LnIndIPOVol_i + \beta_{12} IndRFOption_i + \beta_{13} LnEmp_i + \beta_{14} LnFirmAge_i + \beta_{15} LnAvgTenure_i + \beta_{16} LnAvgAge_i + \beta_{17} LnAvgEdu_i + \beta_{18} LnAvgEarn_i + Industry + Year + \varepsilon_i, \quad (5)$$

where $PostIPOperformance_i$ is either firm *i*'s buy-and-hold abnormal return (*BHAR*) or its average *ROA* in the one-, three-, or five-year windows after its IPO. *PctDiffuserLeft* (*PctLeaverToPub*) is the fraction of a firm's pre-exit employees who move to private (public) firms within one year after the IPO. All other variables are as defined in Section 3.4.3. $LnProceeds$ and *IR* are measured at the time of the IPO; other firm-level characteristics are measured at the end of the first year post-IPO; and employee characteristics are measured at quarter *t-1*. We include industry fixed effects (at the three-digit NAICS level) and year fixed effects in the model. Standard errors are clustered at the industry level.

[73] We only study IPOs rather than acquired private firms in this section for two reasons. First, after sell-outs, the exited firms will be integrated into the acquirers, which are typically much larger. Thus, their combined performance after the acquisition will be largely determined by the acquirers rather than the acquired start-ups that lose entrepreneurial diffusers. Second, the IPO sample allows us to control for various firm characteristics that might be correlated with post-exiting performance, whereas there are no readily available financial data on the characteristics of acquired private firms.

Panel A of Table 3.8 reports the results. Columns (1)-(3) use one-, three-, and five-year post-IPO *BHAR* as the dependent variables, respectively. Columns (4)-(6) use one-, three-, and five-year post-IPO average annual *ROA* as the dependent variables, respectively. We redact the regression coefficients of control variables in Columns (4)-(6) due to the disclosure restriction of the U.S. Census Bureau. The results show that both post-exit *BHAR* and *ROA* are negatively associated with the fraction of entrepreneurial diffusers that leave an IPO firm. Moreover, the economic magnitude of this impact increases over time, especially for abnormal returns. For example, a one standard deviation increase in the fraction of entrepreneurial diffusers (i.e., 0.046) is associated with a 0.11 (=0.046×6.126/2.679) standard deviation decrease in the five-year post-IPO *BHAR* but only a 0.06 (=0.046×1.114/0.813) standard deviation decrease in the one-year post-IPO *BHAR*. Meanwhile, the fraction of leavers to public firms is not significantly associated with post-IPO performance, except for the one-year *BHAR*, suggesting that the departure of leavers to public firms is not as costly to the newly exited firms as that of entrepreneurial diffusers. Interestingly, the fraction of new hires is insignificantly related to post-IPO *BHAR* but has a significantly negative association with post-IPO *ROA*, which possibly reflects the higher labor expenses but no greater labor productivity following the post-IPO expansion.

We further estimate a similar model to Equation (3.5) using the inventor sample to explore the impact of entrepreneurial diffusing inventors on firms' post-IPO performance. *PctDiffuserLeft*, *PctLeaverToPub*, and *PctNewHire* are now calculated using inventors instead of the LEHD employees. We control for *LnInventor*, the natural logarithm of the number of inventors (instead of employees), and drop employee demographics from the control list as these variables cannot be calculated for the inventor sample.

Consistent with the results using the LEHD sample, Panel B of Table 3.8 shows that the fraction of entrepreneurial diffusing inventors (i.e., those leaving for private firms) also has a significantly negative association with their original employers' post-IPO performance, especially over the long run. In terms of economic magnitudes, a one standard deviation increase in the fraction of entrepreneurial diffusers (i.e., 0.213) is associated with a 0.09 (=0.213×0.934/2.127) standard deviation decrease in the five-year post-IPO *BHAR* and a 0.11 (=0.213×0.169/0.332) standard deviation decrease in the five-year average annual *ROA*. Again, the fraction of inventors leaving to public firms is not significantly associated with post-IPO performance. However, the fraction of newly hired inventors now positively predicts post-IPO *ROA*.

For ease of exposition and interpretation, we also plot in Figure 3.1 the decrease in *BHAR* one-, three-, and five-year post- IPO associated with a one-standard-deviation increase in the fraction of entrepreneurial diffusers for both the LEHD sample and the inventor sample. As can be seen, the decrease in shareholder value associated with the departure of entrepreneurial diffusers increases over the post-IPO time horizon.

The above OLS analysis is, however, subject to endogeneity concerns. On the one hand, firms that suffer from worse post-IPO performance may choose to fire their employees, including diffusers. This concern is partially mitigated as we measure the long-run performance at three and five years after the IPOs, whereas the departure of entrepreneurial diffusers is defined in the first year post-IPO. On the other hand, the entrepreneurial diffusers (i.e., those who leave for private firms right after the IPOs) might be able to anticipate negative future firm performance and thus choose to leave the newly exited firms in advance. If this is the case, however, we should also expect a significantly negative association between the fraction of leavers to public firms and post-

IPO performance, which we do not find. As a result, reverse causality seems not to be a severe concern for our analysis.

Nevertheless, omitted variables (e.g., organizational features that lead to both bad performance and an exodus of talented employees) might still plague our causal inference. Hence, we conduct a two-stage least squares (2SLS) analysis for the inventor sample. Our instrument, following the spirit of Gao, Hsu, and Li (2018), is the change in the fraction of patents filed by private firms (as opposed to public firms) in an IPO firm's three-digit NAICS industry. Intuitively, this instrument captures the change in the quality of the entrepreneurial environment (in terms of overall innovation intensity) that private firms can offer relative to public firms in the same industry. The enhanced entrepreneurial environment offered by private firms will be more likely to attract entrepreneurial diffusers, who are motivated by their entrepreneurial spirit (as shown in Section 3.5.5), which in turn makes them more willing to jump to private firms after their employers' IPOs. Therefore, we use *ChgPctPatentsPrv*, the change in the share of innovation activities (in terms of patent filings) that are conducted by private firms in an industry, to predict the fraction of inventors who move to private firms shortly after IPOs. The details of the construction of this instrument are provided in Appendix E.[74]

Table 3.9 presents the results of the 2SLS analysis. Column (1) reports the first-stage regression. As we predicted, *ChgPctPatentsPrv* has a significantly positive effect on the fraction of entrepreneurial diffusers: a one percentage point greater change in the fraction of patents assigned to private firms in an IPO firm's industry leads to a 1.45 percentage point increase in the

[74] It is worth noting that we cannot apply the same 2SLS design to the analysis of the association between the presence of entrepreneurial diffusers and private firms' likelihood of successfully exiting (i.e., the tests reported in Table 5). The reason is that diffusers in a private firm's workforce could have joined the firm at multiple time points and from multiple industries, which prohibits the use of an industry-level time-varying instrumental variable (such as *ChgPctPatentsPrv*).

fraction of departing entrepreneurial diffusers. Our instrument is also unlikely to suffer from weak instrument problems, as the Kleibergen-Paap Wald test on weak instruments has an F-statistic of 12. Columns (2)-(4) and (5)-(7) report the second-stage regressions using post-IPO *BHAR* and *ROA*, respectively, as the dependent variables. Consistent with our OLS results in Table 3.8, the instrumented fraction of entrepreneurial diffusers significantly reduces firms' post-IPO long-term *BHAR* and *ROA*. These results suggest that the loss of human capital due to the departure of entrepreneurial diffusers has a causal negative impact on their original employers in terms of operating performance and shareholder value.

Taken together, the results in this section suggest that the departure of entrepreneurial diffusers is costly to their original employers, and that the loss of talented employees with entrepreneurial experience and spirit might be one underexplored explanation for the well-known IPO long-run underperformance puzzle (e.g., Ritter (1991), Jain and Kini (1994), Teoh, Welch, and Wong (1998), and Chemmanur and Paeglis (2005)).

3.6 Conclusion

This paper studies the emerging phenomenon in which talented employees leave successfully exited (via IPOs or sell-outs) entrepreneurial firms to join less mature start-ups. Using both unique data drawn from the U.S. Census Bureau and a sample of individual inventors, we find that such entrepreneurial diffusers seem to be the most talented among all types of employees in the newly exited firms, and the loss of these talents cannot be easily mitigated by hiring new employees. These diffusers also add value to their new employers by enhancing the latter's innovation potential and likelihood of a successful exit. Further analyses reveal that entrepreneurial diffusers are more likely to be motivated by an entrepreneurial spirit than by monetary gains.

Finally, we find that the departure of entrepreneurial diffusers contributes to the long-run IPO underperformance documented by accounting and finance researchers.

Overall, these results indicate that entrepreneurial diffusers represent a valuable form of human capital and contribute to the cross-firm diffusion of entrepreneurship, which is critical to the sustainability of a vibrant entrepreneurial ecosystem. Unlike previous literature that focuses on how skilled employees can enhance the value and performance of their *current* employers, our paper shows how such employees can benefit their *next* employers by diffusing the entrepreneurial knowledge and technological know-how from their current workplace to new start-ups in the economy. Our study idenfities a human capital flow channel through which entrepreneurship is diffused, which sets the stage for a new conversation in the entrepreneurial finance literature. Future research could extend this line of inquiry in various dimensions. First, it might be fruitful to explore more potential incentives that drive entrepreneurial diffusers (that is, other than the monetary incentive and the entrepreneurial spirit incentive studied here). Second, future studies could strengthen the causal link between entrepreneurial diffusers and firm performance by overcoming the data hurdles on private firms and adopting better identification strategies. Finally, given our findings that entrepreneurial diffusers positively relate to the success of the start-ups they join but negatively affect the value of the firms they leave, future studies could try to evaluate the overall welfare implications of diffusers for the entire entrepreneurial market in an economy.

Table 3.1: Summary Statistics

This table reports the summary statistics of variables for the LEHD sample. Panel A reports the summary statistics at the employee-level for 931,000 employees from IPO firms and acquired private firms. Panel B reports the summary statistics at the firm-level for 11,000 IPO firms, acquired private firms, and their matched non-exiting private firms. The statistics are rounded following the disclosure requirement by the U.S. Census Bureau. The definitions of all variables are presented in Appendix D.

Panel A: Summary Statistics at the Employee Level

Variables	Mean	Std	N
EntreDiffuser	0.111	0.313	931,000
LeaverToPub	0.048	0.215	931,000
Stayer	0.841	0.365	931,000
LnTenure	2.241	0.922	931,000
LnAge	3.681	0.281	931,000
LnEdu	2.680	0.170	931,000
LnEarn	9.307	0.654	931,000

Panel B: Summary Statistics at the Firm Level

Variables	Mean	Std	N
EntrepreneurialExit	0.164	0.370	11,000
LnDiffuser	0.054	0.203	11,000
PctDiffuser	0.001	0.006	11,000
PctEarnDiffuser	0.001	0.006	11,000
LnEmpLeaveToPubExp	0.013	0.095	11,000
PctEmpLeaveToPubExp	<0.001	0.001	11,000
PctEarnLeaveToPubExp	<0.001	0.001	11,000
LnEmp	3.052	1.401	11,000
LnFirmAge	2.272	0.754	11,000
LnAvgAge	3.699	0.156	11,000
LnAvgEdu	2.689	0.078	11,000
Gender	0.544	0.296	11,000
Ethnicity	0.707	0.279	11,000

Table 3.2: Innovation Quality of Entrepreneurial Diffusers and Other Inventors

This table reports and compares the innovation quality of entrepreneurial diffusers, leavers to public firms, stayers, and new hires. *Patents* is the average number of patents filed per year by an inventor. *CitePat* is the average number of citations received per patent. *Originality* is the average number of unique technological classes cited per patent. *Exploratory* is the average number of exploratory patents filed per year. All variables are calculated over the five-year window before the exit. In addition, we report the differences among inventor categories along with the associated t-statistics. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	EntreDiffuser	*LeaverToPub*	*Stayer*	*NewHire*	*Difference (t-statistics)*		
	(1)	(2)	(3)	(4)	(1)-(2)	(1)-(3)	(1)-(4)
Patents	1.678	1.287	0.829	0.085	0.391***	0.849***	1.593***
					(5.278)	(17.328)	(33.468)
CitePat	27.300	26.545	22.197	3.309	0.755	5.102***	23.991***
					(0.402)	(4.391)	(21.929)
Originality	9.010	8.241	8.141	1.065	0.769**	0.869***	7.945***
					(1.990)	(3.380)	(32.830)
Exploratory	0.664	0.587	0.361	0.046	0.077**	0.303***	0.618***
					(2.572)	(15.955)	(33.579)

Table 3.3: Entrepreneurial Diffusers and Private Firms' Likelihood to Exit

This table presents the linear probability regressions on the association between private firms' likelihood of exiting and the presence of entrepreneurial diffusers in these firms. For each private firm that goes public or gets acquired in year *t*, we find all the private firms that remain private in year *t*, and are in the same three-digit NAICS industry, state, size group, and age group with the exiting firm. We further require the matched non-exiting firms to have the same VC-backing status and multi-unit status as the exiting firm. Finally, for each exiting firm *i*, we retain five eligible matched non-exiting firms that are the closest to firm *i* in terms of size. The dependent variable, *EntrepreneurialExit*, is a dummy variable that equals one if a private firm *i* exits through IPO or sell-out in year *t*, and zero otherwise. *LnDiffuser* is the natural logarithm of one plus the number of entrepreneurial diffusers in a firm. *PctDiffuser* is the fraction of entrepreneurial diffusers in a firm's workforce. *PctEarnDiffuser* is the fraction of a firm's total payroll earned by entrepreneurial diffusers. All other variables are defined in Appendix D. Each regression includes a separate intercept. We include matched-pair fixed effects in all regressions. Standard errors are clustered by three-digit NAICS industry. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.		*EntrepreneurialExit*	
	(1)	(2)	(3)
LnDiffuser	0.089***		
	(3.923)		
PctDiffuser		3.239***	
		(3.925)	
PctEarnDiffuser			2.743***
			(4.033)
LnEmpLeaveToPubExp	0.083		
	(1.569)		
PctEmpLeaveToPubExp		4.140	
		(1.042)	
PctEarnLeaveToPubExp			4.375
			(1.118)
LnEmp	0.079***	0.082***	0.082***
	(6.838)	(6.768)	(6.785)
LnFirmAge	-0.119***	-0.119***	-0.119***
	(-5.323)	(-5.406)	(-5.374)
LnAvgAge	-0.046	-0.047*	-0.047*
	(-1.660)	(-1.693)	(-1.692)
LnAvgEdu	0.417***	0.417***	0.419***
	(6.344)	(6.417)	(6.388)
Gender	0.083**	0.083**	0.083**
	(2.019)	(2.004)	(2.010)
Ethnicity	0.058*	0.058*	0.058*
	(1.907)	(1.907)	(1.919)
Pair Fixed Effects	Yes	Yes	Yes

Observations	11,000	11,000	11,000
R-squared	0.064	0.064	0.063

Table 3.4: Innovation Productivity of Private Firms Joined by Entrepreneurial Diffusers

This table presents the analyses on the innovation productivity of the firms joined by entrepreneurial diffusers and that of the diffusers' new colleagues after the joining of entrepreneurial diffusers. Panel A presents the average differences in post-joining innovation productivity between treatment firms (i.e., the firms that entrepreneurial diffusers newly join) and matched firms. Specifically, for each treatment firm *i*, i.e., private firm *i* with at least one entrepreneurial diffuser joining the firm on date *t*, we find all the private firms who share the same major patent class (i.e., the technology class in which a firm files the largest number of patents) with firm *i* and whose total number of patents filed in the five years before *t* is between 0.8 and 1.2 times of that of firm *i*. We then calculate these firms' average number of patents filed per year (*FirmPatentsPostJoin*), the average number of citations received per patent (*FirmCitePatPostJoin*), the patents' average originality score (*FirmOriginalityPostJoin*), and the average number of exploratory patents filed per year (*FirmExploratoryPostJoin*) in the five years after *t*. For each treatment firm *i*, we report the differences between its four innovation activity measures and the median values of these measures of its matched firms. Panel B reports the average differences in innovation productivity between entrepreneurial diffusers' new colleagues (i.e., the non-diffuser inventors in the treatment firms) and their matched inventors in the matched firms. Specifically, for each non-diffuser inventor *j* who works for treatment firm *i* (with at least one entrepreneurial diffuser joining the firm on date *t*), we find all the inventors who work for firm *i*'s matched firms on date *t*, and whose average annual number of patents filed in the five-year period before *t* is no more than one from that of inventor *j*. We then compare the innovation productivity (i.e., *PatentsPostJoin*, *CitePatPostJoin*, *OriginalityPostJoin*, and *ExploratoryPostJoin*) of inventor *j* and the median of her matched inventors in the five-year period after *t*. In addition, we report the t-statistics on whether the differences are significantly different from zero. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Difference in Innovation Productivity between Treatment Firms Joined by Entrepreneurial Diffusers and Matched Firms

Difference	Variable	N	Mean	t-statistics
Firms joined by diffusers - Matched firms	*FirmPatentsPostJoin*	1,430	4.208***	9.540
	FirmCitePatPostJoin	1,430	6.514***	20.496
	FirmOriginalityPostJoin	1,430	6.437***	29.544
	FirmExploratoryPostJoin	1,430	1.448***	7.344

Panel B: Difference in Innovation Productivity between Entrepreneurial Diffusers' New Colleagues and Matched Inventors in Matched Firms

Difference	Variable	N	Mean	t-statistics
Peer inventors - Matched inventors	*PatentsPostJoin*	42,414	0.186***	67.202
	CitePatPostJoin	42,414	3.507***	73.233
	OriginalityPostJoin	42,414	2.277***	76.134
	ExploratoryPostJoin	42,414	0.028***	23.010

Table 3.5: Decisions to Become Entrepreneurial Diffusers and Post-exit Labor Income

This table presents the OLS regressions on the association between an employee's decision to become an entrepreneurial diffuser and post-exit labor income in the LEHD sample. *EarnGap* is the difference between an employee's post-exit quarterly earnings and her pre-exit quarterly earnings (in terms of thousands, 2007 dollars). *LnEarnPost* is the natural logarithm of the average quarterly earnings (in thousands, 2007 dollars) of an employee in the five years post the exit. *EntreDiffuser* (*LeaverToPub*) is a dummy variable that equals one if an employee moves to a private (public) firm within one year after her original employer's exit, and zero otherwise. We report the F-statistics and the associated P-values for the difference between the coefficients of *EntreDiffuser* and *LeaverToPub*. The control variables are defined in Appendix D. Each regression includes a separate intercept. We include deal fixed effects, gender fixed effects, and *ethnicity* fixed effects in the regressions. Standard errors are clustered by exit deals. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	*EarnGap*	*LnEarnPost*
	(1)	(2)
EntreDiffuser	-0.005	0.008
	(-0.050)	(1.115)
LeaverToPub	0.259**	0.031***
	(2.224)	(5.467)
LnTenure	-0.067*	-0.007***
	(-1.865)	(-3.599)
LnAge	0.268***	-0.076***
	(3.551)	(-13.340)
LnEdu	1.054***	0.093***
	(12.540)	(21.680)
LnEarn	-1.206***	0.783***
	(-4.385)	(76.900)
F-statistics	6.637	11.680
P-value	0.010	0.001
Gender Fixed Effects	Yes	Yes
EthnicityFixed Effects	Yes	Yes
Deal Fixed Effects	Yes	Yes
Observations	931,000	931,000
R-squared	0.158	0.796

Table 3.6: Decisions to Become Entrepreneurial Diffusers and Post-exit Innovation Activities
This table presents the average differences in post-exit innovation activities between entrepreneurial diffusers and their matched inventors in other categories. For each entrepreneurial diffuser whose employer exits in year *t*, we find all the leavers to public firms and stayers whose employers also exit in year *t*, and whose difference with the entrepreneurial diffuser in terms of average number of patents filed per year in the five years before exits is no more than one. We then calculate the average number of patents filed per year (*PatentsPostExit*), the average number of citations received per patent (*CitePatPostExit*), the patents' average originality score (*OriginalityPostExit*), and the average number of exploratory patents filed per year (*ExploratoryPostExit*) by each inventor in the five years after exits. We report the average differences between an entrepreneurial diffuser's innovation activity measures mentioned above and those of her matched inventors in other categories. In addition, we report the t-statistics on whether the differences are significantly different from zero. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Difference	Variable	N	Mean	t-statistics
EntreDiffuser - LeaverToPub	*PatentsPostExit*	753	0.631***	12.749
	CitePatPostExit	753	3.098***	5.604
	OriginalityPostExit	753	1.670***	5.556
	ExploratoryPostExit	753	0.210***	10.686
EntreDiffuser - Stayer	*PatentsPostExit*	781	0.908***	19.978
	CitePatPostExit	781	5.860***	11.417
	OriginalityPostExit	781	2.010***	7.171
	ExploratoryPostExit	781	0.411***	22.310

Table 3.7: Employee Job Risk Tolerance and Decisions to Become Entrepreneurial Diffusers
This table presents the linear probability regressions on the association between employees' job risk tolerance and their choices of destination firms conditional on the decision to leave the exiting firms, using the LEHD sample of employees from both IPO firms and acquired private firms. The dependent variable, *EntreDiffuser,* is defined as a dummy variable that equals one if an employee is an entrepreneurial diffuser, and zero if the employee is a leaver to public firms. *JobRiskTolerance* is defined as the difference between an employee's total household labor income and her earnings from the exited firm scaled by her household's total labor income. The control variables are defined in Appendix D. Each regression includes a separate intercept. All columns include gender fixed effects and ethnicity fixed effects. In addition, we include year fixed effects in Column (1), three-digit NAICS industry fixed effects in Column (2), year and industry fixed effects in Column (3), and deal fixed effects in Column (4). Standard errors are clustered by deals. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	*EntreDiffuser*			
	(1)	(2)	(3)	(4)
JobRiskTolerance	0.022*	0.019**	0.018**	0.013*
	(1.765)	(2.339)	(2.261)	(1.816)
LnTenure	0.008	0.006	0.004	0.003
	(0.802)	(0.874)	(0.638)	(0.672)
LnAge	0.074***	0.059***	0.054***	0.041***
	(4.092)	(4.255)	(3.995)	(3.432)
LnEdu	-0.005	-0.010	-0.004	0.005
	(-0.350)	(-0.876)	(-0.349)	(0.529)
LnEarn	-0.026*	-0.047***	-0.046***	-0.039***
	(-1.914)	(-5.161)	(-5.029)	(-4.034)
Gender Fixed Effects	Yes	Yes	Yes	Yes
EthnicityFixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No
Industry Fixed Effects	No	Yes	Yes	No
Deal Fixed Effects	No	No	No	Yes
Observations	94,000	94,000	94,000	94,000
R-squared	0.023	0.074	0.077	0.170

Table 3.8: Entrepreneurial Diffusers and Their Original Employers' Post-IPO Performance
This table presents the OLS regressions on the association between the departure of entrepreneurial diffusers and their original employers' post-IPO performance. Panel A reports the results in the LEHD sample. We redact the regression coefficients of control variables in Columns (4)-(6) due to the disclosure restriction by the U.S. Census Bureau. Panel B reports the results in the inventor sample. Columns (1)-(3) in both panels report the regressions using firms' buy-and-hold abnormal returns in the one, three, and five years after IPO (*AR1yr*, *AR3yr*, and *AR5yr*, respectively) as the measure of post-IPO performance. Columns (4)-(6) in both panels report the regressions using firms' average *ROA* in the one, three, and five years after IPO (*ROA1yr*, *ROA3yr*, and *ROA5yr*, respectively) as the measure of post-IPO performance. *PctDiffuserLeft* (*PctLeaverToPub*) is the fraction of a firm's pre-exit employees who move to private (public) firms within one year after IPO. All other variables are defined in Appendix D. Each regression includes a separate intercept. We include industry fixed effects (at the three-digit NAICS level) and year fixed effects in the regressions. Standard errors are clustered by three-digit NAICS industry. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Entrepreneurial Diffusers and Original Employers' Post-IPO Performance in the LEHD Sample

Dep. Var.	*AR1yr*	*AR3yr*	*AR5yr*	*ROA1yr*	*ROA3yr*	*ROA5yr*
	(1)	(2)	(3)	(4)	(5)	(6)
PctDiffuserLeft	-1.114*	-4.343***	-6.126**	-0.885***	-1.068***	-0.951***
	(-1.942)	(-3.530)	(-2.301)	(-3.327)	(-5.094)	(-4.125)
PctLeaverToPub	-2.670***	-1.689	3.099	-0.171	-0.548	-0.405
	(-2.925)	(-1.241)	(0.996)	(-0.425)	(-1.357)	(-1.291)
PctNewHire	-0.002	0.027	-0.006	-0.024*	-0.027*	-0.037***
	(-0.052)	(0.185)	(-0.032)	(-1.690)	(-1.827)	(-3.100)
IR	-0.227***	-0.178***	0.123	+*	+	+**
	(-5.595)	(-2.726)	(0.445)			
LnProceeds	0.244	-0.755	0.196	+	+	+
	(0.959)	(-0.896)	(0.323)			
VC	0.078	0.173*	-0.148	-	-	-
	(1.112)	(1.723)	(-0.507)			
TobinQ	0.071***	0.025	0.014	+	+**	+*
	(9.373)	(0.930)	(0.703)			
LnMV	-0.182**	-0.013	-0.244	-	-	-
	(-2.624)	(-0.062)	(-1.398)			
RDadj	-0.055	-0.336	0.769	-***	-***	-***
	(-0.413)	(-1.322)	(0.721)			
IndVCPct	-13.360***	-23.930**	-65.860**	-***	-***	-***
	(-4.044)	(-2.019)	(-2.540)			
LnIndIPOVol	-0.026	-0.078	0.110	+	+	+
	(-0.624)	(-0.655)	(0.618)			
IndRFOption	7.515	13.860	-67.160	-	-	-

	(0.583)	(0.463)	(-0.794)			
LnEmp	0.130***	0.512***	0.736***	+***	+***	+***
	(3.186)	(3.830)	(2.911)			
LnFirmAge	0.006	-0.230	-0.676*	+**	+***	+***
	(0.173)	(-1.259)	(-1.903)			
LnAvgTenure	-0.065	0.306	0.691**	+	+*	+*
	(-1.493)	(1.342)	(2.328)			
LnAvgAge	0.531*	1.648*	2.801*	-	+	+
	(1.901)	(1.759)	(1.975)			
LnAvgEdu	-0.791	-0.543	-1.038	-	-	-
	(-1.286)	(-0.245)	(-0.204)			
LnAvgEarn	0.377***	0.316	0.541	+***	+***	+***
	(3.981)	(0.935)	(1.351)			
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R-squared	0.365	0.244	0.223	0.632	0.61	0.592

Panel B: Entrepreneurial Diffusers and Original Employers' Post-IPO Performance in the Inventor Sample

Dep. Var.	*AR1yr*	*AR3yr*	*AR5yr*	*ROA1yr*	*ROA3yr*	*ROA5yr*
	(1)	(2)	(3)	(4)	(5)	(6)
PctDiffuserLeft	-0.188	-0.695**	-0.934**	-0.138*	-0.152**	-0.169**
	(-1.701)	(-2.473)	(-2.479)	(-1.989)	(-2.299)	(-2.629)
PctLeaverToPub	0.274	-0.498	-0.979	-0.121	-0.097	-0.068
	(0.584)	(-0.560)	(-0.846)	(-0.991)	(-1.218)	(-0.885)
PctNewHire	0.010	0.022	0.042	0.025**	0.019**	0.013
	(0.493)	(0.591)	(0.731)	(2.620)	(2.155)	(1.533)
IR	-0.481***	-0.330***	-0.244***	-0.014	-0.017	-0.010
	(-3.672)	(-3.603)	(-4.188)	(-0.976)	(-1.152)	(-1.087)
LnProceeds	-0.023	-0.161	-0.189	0.076	0.062	0.050
	(-0.137)	(-0.611)	(-0.485)	(1.492)	(1.554)	(1.643)
VC	-0.063	0.190	0.286	-0.056	-0.039	-0.027
	(-0.609)	(1.234)	(1.103)	(-1.308)	(-1.174)	(-0.903)
TobinQ	0.076***	0.014	0.010	-0.001	-0.005**	-0.003
	(7.164)	(0.886)	(0.863)	(-0.650)	(-2.907)	(-1.698)
LnMV	0.050	0.291	0.191	-0.041	-0.008	0.004
	(0.335)	(1.284)	(0.604)	(-0.807)	(-0.195)	(0.155)
RDadj	-0.618	-0.569	-0.876	-1.146***	-0.990***	-1.014***
	(-1.682)	(-0.664)	(-1.521)	(-7.258)	(-8.496)	(-8.863)
IndVCPct	-0.242	-0.882*	-0.958	-0.060	-0.108	-0.130
	(-1.264)	(-1.818)	(-1.529)	(-0.630)	(-1.143)	(-1.282)
LnIndIPOVol	-0.033	-0.273**	-0.028	0.023	0.010	0.006
	(-0.683)	(-2.455)	(-0.164)	(1.485)	(0.618)	(0.304)
IndRFOption	6.968	-11.664	-17.984	-5.665*	-4.314*	-3.888*
	(1.355)	(-0.962)	(-1.098)	(-2.072)	(-1.933)	(-2.048)
LnInventor	0.044	0.031	0.133	0.054**	0.041*	0.033*
	(0.834)	(0.290)	(1.041)	(2.507)	(2.139)	(1.988)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	697	697	697	697	697	697
R-squared	0.297	0.141	0.092	0.370	0.364	0.370

Table 3.9: 2SLS Analysis on the Impact of Entrepreneurial Diffusers on Their Original Employers' Post-IPO Performance

This table reports the 2SLS regressions on the impact of entrepreneurial diffusers on their original employers' post-IPO performance in the inventor sample. The instrumental variable, *ChgPctPatentsPrv*, is the change in the fraction of patents filed by private firms (as opposed to public firms) in an IPO firm's three-digit NAICS industry. *PctDiffuserLeft* is the fraction of a firm's pre-exit employees who move to private firms within one year after IPO. *FittedPctDiffuserLeft* is the fitted value of *PctDiffuserLeft* obtained from the first-stage regression. All other variables are defined in Appendix D. Column (1) reports the first-stage regression and the Kleibergen-Paap Wald F-statistic on the weak instrument test. Columns (2)-(4) report the regressions using firms' buy-and-hold abnormal return in the one, three, and five years after IPO (*AR1yr*, *AR3yr*, and *AR5yr*, respectively) as the measure of post-IPO performance. Columns (5)-(7) report the regressions using firms' average *ROA* in the one, three, and five years after IPO (*ROA1yr*, *ROA3yr*, and *ROA5yr*, respectively) as the measure of post-IPO performance. Each regression includes a separate intercept. We include industry fixed effects (at the three-digit NAICS level) and year fixed effects in the regressions. Standard errors are clustered by three-digit NAICS industry. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	1st Stage	2nd Stage					
Dep. Var.	*PctDiffuserLeft*	*AR1yr*	*AR3yr*	*AR5yr*	*ROA1yr*	*ROA3yr*	*ROA5yr*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ChgPctPatentsPrv	1.450***						
	(3.464)						
FittedPctDiffuserLeft		-0.353	-7.917***	-3.577**	-0.714	-1.167**	-0.949**
		(-0.318)	(-3.350)	(-2.006)	(-1.541)	(-2.523)	(-2.366)
PctLeaverToPub	-0.153**	0.250	-1.555*	-1.366	-0.205**	-0.246**	-0.183*
	(-2.542)	(0.735)	(-1.744)	(-1.314)	(-2.131)	(-2.487)	(-1.903)
PctNewHire	0.010	0.011	0.093	0.067	0.030***	0.029***	0.021*
	(1.280)	(0.516)	(1.213)	(1.076)	(2.848)	(2.703)	(1.903)
IR	0.007	-0.480***	-0.289**	-0.229***	-0.010	-0.012	-0.005
	(0.402)	(-4.041)	(-2.068)	(-3.915)	(-0.694)	(-1.028)	(-0.431)
LnProceeds	-0.017	-0.025	-0.257	-0.224	0.068	0.049	0.040
	(-0.553)	(-0.162)	(-0.740)	(-0.596)	(1.193)	(0.927)	(1.171)
VC	-0.001	-0.063	0.190	0.286	-0.056	-0.040	-0.027
	(-0.043)	(-0.652)	(0.670)	(1.046)	(-1.294)	(-0.858)	(-0.761)
TobinQ	-0.002	0.076***	0.001	0.005	-0.002	-0.007***	-0.005**
	(-1.325)	(8.017)	(0.045)	(0.403)	(-1.045)	(-2.842)	(-2.052)
LnMV	-0.002	0.049	0.250	0.176	-0.045	-0.014	-0.000
	(-0.060)	(0.352)	(0.761)	(0.540)	(-0.777)	(-0.262)	(-0.002)
RDadj	0.084	-0.605*	0.042	-0.652	-1.097***	-0.904***	-0.948***

	(0.839)	(-1.744)	(0.041)	(-1.034)	(-6.417)	(-5.282)	(-6.695)
IndVCPct	-0.027	-0.243	-0.933	-0.977*	-0.064	-0.115	-0.136
	(-0.427)	(-1.396)	(-1.414)	(-1.686)	(-0.687)	(-1.089)	(-1.385)
LnIndIPOVol	0.011	-0.031	-0.181	0.005	0.030	0.023	0.016
	(0.758)	(-0.624)	(-1.262)	(0.035)	(1.415)	(0.979)	(0.722)
IndRFOption	2.036**	7.224	-0.433	-13.874	-4.769**	-2.736	-2.674
	(2.448)	(1.644)	(-0.033)	(-0.939)	(-2.073)	(-1.195)	(-1.343)
LnInventor	0.006	0.045	0.080	0.151	0.057**	0.048*	0.038*
	(0.485)	(0.880)	(0.688)	(1.447)	(2.265)	(1.840)	(1.767)
F-statistics	12.001						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	697	697	697	697	697	697	697

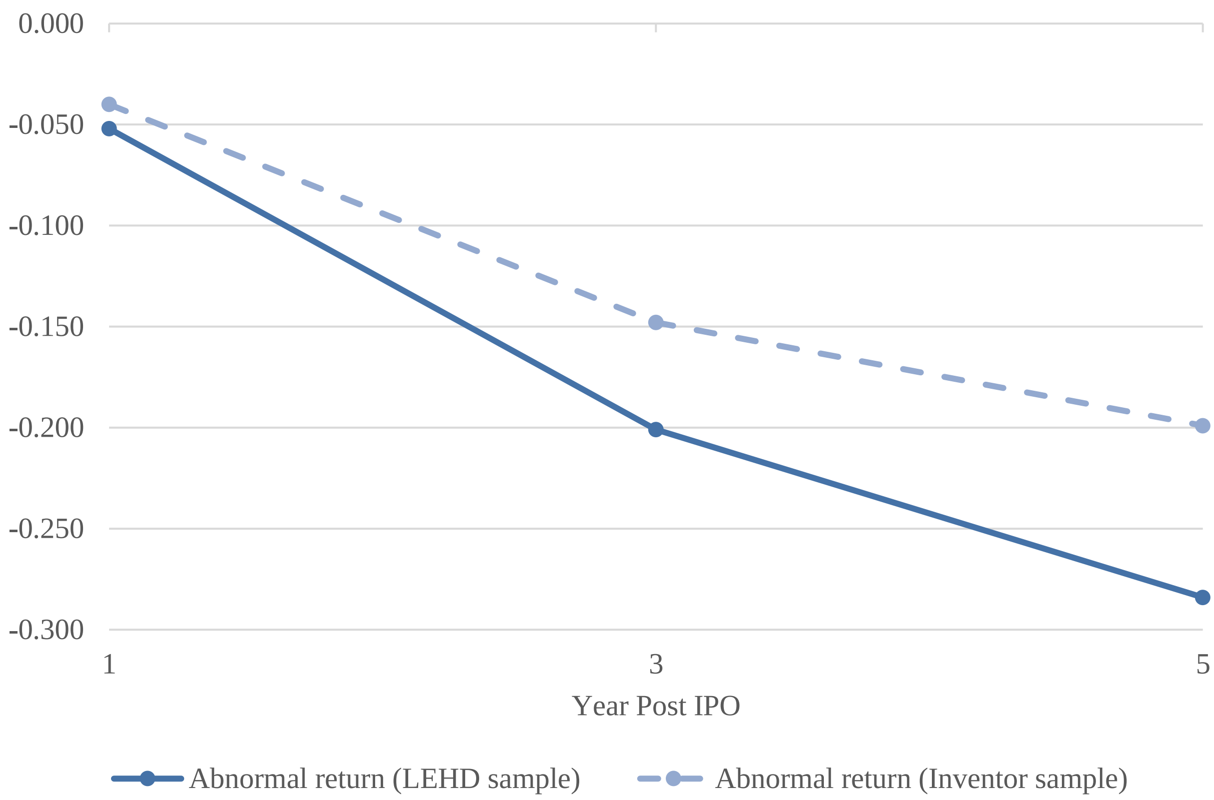


Figure 3.1: Entrepreneurial Diffusers and Their Original Employers' Post-IPO Buy-and-hold Abnormal Returns

This figure displays the association between the departure of entrepreneurial diffusers and their original employers' post-IPO buy-and-hold abnormal returns (*BHAR*), based on the regression coefficients reported in Table 3.8. The solid line (dashed line) presents the decrease in *BHAR* in the one, three, and five years after IPO associated with a one standard deviation increase in the fraction of a firm's employees who move to private firms after IPO in the LEHD sample (inventor sample).

References

Abowd, J.M., Stephens, B.E., Vilhuber, L., Andersson, F., McKinney, K.L., Roemer, M. and Woodcock, S., 2009. The LEHD infrastructure files and the creation of the Quarterly Workforce Indicators. In *Producer dynamics: New evidence from micro data* (pp. 149-230). University of Chicago Press.

Agarwal, R. and Shah, S.K., 2014. Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Research policy*, *43*(7), pp.1109-1133.

Aggarwal, V.A. and Hsu, D.H., 2014. Entrepreneurial exits and innovation. *Management Science*, *60*(4), pp.867-887.

Akey, P., 2015. Valuing changes in political networks: Evidence from campaign contributions to close congressional elections. *The Review of Financial Studies*, *28*(11), pp.3188-3223.

Aldatmaz, S., Ouimet, P. and Van Wesep, E.D., 2018. The option to quit: The effect of employee stock options on turnover. *Journal of Financial Economics*, *127*(1), pp.136-151.

American Psychological Association, 2017. '2017 Work and well-being survey: special focus on politics'.

Babenko, I., Fedaseyeu, V. and Zhang, S., 2020. Do CEOs Affect Employees' Political Choices?. *The Review of Financial Studies*, *33*(4), pp.1781-1817.

Babina, T., Ma, W., Moser, C., Ouimet, P. and Zarutskie, R., 2020. Pay, employment, and dynamics of young firms. *Working paper*.

Babina, T., Ouimet, P. and Zarutskie, R., 2020. IPOs, human capital, and labor reallocation. *Working paper*.

Ball, E., Chiu, H.H. and Smith, R., 2011. Can VCs time the market? An analysis of exit choice for venture-backed firms. *The Review of Financial Studies*, *24*(9), pp.3105-3138.

Bayar, O. and Chemmanur, T.J., 2011. IPOs versus acquisitions and the valuation premium puzzle: a theory of exit choice by entrepreneurs and venture capitalists. *Journal of Financial and Quantitative Analysis*, *46*(6), pp.1755-1793.

Bayar, O. and Chemmanur, T.J., 2012. What drives the valuation premium in IPOs versus acquisitions? An empirical analysis. *Journal of Corporate Finance*, *18*(3), pp.451-475.

Belo, F., Li, J., Lin, X. and Zhao, X., 2017. Labor-force heterogeneity and asset prices: The importance of skilled labor. *The Review of Financial Studies, 30(10),* pp.3669-3709.

Bernstein, S., 2015. Does going public affect innovation? *The Journal of Finance*, *70*(4), pp.1365-1403.

Bhattacharya, S. and Ritter, J.R., 1983. Innovation and communication: Signaling with partial disclosure. *The Review of Economic Studies*, *50*(2), pp.331-346.

Boone, A.L., Floros, I.V. and Johnson, S.A., 2016. Redacting proprietary information at the initial public offering. *Journal of Financial Economics*, *120*(1), pp.102-123.

Borghesi, R., 2018. Employee political affiliation as a driver of corporate social responsibility intensity. *Applied Economics*, *50*(19), pp.2117-2132.

Bowen, D., Frésard, L. and Hoberg, G., 2020. Rapidly Evolving Technologies and Startup Exits. *Working Paper*.

Brau, J.C., Francis, B. and Kohers, N., 2003. The choice of IPO versus takeover: Empirical evidence. *The Journal of Business*, *76*(4), pp.583-612.

Brav, A., Jiang, W., Ma, S. and Tian, X., 2018. How does hedge fund activism reshape corporate innovation?. *Journal of Financial Economics*, *130*(2), pp.237-264.

Call, A.C., Kedia, S. and Rajgopal, S., 2016. Rank and file employees and the discovery of misreporting: The role of stock options. *Journal of Accounting and Economics*, *62*(2-3), pp.277-300.

Cassar, L. and Meier, S., 2018. Nonmonetary incentives and the implications of work as a source of meaning. *Journal of Economic Perspectives*, *32*(3), pp.215-38.

Chaplinsky, S., Hanley, K.W. and Moon, S.K., 2017. The JOBS Act and the costs of going public. *Journal of Accounting Research*, *55*(4), pp.795-836.

Chemmanur, T.J. and He, J., 2011. IPO waves, product market competition, and the going public decision: Theory and evidence. *Journal of Financial Economics*, *101*(2), pp.382-412.

Chemmanur, T.J., He, J., He, S. and Nandy, D., 2018. Product market characteristics and the choice between IPOs and acquisitions. *Journal of Financial and Quantitative Analysis*, *53*(2), pp.681-721.

Chemmanur, T.J., He, S. and Nandy, D.K., 2009. The going-public decision and the product market. *The Review of Financial Studies*, *23*(5), pp.1855-1908.

Chemmanur, T.J., Kong, L., Krishnan, K. and Yu, Q., 2019. Top management human capital, inventor mobility, and corporate innovation. *Journal of Financial and Quantitative Analysis*, *54*(6), pp.2383-2422.

Chemmanur, T.J., Krishnan, K. and Nandy, D.K., 2011. How does venture capital financing improve efficiency in private firms? A look beneath the surface. *The Review of Financial Studies*, *24*(12), pp.4037-4090.

Chemmanur, T.J., Loutskina, E. and Tian, X., 2014. Corporate venture capital, value creation, and innovation. *The Review of Financial Studies*, *27*(8), pp.2434-2473.

Chemmanur, T.J. and Paeglis, I., 2005. Management quality, certification, and initial public offerings. *Journal of Financial Economics*, *76*(2), pp.331-368.

Chen, J., Hshieh, S. and Zhang, F., 2020. The role of high-skilled foreign labor in startup performance: Evidence from two natural experiments. *Journal of Financial Economics, forthcoming*.

Clementi, G.L., 2002. IPOs and the growth of firms. *Working paper*.

Cohen, A., Hazan, M., Tallarita, R. and Weiss, D., 2019. The Politics of CEOs. *Working Paper*.

Cooper, M.J., Gulen, H. and Ovtchinnikov, A.V., 2010. Corporate political contributions and stock returns. *The Journal of Finance*, *65*(2), pp.687-724.

Cumming, D., 2008. Contracts and exits in venture capital finance. *The Review of Financial Studies*, *21*(5), pp.1947-1982.

Cunningham, C., Ederer, F. and Ma, S., 2020. Killer acquisitions. *Journal of Political Economy, forthcoming.*

Dambra, M., Field, L.C. and Gustafson, M.T., 2015. The JOBS Act and IPO volume: Evidence that disclosure costs affect the IPO decision. *Journal of Financial Economics*, *116*(1), pp.121-143.

Davis, S.J., Haltiwanger, J., Handley, K., Jarmin, R., Lerner, J. and Miranda, J., 2014. Private equity, jobs, and productivity. *American Economic Review*, *104*(12), pp.3956-90.

de Fontenay, E., 2017. The deregulation of private capital and the decline of the public company, *Hastings Law Journal*, *68*, pp. 445-502.

Decker, R.A., Haltiwanger, J., Jarmin, R.S. and Miranda, J., 2016a. Declining business dynamism: What we know and the way forward. *American Economic Review*, *106*(5), pp.203-07.

Decker, R.A., Haltiwanger, J., Jarmin, R.S. and Miranda, J., 2016b. Where has all the skewness gone? The decline in high-growth (young) firms in the US. *European Economic Review*, *86*, pp.4-23.

DellaVigna, S. and Kaplan, E., 2007. The Fox News effect: Media bias and voting. *The Quarterly Journal of Economics*, *122*(3), pp.1187-1234.

Di Giuli, A. and Kostovetsky, L., 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. *Journal of Financial Economics*, *111*(1), pp.158-180.

Dimmock, S.G., Huang, J. and Weisbenner, S.J., 2019. Give me your tired, your poor, your high-skilled labor: H-1B lottery outcomes and entrepreneurial success. *NBER Working Paper*.

Doidge, C., Kahle, K.M., Karolyi, G.A. and Stulz, R.M., 2018. Eclipse of the public corporation or eclipse of the public markets? *Journal of Applied Corporate Finance*, *30*(1), pp.8-16.

Doidge, C., Karolyi, G.A. and Stulz, R.M., 2013. The US left behind? Financial globalization and the rise of IPOs outside the US. *Journal of Financial Economics*, *110*(3), pp.546-573.

Doidge, C., Karolyi, G.A. and Stulz, R.M., 2017. The US listing gap. *Journal of Financial Economics*, *123*(3), pp.464-487.

Donangelo, A., 2014. Labor mobility: Implications for asset pricing. *The Journal of Finance*, *69*(3), pp.1321-1346.

Eckbo, B.E. and Lithell, M., 2020. Follow the assets: Is the US listing gap “real”? *Working Paper*.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, *101*(3), pp.621-640.

Eiling, E., 2013. Industry-specific human capital, idiosyncratic risk, and the cross-section of expected stock returns. *The Journal of Finance*, *68*(1), pp.43-84.

Ewens, M. and Farre-Mensa, J., 2020. The deregulation of the private equity markets and the decline in IPOs. *Working Paper*.

Ewens, M., Xiao, K. and Xu, T., 2020. Regulatory costs of being public: Evidence from bunching estimation. *Working paper*.

Farre-Mensa, J., 2017. The benefits of selective disclosure: Evidence from private firms. *Working paper*.

Francis, B.B., Hasan, I., Sun, X. and Wu, Q., 2016. CEO political preference and corporate tax sheltering. *Journal of Corporate Finance*, *38*, pp.37-53.

Cronqvist, H., Heyman, F., Nilsson, M., Svaleryd, H. and Vlachos, J., 2009. Do entrenched managers pay their workers more?. *The Journal of Finance*, *64*(1), pp.309-339.

Gao, M. and Huang, J., 2016. Capitalizing on Capitol Hill: Informed trading by hedge fund managers. *Journal of Financial Economics*, *121*(3), pp.521-545.

Gao, H., Hsu, P.H. and Li, K., 2018. Innovation strategy of private firms. *Journal of Financial and Quantitative Analysis*, *53*(1), pp.1-32.

Gao, X., Ritter, J.R. and Zhu, Z., 2013. Where have all the IPOs gone? *Journal of Financial and Quantitative Analysis*, *48*(6), pp.1663-1692.

Ghaly, M., Anh Dang, V. and Stathopoulos, K., 2017. Cash holdings and labor heterogeneity: the role of skilled labor. *The Review of Financial Studies*, *30*(10), pp.3636-3668.

Giroud, X., 2013. Proximity and investment: Evidence from plant-level data. *The Quarterly Journal of Economics*, *128*(2), pp.861-915.

Glaser, A., 2018. 'Public Shaming Won't Stop Sinclair'. *Slate*, 2 April, 2018.

Goldman, E., Rocholl, J. and So, J., 2008. Do politically connected boards affect firm value?. *The Review of Financial Studies*, *22*(6), pp.2331-2360.

Gompers, P., Kovner, A., Lerner, J. and Scharfstein, D., 2010. Performance persistence in entrepreneurship. *Journal of Financial Economics*, *96*(1), pp.18-32.

Grullon, G., Larkin, Y. and Michaely, R., 2019. Are US industries becoming more concentrated? *Review of Finance*, *23*(4), pp.697-743.

Gu, L., Huang, R., Mao, Y. and Tian, X., 2019. How does human capital matter? Evidence from venture capital. *Working Paper*.

Guiso, L., Pistaferri, L. and Schivardi, F., 2020. Learning entrepreneurship from other entrepreneurs?. *Journal of Labor Economics*, *39*(1), pp.000-000.

Guiso, L., Sapienza, P. and Zingales, L., 2015. The value of corporate culture. *Journal of Financial Economics*, *117*(1), pp.60-76.

Gupta, A., Briscoe, F. and Hambrick, D.C., 2017. Red, blue, and purple firms: Organizational political ideology and corporate social responsibility. *Strategic Management Journal*, *38*(5), pp.1018-1040.

Guzman, J. and Stern, S., 2020. The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 US states, 1988–2014. *American Economic Journal: Economic Policy*, *12*(4), pp.212-43.

Hamilton, B.H., 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*(3), pp.604-631.

He, S. and Li, C.W., 2016. Human capital, management quality, and the exit decisions of entrepreneurial firms. *Journal of Financial and Quantitative Analysis*, *51*(4), pp.1269-1295.

He, J., Shu, T. and Yang, H., 2018. The Employee Clientele of Corporate Leverage: Evidence from Personal Labor Income Diversification. *Working Paper*.

Hellmann, T. and Puri, M., 2002. Venture capital and the professionalization of starp-up firms: Empirical evidence. *The Journal of Finance*, *57*(1), pp.169-197.

Hensarling, J., 2018. To restore U.S. competitiveness, pass the JOBS Act 3.0. *Wall Street Journal*.

Hirshleifer, D., Hsu, P.H. and Li, D., 2018. Innovative originality, profitability, and stock returns. *The Review of Financial Studies*, *31*(7), pp.2553-2605.

Hochberg, Y.V., Ljungqvist, A. and Lu, Y., 2007. Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, *62*(1), pp.251-301.

Hong, H. and Kostovetsky, L., 2012. Red and blue investing: Values and finance. *Journal of Financial Economics*, *103*(1), pp.1-19.

Huang, M., Li, P., Meschke, F. and Guthrie, J.P., 2015. Family firms, employee satisfaction, and corporate performance. *Journal of Corporate Finance*, *34*, pp.108-127.

Hutton, I., Jiang, D. and Kumar, A., 2014. Corporate policies of Republican managers. *Journal of Financial and Quantitative Analysis*, *49*(5-6), pp.1279-1310.

Hvide, H.K. and Panos, G.A., 2014. Risk tolerance and entrepreneurship. *Journal of Financial Economics*, *111*(1), pp.200-223.

Hvide, H.K. and Oyer, P., 2019. Dinner table human capital and entrepreneurship. *NBER Working Paper*.

Hymowitz, C. and Greenfield, R., 2017. 'Anti-Trump employees put their bosses in the hot seat'. *Bloomberg*, 8 February, 2017.

Islam, E. and Zein, J., 2020. Inventor CEOs. *Journal of Financial Economics*, *135*(2), pp.505-527.

Israelsen, R.D. and Yonker, S.E., 2017. Key human capital. *Journal of Financial and Quantitative Analysis*, *52*(1), pp.175-214.

Jain, B.A. and Kini, O., 1994. The post-issue operating performance of IPO firms. *The Journal of Finance*, *49*(5), pp.1699-1726.

Jarmin, R.S. and Miranda, J., 2002. The longitudinal business database. *Available at SSRN 2128793*.

Kahle, K.M. and Stulz, R.M., 2017. Is the US public corporation in trouble? *Journal of Economic Perspectives*, *31*(3), pp.67-88.

Kale, J.R., Ryan Jr, H.E. and Wang, L., 2016. Outside employment opportunities, employee productivity, and debt discipline. *Journal of Corporate Finance*.

Kerr, W.R., Lerner, J. and Schoar, A., 2014. The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, *27*(1), pp.20-55.

Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), pp.665-712.

Krishnan, K., Nandy, D.K. and Puri, M., 2015. Does financing spur small business productivity? Evidence from a natural experiment. *The Review of Financial Studies*, *28*(6), pp.1768-1809.

Kuehn, L.A., Simutin, M. and Wang, J.J., 2017. A labor capital asset pricing model. *The Journal of Finance*, *72*(5), pp.2131-2178.

Lafontaine, F. and Shaw, K., 2016. Serial entrepreneurship: Learning by doing?. *Journal of Labor Economics*, *34*(S2), pp.S217-S254.

Laspita, S., Breugst, N., Heblich, S. and Patzelt, H., 2012. Intergenerational transmission of entrepreneurial intentions. *Journal of Business Venturing*, *27*(4), pp.414-435.

Lattanzio, G., Megginson, W.L. and Sanati, A., 2019. Listing gaps, merger Waves, and the privatization of American equity finance. *Working Paper*.

Lee, J., Lee, K.J. and Nagarajan, N.J., 2014. Birds of a feather: Value implications of political alignment between top management and directors. *Journal of Financial Economics*, *112*(2), pp.232-250.

Lerner, J. and Malmendier, U., 2013. With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *The Review of Financial Studies*, *26*(10), pp.2411-2452.

Li, G.C., Lai, R., D'Amour, A., Doolin, D.M., Sun, Y., Torvik, V.I., Amy, Z.Y. and Fleming, L., 2014. Disambiguation and co-authorship networks of the US patent inventor database (1975–2010). *Research Policy*, *43*(6), pp.941-955.

Lin, C., Liu, S. and Manso, G., 2020. Shareholder litigation and corporate innovation. *Management Science, forthcoming*.

Lindquist, M.J., Sol, J. and Van Praag, M., 2015. Why do entrepreneurial parents have entrepreneurial children?. *Journal of Labor Economics*, *33*(2), pp.269-296.

Liu, T., Mao, Y. and Tian, X., 2017. The role of human capital: Evidence from patent generation.

Loveland, R., Mulherin, J.H., and Okoeguale, K., 2018. Deregulation, listing and delisting. *Working Paper*.

Ma, S., Murfin, J. and Pratt, R., 2020. Young firms, old Capital. *Working Paper*.

Maksimovic, V., Phillips, G.M. and Yang, L., 2019. Do public firms respond to industry opportunities more than private firms? The impact of initial firm quality. *Working Paper*.

Maksimovic, V. and Pichler, P., 2001. Technological innovation and initial public offerings. *The Review of Financial Studies*, *14*(2), pp.459-494.

Martin, G.J. and McCRAIN, J., 2018. Local news and national politics. *American Political Science Review*, pp.1-13.

Martin, G.J. and Yurukoglu, A., 2017. Bias in cable news: Persuasion and polarization. *American Economic Review*, *107*(9), pp.2565-99.

Matray, A., 2020. The local innovation spillovers of listed firms. *Journal of Financial Economics, forthcoming.*

Mayer, R.C., Warr, R.S. and Zhao, J., 2018. Do Pro-Diversity Policies Improve Corporate Innovation?. *Financial Management*, *47*(3), pp.617-650.

Maxey, D., 2020. Private equity could be coming to your 401(k). Here are a few things to know. *Barron's*.

McGregor, J., 2016. 'This IBM employee quit over her CEO's letter to Donald Trump'. *The Washington Post*, 29 November, 2016.

Nahata, R., 2019. Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting. *Journal of Corporate Finance*, *58*, pp.624-649.

Østergaard, C.R., Timmermans, B. and Kristinsson, K., 2011. Does a different view create something new? The effect of employee diversity on innovation. *Research Policy*, *40*(3), pp.500-509.

Oswald, A.J., Proto, E. and Sgroi, D., 2015. Happiness and productivity. *Journal of Labor Economics*, *33*(4), pp.789-822.

Ouimet, P. and Zarutskie, R., 2014. Who works for startups? The relation between firm age, employee age, and growth. *Journal of Financial Economics*, *112*(3), pp.386-407.

Ovtchinnikov, A.V. and Pantaleoni, E., 2012. Individual political contributions and firm performance. *Journal of Financial Economics*, *105*(2), pp.367-392.

Parker, S.C., 2013. Do serial entrepreneurs run successively better-performing businesses?. *Journal of Business Venturing*, *28*(5), pp.652-666.

Parker, S.C., 2018. Entrepreneurship and economic theory. *Oxford Review of Economic Policy*, *34*(4), pp.540-564.

Poulsen, A.B. and Stegemoller, M., 2008. Moving from private to public ownership: selling out to public firms versus initial public offerings. *Financial Management*, *37*(1), pp.81-101.

Rajan, R.G. and Zingales, L., 2001. The influence of the financial revolution on the nature of firms. *American Economic Review*, *91*(2), pp.206-211.

Richard, O.C., 2000. Racial diversity, business strategy, and firm performance: A resource-based view. *Academy of Management Journal*, *43*(2), pp.164-177.

Ritter, J.R., 1991. The long-run performance of initial public offerings. *The Journal of Finance*, *46*(1), pp.3-27.

Ritter, J.R., Signori, A. and Vismara, S., 2013. Economies of scope and IPO activity in Europe. *Handbook of research on IPOs*.

Ritter, J.R. and Welch, I., 2002. A review of IPO activity, pricing, and allocations. *The Journal of Finance*, *57*(4), pp.1795-1828.

Roach, M. and Sauermann, H., 2015. Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. *Management Science*, *61*(9), pp.2160-2184.

Roonie, K., 2020. 'Coinbase CEO discourages politics at work, offers generous severance to employees who want to quit'. *CNBC*, 30 September, 2020.

Samila, S. and Sorenson, O., 2011. Venture capital, entrepreneurship, and economic growth. *The Review of Economics and Statistics*, *93*(1), pp.338-349.

Schoar, A., 2002. Effects of corporate diversification on productivity. *The Journal of Finance*, *57*(6), pp.2379-2403.

Shen, M., 2018. Skilled labor mobility and firm value: Evidence from a natural experiment. *Working Paper*.

Stulz, R.M., 2020. Public versus private equity. *Oxford Review of Economic Policy*, *36*(2), pp.275-290.

Tate, G. and Yang, L., 2015. The bright side of corporate diversification: Evidence from internal labor markets. *The Review of Financial Studies*, *28*(8), pp.2203-2249.

Teoh, S.H., Welch, I. and Wong, T.J., 1998. Earnings management and the long-run market performance of initial public offerings. *The Journal of Finance*, *53*(6), pp.1935-1974.

Tian, X., 2011. The causes and consequences of venture capital stage financing. *Journal of Financial Economics*, *101*(1), pp.132-159.

Unsal, O., Hassan, M.K. and Zirek, D., 2016. Corporate lobbying, CEO political ideology and firm performance. *Journal of Corporate Finance*, *38*, pp.126-149.

Vladasel, T., Lindquist, M.J., Sol, J. and van Praag, M., 2020. On the origins of entrepreneurship: Evidence from sibling correlations. *Journal of Business Venturing*, p.106017.

Weild, D., 2011. How to revive small-cap IPOs. *Wall Street Journal*.

Weise, K., 2017. 'The lonely lives of Silicon Valley Conservatives'. *Bloomberg*, 5 September, 2017.

Weller, C. and Wenger, J., 2015. Income diversification as insurance in an increasingly risky world: Identifying policy goals. *Inequality, uncertainty and opportunity: The varied and growing influence of finance on labor relations. Labor and employment relations association research*, pp.299-327.

Zhang, J., 2011. The advantage of experienced start-up founders in venture capital acquisition: evidence from serial entrepreneurs. *Small Business Economics*, *36*(2), pp.187-208

Zweig, J., 2010. The demise of the IPO market–and ideas on how to revive it. *Wall Street Journal*.

Appendix A: Definition of Variables in Chapter 1

Variables	Definition
DEM%	The dollar amount of capaign donations to Democratic recipients divided by the dollar amount of donations to either Democratic recipients or Republican recipients made by an employee in a given year.
EmpConflict	A score ranging from one to five assigned to each firm-year based on the percentages of strong Republican employees and strong Democratic employees in the firm-year.
CEOempDiff	The absolute value of the difference between the CEO's *DEM%* and the non-CEO employees' average *DEM%* in a firm-year.
CEOkeyDiff	The absolute value of the difference between the CEO's *DEM%* and the key employees' average *DEM%* in a firm-year.
CEOboardDiff	The absolute value of the difference between the CEO's *DEM%* and the board members' average *DEM%* in a firm-year.
CEOkeyNbDiff	The absolute value of the difference between the CEO's *DEM%* and the non-board key employees' average *DEM%* in a firm-year.
CEOempRfDiff	The absolute value of the difference between the CEO's *DEM%* and the rank-and-file employees' average *DEM%* in a firm-year.
ROA	The ratio of operating income before depreciation (OIBDP) to book value of total assets (AT).
MB	Market value of equity (PRCC_F*CSHO) plus book value of total assets (AT) minus book value of equity (CEQ) minus deferred taxes (TXDB) (set to zero if missing) divided by book value of total assets.
Lev	Book value of long-term debt (DLTT) divided by book value of total assets (AT).
LnAsset	The natural logarithm of book value of total assets (AT).
CAPEX	Capital expenditures (CAPX) divided by net property, plant, and equipment (PPENT).
PPE	Net property, plant, and equipment (PPENT) divided by book value of total assets (AT).
RD	Research and development expenses (XRD) (set to zero if missing) divided by book value of total assets (AT).
LnFirmAge	The natural logarithm of one plus a firm's age, approximated by the number of years that the firm has been listed on Compustat.
LnCEOAge	The natural logarithm of one plus a CEO's age.
CEOchair	A dummy variable that equals one if a CEO also serves as the chairman of board of directors, and zero otherwise.
LnCEOpay	The natural logarithm of the sum of a CEO's total current compensation (salary + bonus).
LnCEOtenure	The natural logarithm of one plus a CEO's tenure.

HighHqStatePct	A dummy variable that equals one if the percentage of a firm's employees who live in the state where the firm's headquarter is located is above the sample median, and zero otherwise.
HighLaborSkill	A dummy variable that equals one if a firm's labor skill index is above the sample median, and zero otherwise. Labor skill index is defined as the average skill level of occupations, weighted by number of employees in each occupation, in a firm's industry (three-digit SIC industry for pre-2002 period and four-digit NAICS industry for 2002 and beyond).
LaborProd	Labor productivity, defined as operating income before depreciation (OIBDP) divided by the number of employees (EMP).
OutputPerEmp	Output per employee, defined as the sum of sales (SALE) and change in inventory (calculated as the sum of INVWIP and INVFG) divided by the number of employees (EMP)
LnEmp	The natural logarithm of a firm's number of employees (EMP).
AssetInt	Asset intensity, defined as the natural logarithm of book value of total assets (AT) divided by number of employees (EMP).
CEOinventorDiff	The absolute value of the difference between an inventor's *DEM%* her CEO's *DEM%*.
LnPatent	The natural logarithm of the number of patents filed by an inventor in a year.
LnCitePat	The natural logarithm of the average number of citations received per patents filed by an inventor in a year.
Leave	A dummy variable that equals one if a key employee leaves her firm in year *t+1*, and zero otherwise.
KeyOtherDiff	The absolute value of the difference between a key employee's *DEM%* and the average *DEM%* of other employees in her firm.
KeyCEODiff	The absolute value of the difference between a key employee's *DEM%* and the *DEM%* of the CEO of her firm.
SinclairIndiv	A dummy that equals one if an employee is affected by a Sinclair acquisition in her city of residence in year *t-1,* and zero otherwise.
SinclairFirm	The percentage of a firm's employees who are affected by a Sinclair acquisition in their city of residence in year *t-1*.

Appendix B: Measurement of Total Factor Productivity (TFP)

Following the existing literature (e.g., Chemmanur, He, and Nandy (2009), Chemmanur, Krishnan, and Nandy (2011)), we construct plant-level total factor productivity (TFP) by first estimating the following log-linear Cobb-Douglas production function for each six-digit NAICS industry and year:

$$ln(Y_{ijt}) = \alpha_{jt} + \beta_{jt} \ln K_{ijt} + \gamma_{jt} \ln L_{ijt} + \varepsilon_{ijt} \qquad \text{(A1)}$$

where Y_{ijt}, K_{ijt}, and L_{ijt} are sales (total value of shipments), capital stock, and labor cost, respectively, for plant j in industry i and year t.[75] Then we calculate the plant-level TFP as the residual from the above regression. Finally, we compute the weighted-average TFP at the firm level using sales as the weight.

The input variables of the Cobb-Douglas function are obtained from the ASM and CMF databases. Labor cost is defined as production worker equivalent man hours, which is the product of production worker man-hours and the ratio of total wages and salaries to production worker wages. Capital stock is estimated using the perpetual inventory method. For each plant in the ASM and CMF databases, we first identify the years for which the plant has a non-missing book value of capital. We then write forward annually the last available book value of capital with nominal capital expenditures (deflated at the industry level using information from the NBER-CES Manufacturing Industry Database) and depreciate it by the depreciation rate at the industry level

[75] Our results are robust to including material costs and/or energy costs as independent variables and using an index method to estimate the Cobb-Douglas function.

obtained from the Bureau of Economic Analysis. The resulting series are then added together to yield our capital stock measure.

Appendix C: Definition of Variables in Chapter 2

Variable	Definition
IPO	A dummy variable that equals one if a private firm goes public in year *t*, and zero otherwise.
ACQ	A dummy variable that equals one if a private firm gets acquired in year *t*, and zero otherwise.
Post2000	A dummy variable that equals one if the year of an observation is later than 2000, and zero otherwise.
PostReg	A dummy variable that equals one if the year of an observation is between 2001 and 2003, and equals zero if it is between 2004 and 2006.
TFP	The weighted-average of plant-level total factor productivity, which is calculated using the method described in Appendix B.
Sales	Total value of shipments in $1,000 in terms of 1997 dollars.
SalesGrowth	Average annual percentage change in sales (total value of shipments) in the past three years.
LnSales	The natural logarithm of sales (total value of shipments in $1,000) in terms of 1997 dollars.
LnAge	The natural logarithm of the age (in years) of the oldest plant of a firm.
CapInt	Capital intensity, defined as capital stock over total employment, where capital stock is calculated using perpetual inventory method as described in Appendix B.
Capex	Capital expenditure ratio, defined as capital expenditures over capital stock.
MktShr	The weighted-average of plant-level market share in terms of sales at the three-digit NAICS level.
WhiteProp	The average proportion of total wages that is for white-collar workers in the past three years.
VC	A dummy variable that equals one if a firm is backed by venture capital, and zero otherwise.
LnNumSeg	The natural logarithm of the number of industries (at the six-digit NAICS level) that a firm operates in.
VCFracSt	The fraction of firms in a given state-year that are backed by venture capital.
VCFracInd	The fraction of firms in a given industry-year (at the three-digit NAICS level) that are backed by venture capital.
HighTech	A dummy variable that equals one if a firm operates in one of the following six-digit NAICS industries (following the definition given by the U.S. Bureau of Census): 333295, 333315, 334111, 334112, 334113, 334119, 334210, 334220, 334413, 334511, 421430, 421690, 423430, 423690, 443120, 511140, 511210, 514210, 518210, 519130, 541330, 541511, 541512, 541513, 541519, 541710, 541711, 541712, and zero otherwise.

LnNumAna	The natural logarithm of one plus the average number of analysts following a public firm over a given industry-year (at the three-digit NAICS level).
HHI	The weighted-average of plant-level Herfindahl Index in terms of sales at the three-digit NAICS level.

Appendix D: Definition of Variables in Chapter 3

Employee-level Variables:

EntreDiffuser	A dummy variable that equals one if an employee of an IPO or acquired private firm moves to another private firm in the year after his/her original employer's exit date, and zero otherwise.
LeaverToPub	A dummy variable that equals one if an employee of an IPO or acquired private firm moves to another public firm in the year after his/her original employer's exit date, and zero otherwise.
Stayer	A dummy variable that equals one if an employee of an IPO or acquired private firm still works for his/her original employer in the year after the exit date, and zero otherwise.
LnTenure	The natural logarithm of an employee's tenure (in quarters) in the exited firm, measured at the quarter right before his/her employer's exit date.
LnAge	The natural logarithm of an employee's age (in years), measured at the quarter right before his/her employer's exit date.
LnEdu	The natural logarithm of an employee's education level (in years), measured at the quarter right before his/her employer's exit date.
LnEarn	The natural logarithm of an employee's quarterly earnings (in 2007 dollars), measured at the quarter right before his/her employer's exit date. The LEHD earnings data include all forms of monetary compensation that are taxed as ordinary income, such as gross wages and salaries, bonuses, stocks, stock options, tips and other gratuities, and meals and lodging.
NewHire	A dummy variable that equals one if an employee is hired by an IPO firm in the year after the IPO date or by a merged firm in the year after the merger completion date, and zero otherwise.
Patents	The average number of patents filed per year by an inventor from an exited firm in the five years before the exit date.
CitePat	The average number of citations received per patent by an inventor from an exited firm in the five years before the exit date.
Originality	The average originality of patents filed by an inventor from an exited firm in the five years before the exit date. Each patent's originality is calculated as the number of unique technological classes cited by the patent, following Hirshleifer et al. (2018).
Exploratory	The average number of exploratory patents filed per year by an inventor from an exited firm in the five years before the exit date. Following Gao et al. (2018), Brav et al. (2018), ad Lin et al. (2020), a patent is defined as an exploratory patent if 80 percent or more of its citations are not based on the existing knowledge of the firm, i.e., all the patents filed by the firm and the patents that were cited by the firms' patents over past five years.

PatentsPostJoin	The average number of patents filed per year by an entrepreneurial diffuser's new colleague or his/her matched inventor in the five years after the joining of the entrepreneurial diffuser.
CitePatPostJoin	The average number of citations received per patent by an entrepreneurial diffuser's new colleague or his/her matched inventor in the five years after the joining of the entrepreneurial diffuser.
OriginalityPostJoin	The average originality of patents filed by an entrepreneurial diffuser's new colleague or his/her matched inventor in the five years after the joining of the entrepreneurial diffuser.
ExploratoryPostJoin	The average number of exploratory patents filed per year by an entrepreneurial diffuser's new colleague or his/her matched inventor in the five years after the joining of the entrepreneurial diffuser.
EarnGap	The difference between the post-exit quarterly earnings and the pre-exit quarterly earnings (in 2007 dollars) of an employee from an exited firm. The pre-exit quarterly earnings are an employee's earnings from the exited firm in quarter -1 (i.e., the quarter immediately before the exit date). The post-exit quarterly earnings of an entrepreneurial diffuser or a leaver to public firm are his/her full-time quarterly earnings from his/her new employer. A stayer's post-exit quarterly earnings are his/her earnings from the exited firm in the fourth quarter after the exit.
LnEarnPost	The natural logarithm of the average quarterly earnings in the five years after exit of an employee from an exited firm.
PatentsPostExit	The average number of patents filed per year by an inventor from an exited firm in the five years after the exit date.
CitePatPostExit	The average number of citations received per patent by an inventor from an exited firm in the five years after the exit date.
OriginalityPostExit	The average originality of patents filed by an inventor from an exited firm in the five years after the exit date.
ExploratoryPostExit	The average number of exploratory patents filed per year by an inventor from an exited firm in the five years after the exit date.
JobRiskTolerance	The difference between an employee's household total labor income and his/her earnings from the exited firm scaled by total household income.

Firm-level Variables:

EntrepreneurialExit	A dummy variable that equals one if a private firm exits through going public or getting acquired in year t, and zero if the firm remains private in t.
LnDiffuser	The natural logarithm of the number of entrepreneurial diffusers in a firm.
PctDiffuser	The fraction of a firm's employees who are entrepreneurial diffusers.
PctEarnDiffuser	The fraction of a firm's total payroll earned by entrepreneurial diffusers.
LnEmpLeavePubExp	The natural logarithm of the number of employees in a firm who have previous experiences of moving from an exited firm to a public firm in the year after the exit date.

PctEmpLeavePubExp	The fraction of a firm's employees who have previous experiences of moving from an exited firm to a public firm in the year after the exit date.
PctEarnLeavePubExp	The fraction of a firm's total payroll earned by employees who have previous experiences of moving from an exited firm to a public firm in the year after the exit date.
LnEmp	The natural logarithm of the total number of employees in a firm.
LnFirmAge	The natural logarithm of a firm's age in year t, measured as one plus the difference between t and the firm's first establishment/founding year.
LnAvgAge	The natural logarithm of employees' average age (in years).
LnAvgEdu	The natural logarithm of employees' education level (in years).
Gender	The fraction of male employees in a firm.
Ethnicity	The fraction of white employees in a firm.
FirmPatentsPostJoin	The average number of patents filed per year by a firm joined by an entrepreneurial diffuser or its matched firms in the five years after the joining of the entrepreneurial diffuser.
FirmCitePatPostJoin	The average number of citations received per patent by a firm joined by an entrepreneurial diffuser or its matched firms in the five years after the joining of the entrepreneurial diffuser.
FirmOriginalityPostJoin	The average originality of patents filed by a firm joined by an entrepreneurial diffuser or its matched firms in the five years after the joining of the entrepreneurial diffuser.
FirmExploratoryPostJoin	The average number of exploratory patents filed per year by a firm joined by an entrepreneurial diffuser or its matched firmss in the five years after the joining of the entrepreneurial diffuser.
AR1yr	The post-IPO one-year buy-and-hold abnormal return (using CRSP value-weighted index return as the benchmark) of an IPO firm, calculated using monthly returns.
AR3yr	The post-IPO three-year buy-and-hold abnormal return of an IPO firm.
AR5yr	The post-IPO five-year buy-and-hold abnormal return of an IPO firm.
ROA1yr	The return to assets (ROA), defined as net income (NI) divided by the average of total assets (AT) and lagged total assets, one year post the IPO.
ROA3yr	The average annual ROA over the three-year period post the IPO.
ROA5yr	The average annual ROA over the five-year period post the IPO.
PctDiffuserLeft	The fraction of an IPO firm's employees who move to private firms after the IPO date.
PctLeaverToPub	The fraction of an IPO firm's employees who move to public firms after the IPO date.
PctNewHire	The number of employees hired by an IPO firm in the year after the IPO date scaled by the number of employees working for the IPO firm in the quarter before the IPO date.

IR	The percentage difference between the closing price on the IPO day and the offering price.
LnProceeds	The natural logarithm of IPO proceeds (in million dollars).
VC	A dummy variable that equals one if a firm is backed by venture capital at the time of the IPO, and zero otherwise.
TobinQ	The market value of equity (PRCC_F×CSHO) plus book value of assets (AT) minus book value of equity (CEQ) minus deferred taxes (TXDB) divided by book value of assets (AT) at the first fiscal year end post the IPO.
LnMV	The natural logarithm of the market value of equity (PRCC_F×CSHO) at the first fiscal year end post the IPO.
RDadj	An IPO firm's R&D expenses (XRD) scaled by total assets (AT) in the first fiscal year post the IPO subtracting the mean R&D expenses scaled by total assets in the firm's three-digit NAICS industry over the same window.
IndVCPct	The fraction of firms in an IPO firm's three-digit NAICS industry that are backed by venture capital.
LnIndIPOVol	The natural logarithm of the total IPO volume in a firm's three-digit NAICS industry in its IPO year.
IndRFOption	The number of shares in options granted to rank-and-file employees scaled by the total number of shares outstanding of a firm, averaged to the three-digit NAICS industry level, following Call, Kedia, and Rajgopal (2016) and Aldatmaz et al. (2018).
LnAvgTenure	The natural logarithm of average tenure (in quarters) of a firm's employees.
LnAvgEarn	The natural logarithm of employee quarterly earnings (in 2007 dollars).
LnInventor	The natural logarithm of the total number of inventors in a firm.

Appendix E: Construction of *ChgPctPatentsPrv*, the Instrument for the 2SLS Analysis

We calculate the change in the fraction of patents assigned to private firms in an industry as the instrumental variable for the fraction of employees leaving for private firms after their original employers' IPO. The empirical difficulty of calculating such measure is that it is hard to identify the industry classification of patent assignees that are private firms. Therefore, we construct the measure in five steps using classifications of patents filed by public firms in an industry to identify the industry's knowledge base.[76]

In the first step, for an IPO firm i in industry j (at the three-digit NAICS level) and year t, we identify all the patents assigned to public firms in industry j in year t.

In the second step, we define industry j's "major patent classes" in year t as all the patent classes under which the number of patents assigned to public firms in industry j and year t is greater than or equal to five percent of total number of patents assigned to these public firms in year t.[77] The major patent classes of an industry identify the knowledge base of the industry, which consists of patents that are likely to be assigned to a typical firm in the industry.[78]

[76] We use patent classifications under the United States Patent Classification (USPC) system, obtained from the HBS Patenting Database.
[77] Our results are robust if we use one percent or ten percent as the threshold when defining major patent classes.
[78] Note that one patent class may be identified as the major patent class of more than one industry. This is not a significant problem as our definition of entrepreneurial diffusers is not limited to those who move to private firms within the IPO firms' industry. If an inventor possesses knowledge and skills that can be used in another industry, she could choose to move to private firms in that industry as well.

In the third step, we identify all the patents in industry *j*'s major patent classes that are assigned to private firms in year *t*. We treat these patents as patents assigned to private firms in industry *j* and year *t*.

In the fourth step, we calculate the fraction of patents assigned to private firms in industry *j* and year *t* as the number of patents assigned to private firms divided by the total number of patents assigned to private firms and public firms in industry *j* and year *t*.

In the fifth step, we calculate the change in the fraction of patents assigned to private firms in industry *j* from year *t-1* to *t* (*ChgPctPatentsPrv*).