RFS Advance Access published December 4, 2009

The Going-Public Decision and the Product Market

Thomas J. Chemmanur
Carroll School of Management, Boston College

Shan He
E. J. Ourso College of Business, Louisiana State University

Debarshi K. Nandy
Schulich School of Business, York University

At what point in a firm's life should it go public? How do a firm's ex ante product market characteristics relate to its going-public decision? Further, what are the implications of a firm going public on its post-IPO operating and product market performance? In this article, we answer the above questions by conducting the first large sample study of the going-public decisions of U.S. firms in the literature. We use the Longitudinal Research Database (LRD) of the U.S. Census Bureau, which covers the entire universe of private and public U.S. manufacturing firms. Our findings can be summarized as follows. First, a private firm's product market characteristics (total factor productivity [TFP], size, sales growth, market share, industry competitiveness, capital intensity, and cash flow riskiness) significantly affect its likelihood of going public after controlling for its access to private financing (venture capital or bank loans). Second, private firms facing less information asymmetry and those with projects that are cheaper for outsiders to evaluate are more likely to go public. Third, as more firms in an industry go public, the concentration of that industry increases in subsequent years. The above results are robust to controlling for the interactions between various product market and firm-specific variables. Fourth, IPOs of firms occur at the peak of their productivity cycle: the dynamics of TFP and sales

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For helpful comments or discussions, we thank Sudipto Dasgupta, Jim Davis, Francois Derrien, Wayne Ferson, Itay Goldstein, Vidhan Goyal, William Kerr, Karthik Krishnan, Peter Schott, Jeff Pontiff, Raj Singh, Phil Strahan, and conference participants at the American Finance Association (AFA) Meetings 2007, the HKUST Finance summer symposium 2005, the European Finance Association (EFA) Meetings 2005, the Financial Management Association Meetings (FMA) 2005, the RICAFE Entrepreneurship and Financing of Innovation conference 2005, the Census RDC conference at Cornell University 2005, and the Southern Finance Association Meetings 2005. Special thanks to the editor, Matthew Spiegel, and an anonymous referee for excellent comments and suggestions on the article. The research presented in this article was conducted while the authors were special sworn status researchers at the Boston Research Data Center of the U.S. Census Bureau. The research results and conclusions expressed are those of the authors and do not necessarily indicate concurrence by the Bureau of the Census. This article has been screened to ensure that no confidential data are revealed. Any errors and omissions are the responsibility of the authors. Send correspondence to Thomas J. Chemmanur, Fulton Hall 330, Carroll School of Management, Boston College, Chestnut Hill, MA 02467; telephone: (617) 552-3980; fax: (617) 552-0431. E-mail: chemmanu@bc.edu.

He gratefully acknowledges financial support for this research from the Ewing Marion Kauffman Foundation and the Boston Research Data Center of the U.S. Census Bureau, while Chemmanur and Nandy gratefully acknowledge financial support for this research from the Social Sciences and Humanities Research Council of Canada (SSHRC).

doi:10.1093/rfs/hhp098

growth exhibit an inverted U-shaped pattern, both in our univariate analysis and in our multivariate analysis using firms that remained private throughout as a benchmark. Finally, sales, capital expenditures, and other performance variables exhibit a consistently increasing pattern over the years before and after the IPO. The last two findings are consistent with the view that the widely documented post-IPO operating underperformance of firms is due to the real investment effects of going public rather than being due to earnings management immediately prior to the IPO. (*JEL* G14, G24, G32, L22)

1. Introduction

"Going public" is one of the most important events in the life of a firm. Since an initial public offering (IPO) of equity is the first public offering of equity (and typically the first public offering of *any* security) undertaken by the firm, it not only satisfies the immediate capital requirements of the firm, but also paves the way for the firm to make subsequent public offerings of equity and other corporate securities. Thus, going public allows the firm access to the public capital markets for the first time in its life, and hence may have important implications for a firm's product market performance as well. However, although the going-public decision has generated considerable theoretical research in recent years (see, e.g., Boot, Gopalan, and Thakor 2006; Chemmanur and Fulghieri 1999; Spiegel and Tookes 2007; Clementi 2002), there has been very little empirical research on this topic: two prominent exceptions are Lerner (1994), who studies the timing of going public of a sample of venture-backed biotechnology firms, and Pagano, Panetta, and Zingales (1998), who study the going-public decisions of a sample of Italian firms. Further, there has been no empirical research so far focusing on the relationship between the product market characteristics of a firm and its decision to go public.

The objective of this article is to bridge the gap in the literature by addressing two related questions. First, what is the relationship between the ex ante product market characteristics of a firm and its going-public decision? Second, how does going public affect a firm's subsequent product market performance? Clearly, the answers to the above two questions are complementary, since the motivations of a firm to go public should, in the long run, be consistent with the actual effects of its going public. In the first part of our empirical analysis, we study the relationship between the ex ante product market characteristics of a firm immediately before going public and its likelihood of going public. In this part of the analysis, we control for potential selection effects arising from the fact that higher-quality firms may have a higher probability of attracting venture capital or bank financing. In the second part of our analysis, we study the dynamics of a firm's product market performance: we study the behavior of various performance variables in the years leading up to its IPO, and in the years after it has gone public. We perform this analysis using firms that remained private throughout as the benchmark, which allows us to contemporaneously compare the changes in the performance of firms going public to similar changes in the performance of firms remaining private.

A number of theoretical models have implications (reviewed in detail in Section 2) not only for the relationship between a firm's ex ante product market characteristics and its going-public decision, but also for the dynamics of these characteristics before and after a firm's IPO. Chemmanur and Fulghieri (1999) model the going-public decision in an environment of asymmetric information, which implies that larger and more capital intensive firms, with riskier cash flows, and those operating in industries characterized by lower evaluation (information production) costs (and a smaller extent of asymmetric information) are more likely to go public. Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001) argue that the decision to go public emerges from the tradeoff between the costs to the firm of releasing confidential information (helpful to competitors) at the time of IPO versus the benefits arising from raising capital at a cheaper rate in the public equity markets. These theories imply that firms with greater existing market share, and those operating in industries characterized by a lower degree of competition, are more likely to go public. In a recent paper, Spiegel and Tookes (2007) develop a model of the relationship between product market innovation, competition, and the public-versus-private financing decision in an infinite-horizon model. Their model predicts that firms will finance projects with the greatest revenue-generating ability privately, and will then go to the public markets only when more modest innovations remain. Finally, Clementi (2002) argues that firms go public as a result of a positive and persistent productivity shock that increases the cost to the firm of operating at a suboptimal scale, making it optimal to go public despite the fixed costs of doing so. This theory implies that firms characterized by greater productivity, output growth, and capital expenditures are more likely to go public. We will test these and other implications here.[1]

Ours is the first large sample study of the going-public decisions of U.S. firms in the literature. As noted before, the empirical research on the going-public decisions is scant, since privately held firms are typically not required to report their financial results and, consequently, the data required for this research are not readily available (especially with regard to U.S. firms). There are only four pieces of direct research on the going-public decision to date. Lerner (1994) studies the timing of IPOs and private financings of a sample of privately held venture-backed biotechnology firms. He shows that these companies go public when equity valuations are high and employ private financings when values are lower. Pagano, Panetta, and Zingales (1998) investigate a sample of Italian firms using a data set provided by a consortium of Italian banks.

[1] Our article is also related to several other strands in the theoretical and empirical literature. Two other theoretical analyses with implications for the going-public decision are Pagano and Roell (1998), who analyze how agency considerations affect the going-public decision, and Zingales (1995), who studies corporate control issues related to the going-public decision. However, the above theoretical analyses do not have direct implications for the relationship between a firm's going-public decision and its product market characteristics, which is the focus of this article. This article is also indirectly related to the large theoretical literature on the underpricing of firms going public (see, e.g., Allen and Faulhaber 1989; Chemmanur 1993; Welch 1989), and the extensive empirical literature on the short-term and long-term stock market performance of firms subsequent to going public (see Ritter and Welch 2002 for a review).

While providing important insights into the going-public decision, it is difficult to generalize these Italian results to draw broader conclusions about the going-public decisions of the majority of U.S. firms. For example, only 69 of the more than 2000 firms eligible to go public in the Pagano, Panetta, and Zingales (1998) sample went public in over ten years; of these, more than 40% were equity carve-outs. Further, the typical newly listed company in Italy is several times larger and older than its counterpart in the United States. Finally, the tax and regulatory environment in the United States, and the stage of development of the U.S. capital markets, are dramatically different from those in Italy. Similar concerns apply to generalizing the German evidence of Fischer (2000), who investigates a sample of privately held German firms, some of which went public on the Neuer Market.[2] A recent paper that provides some evidence regarding the going-public decisions of U.S. firms is that of Helwege and Packer (2003), who make use of a sample of 178 nonfinancial firms mainly consisting of firms that had to file financial reports with the Securities and Exchange Commission (SEC) since they issued publicly traded bonds *prior* to their IPO.[3] While providing some insight into the going-public decisions of U.S. firms, it is difficult to generalize their results also to the bulk of private firms in the United States, given that private firms that issue public bonds before their IPO tend to be large and highly leveraged (in contrast to the average firm going public in the United States, which tends to be small and with much less leverage), and that only about 35 firms (one-fifth) of their sample attempted to go public during their study period. In contrast to the above papers, we develop the first large-sample study of the going-public decisions of U.S. firms, using the Longitudinal Research Database (LRD) of the U.S. Census Bureau (which covers the entire universe of private and public manufacturing firms in the United States). Ours is also the first article that explicitly controls for the potential selection effects arising from the fact that higher-quality firms may have a higher probability of attracting venture capital or bank financing.

A secondary objective of this article is to shed new light on the operating underperformance of firms subsequent to IPOs. Although some earlier papers have documented the operating underperformance of firms subsequent to going public (e.g., Jain and Kini 1994; Mikkelson, Partch, and Shah 1997), most of our empirical results on the dynamics of a firm's performance around its going-public decision (especially with respect to variables such as total factor productivity [TFP], market share, capital expenditures, employment, total

[2] Apart from the dramatic differences in the tax and regulatory environment in the United States and in Germany, there are also significant differences in the stage of development of the capital markets in Germany and in the United States. Thus, while the number of IPOs on the Neuer Market rose sharply during the late 1990s, it had fewer than 100 IPOs per year even during the most active period in Germany, the equivalent of a weak year in the United States.

[3] A few of the firms in the Helwege and Packer (2003) sample were not public bond issuers but nevertheless had to file financial reports with the SEC because they had a very large number of shareholders despite their private status.

labor costs, materials costs, and sales and administrative expenses) are new to the literature. The reasons underlying the operating underperformance of firms subsequent to going public have been controversial. Several alternative explanations have been proposed for this underperformance, including the idea that operating underperformance is due to earnings management or "creative accounting" by firms going public (we review some of these hypotheses about the dynamics of firm performance in Section 2.2). Our analysis is able to provide new insights on the relative merits of these hypotheses for two reasons. First, we are able to examine the operating performance of firms going public for a number of (five) years *before* the IPO, in contrast to existing studies, which focus only on operating performance in the two years before the IPO and the years subsequent to the IPO (possibly due to the data limitations discussed earlier). Second, in contrast to earlier studies (which focus on accounting numbers), we focus on performance measures such as the TFP, which are derived from a variety of different measures of firm performance and are thus less subject to manipulation compared with accounting numbers.

Our findings on the relationship between the ex ante product market characteristics of a firm and its likelihood of going public can be summarized as follows.[4] First, we find that firms that are larger in size, have access to private financing, and have higher sales growth are more likely to go public. Second, firms that have greater productivity (TFP) than their industry peers, greater market share, and projects that are cheaper for outsiders to evaluate are more likely to go public. Third, we find that firms operating in less competitive and more capital-intensive industries, and those characterized by riskier cash flows, are more likely to go public. Fourth, we find that firms in industries characterized by less information asymmetry between firm insiders and outsiders (as measured by the averages of various proxies of information asymmetry for firms already listed in that industry, like standard deviation of analyst forecasts, and analyst forecast error) and greater average liquidity of already listed equity are more likely to go public. Fifth, we also show that, as more firms in an industry go public, the concentration of that industry increases in subsequent years. All the above results are robust to controlling for access to private financing (venture capital or bank loans), and interactions between various product market and firm-specific variables. While the first set of findings above is consistent with those documented by Pagano, Panetta, and Zingales (1998) for Italian firms, we are the first in the literature to document the second, third, fourth, and fifth sets of results above. The above findings are consistent with the implications of four of the theories of going public mentioned above—namely, the information production theory of Chemmanur and Fulghieri (1999), the

[4] We conducted our analysis using both a dynamic probit model and a Cox proportional hazard model. Due to space limitations, we report results only from the dynamic probit model, but our results from the Cox hazard model are qualitatively similar.

confidential information release theory of Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001), the competition for market share theory of Spiegel and Tookes (2007), and the productivity shock theory of Clementi (2002).

Our analysis of the dynamic pattern of firm performance before and after the IPO indicates that total factor productivity (TFP) increases steadily in the five years prior to the IPO, reaches a peak in the IPO year, and declines steadily in the years subsequent to the IPO (i.e., TFP exhibits an inverted U shape). Sales growth exhibits a similar pattern, increasing in the years prior to the IPO and declining in the years subsequent to the IPO. However, sales, capital expenditures, employment, total labor costs, materials costs, and sales and administrative expenses exhibit a consistently increasing pattern in the years both before and after the IPO. Our results indicating declines in productivity post-IPO, and the pattern of sales and capital expenditures of firms subsequent to the IPO, are consistent with the prior empirical literature (e.g., Jain and Kini 1994; Mikkelson, Partch, and Shah 1997), which has documented operating underperformance subsequent to the IPO (albeit using accounting measures such as return on assets (ROA)). However, the dynamic pattern in various firm performance variables before and after the IPO (and especially the inverted U-shaped pattern of productivity changes) that we document around the IPO is inconsistent with the notion that the operating post-IPO underperformance of firms is generated solely by earnings management by firms immediately prior to the IPO. In particular, the consistent growth in firm productivity that we document for *five years* before the IPO is unlikely to be generated purely by the manipulation of accounting numbers, since the performance effects of such manipulation are likely to be confined to the years immediately prior to the IPO and would not persist over so many years (especially given the fact that measures of economic performance such as TFP, being derived from a variety of different performance measures, are much harder to manipulate compared with accounting numbers). Instead, the above dynamic pattern of various variables (and especially the inverted U-shaped pattern of productivity changes) is broadly consistent with the performance implications of a firm increasing its scale of operations around the IPO (making use of the external financing raised), as characterized by the theoretical analysis of Clementi (2002). The dynamic pattern of TFP that we document around firms' IPOs is also consistent with Spiegel and Tookes (2007), who predict that firms will first finance projects with the greatest revenue-generating ability privately and will then go to the public markets only when more modest innovations remain, implying that firm productivity will peak around the IPO.

The rest of the article is organized as follows. Section 2 reviews various theories of the going-public decision and develops hypotheses. Section 3 describes our data and explains the construction of various variables used in the study. Section 4 presents our empirical tests and results on the relationship between the ex ante product market characteristics of a firm and its likelihood of going public. Section 5 presents our empirical tests and results on the dynamic pattern of firm performance around the IPO. Section 6 concludes.

2. Theory and Hypotheses

2.1 Relationship between product market characteristics and the going-public decision

Chemmanur and Fulghieri (1999) model a firm's going-public decision in an environment where insiders have private information about firm value, but outsiders can produce information about the firm (i.e., "evaluate the firm") at a cost. If a firm raises capital by going public, it faces duplication in outsiders' information production costs (ultimately, outsiders' information production costs are borne by the firm through a lower share price), since it needs to convince a number of investors that the firm's projects are worth investing in. In contrast, if it raises capital privately, there is no such duplication in information production, but the private financier charges a risk premium over his cost of funds, since he is taking an undiversified position in the firm. When the firm is small, young, or otherwise faces severe information asymmetry, or if it is in a "complex" industry where outsiders' information production costs are high, the cost of duplication in outsiders' information production outweighs the premium demanded by private financiers, and the firm chooses not to go public. Conversely, if the firm is older, larger, or otherwise cheaper for outsiders to evaluate, the effect of the above duplication in information production is outweighed by the premium demanded by private financiers, so that the firm chooses to go public. Further, since more of the private financier's capital will be tied up in a single firm if the firm is in a more capital-intensive industry, or if it is in a riskier industry, it is more likely to go public (ceteris paribus), since, for such a firm, the above discussed tradeoff between staying private and going public is likely to favor going public at a larger level of the outsiders' evaluation cost. This theory implies:

H1: Smaller and younger firms are less likely to go public.

H2: Firms operating in industries characterized by less information asymmetry and more stock market liquidity are more likely to go public.

H3: Firms operating in industries in which it is easier for public investors to evaluate the firm are more likely to go public.

H4: Firms operating in more capital-intensive industries and in those characterized by greater riskiness of cash flows are more likely to go public.

Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001) develop models of the going-public decisions of firms driven by product market competition between innovative private firms in an industry. In their setting, raising capital in the equity market by going public allows a firm that is an industry leader to raise external capital at a cheaper rate than private financing, thus allowing it to operate at its optimal scale. However, going public has the disadvantage of releasing confidential information to competing firms that can then compete more effectively with the firm going public. Thus, if a firm has a larger market share in its industry, its benefit from expanding scale by going public is likely to be greater (for a given cost of going public) so that it is more likely to go public. Conversely, if the degree of concentration in the firm's industry is greater (so that the firm faces less competition), its costs of going public will be lower, making it more likely to go public. Further, firms operating in industries in which the value of confidentiality is greater (e.g., firms in high-tech industries) are less likely to go public. These theories imply:

H5: Firms with a greater market share in their product market are more likely to go public.

H6: Firms operating in more concentrated industries are more likely to go public.

H7: Firms operating in industries in which the value of confidentiality is greater (e.g., high-tech firms) are less likely to go public.

Spiegel and Tookes (2007) argue that firms compete against each other for market share by spending funds to acquire each other's customers. One firm has an opportunity to innovate and has to choose between financing development costs either privately or by going public. The advantage of public financing is the ability to obtain cheaper funding, and the advantage of private financing is the ability to keep the innovation hidden from competitors because disclosure requirements associated with public financing allow the firm's competitors to copy the innovation. The cross-sectional implications of this model for the relationship between industry concentration and the probability of going public and the relationship between the value of confidentiality and the probability of going public are similar to those of Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001), yielding hypotheses H6 and H7, respectively. The implication of Spiegel and Tookes (2007) for the relationship between market share and the probability of going public, however, is quite different from that of the other two papers, since it depends on the competitive position of a firm relative to its industry peers. If a firm is dominant in its industry, a greater market share increases its probability of going public, consistent with H5; if, however, a firm is in a weak competitive position relative to its peers, an increase in its market share reduces the imbalance in its competitive position relative to its peers, making it *less likely* to go public.

Clementi (2002) builds a dynamic model of the going-public (IPO) decision in which the firm operates in an industry characterized by decreasing returns to scale and going public is costly. Prior to going public, a borrowing constraint keeps the firm's scale of production at a suboptimal level. In the above setting, a sudden positive productivity shock (resulting in a new set of positive net present value [NPV] projects becoming viable to the firm) has the effect of widening the gap between the optimal and the actual scales of the firm, so that the marginal benefit of expanding operations by going public outweighs the marginal cost of doing so. This implies that firms that have greater levels of TFP are more likely to go public. Further, firms will have higher levels of output growth and higher levels of capital expenditures relative to their private counterparts immediately prior to going public (since such firms are in the process of expanding the scale of their operations as a result of their productivity shock). This implies:

H8: Firms with higher total factor productivity (TFP) are more likely to go public.

H9: Firms with higher levels of output growth and higher levels of capital expenditures are more likely to go public.

It is also interesting to study how the going-public decision affects the market structure or the level of concentration of the industry that the firm belongs to. Sutton (1991) has argued that firms may use R&D and other sunk costs to erect barriers to entry to keep out competitors. Since going public increases a firm's access to financing on cheaper terms, this means that one firm going public may erect greater barriers for other firms to enter the industry, thus raising industry concentration subsequently.[5] This theory implies:

H10: Industries in which a larger fraction of firms go public in a given year will experience a greater increase in concentration in subsequent years.

2.2 The dynamics of firm characteristics before and after the IPO

Several theories have implications for the dynamics of firm characteristics around the IPO. In particular, the model of Clementi (2002) has implications for firm productivity, sales, and capital expenditures before and after the IPO. In this model, while an infusion of capital would allow the firm to bridge the gap at least partially between actual and efficient scale, going public too early in its life is not optimal, since it involves incurring the fixed costs of doing so. The optimal policy of the entrepreneur is, therefore, to wait for a large enough positive productivity shock so that the benefits of going public exceed the costs of doing so: at this point, the firm goes public, increasing its scale of operations. Once this occurs, however, measures of performance and productivity will start declining due to decreasing returns to scale so that, according to Clementi (2002), one can expect an inverted U shape in the pattern of firm productivity around the IPO (with the peak productivity occurring roughly in the year of the IPO). The model of Spiegel and Tookes (2007) also has predictions for the dynamics of productivity around a firm's IPO. Their model predicts that firms will first finance projects with the greatest revenue-generating ability privately,

[5] We thank an anonymous referee for pointing out this implication of Sutton (1991) for the going-public decision.

and will go to the public markets only when more modest innovations remain, implying that firm productivity will peak around the IPO.

Clementi (2002) also has implications for the dynamic pattern of sales (output), capital expenditures, and employment, as well as materials and other costs of the firm around the IPO. Since the firm experiences a (series of) positive productivity shock(s) prior to the IPO and increases its scale of operations, capital expenditures and output increase in the years prior to the IPO and in the year of the IPO. Further, assuming that it takes time to put physical capital in a condition to be productive, the above model would predict that the firm's scale of operations (capital expenditures, output) would continue to increase for a few years after the IPO. In summary, the above model would predict that sales and capital expenditures would increase monotonically before and after the IPO. Further, total employment, total wages, materials costs, and rental and administrative expenses would also show increases in the periods before and after the IPO corresponding to the increases in the firm's scale of operations. Finally, the above theory would predict that while output (sales) growth will either remain steady (or may even increase) in the years immediately before the IPO (as the firm increases its scale of operations toward its optimal level), output growth will be much smaller subsequent to the IPO (since the firm would have come close to its optimal scale soon after the IPO).[6] The model of Spiegel and Tookes (2007) also predicts a similar pattern of output growth around a firm's IPO. The predictions of the theories of Clementi (2002) and Spiegel and Tookes (2007) for the dynamics of firm characteristics around a firm's IPO differ markedly from those of some other theories. One such theory (see, e.g., Teoh, Welch, and Wong 1998) is the earnings management or "creative accounting" theory. This theory argues that immediately prior to the IPO, firms have the incentive to show superior earnings by increasing current accruals (for example, by advancing the recognition of revenues or by delaying the recognition of expenses), in an attempt to obtain a better share price in the IPO. This theory would predict that while reported operating performance would peak in the pre-IPO year, it would decrease smoothly post-IPO. Our empirical analysis of the dynamics of firm characteristics would allow us to test whether the documented post-IPO decline in operating performance is due to earnings management or not, for two reasons. First, performance measures such as TFP are clearly less subject to manipulation compared with accounting figures, since they are derived from a variety of different measures of firm performance. Second, we study various measures of firm performance for five years before and after the IPO. It is unlikely that, even if firms attempt to manipulate their reporting of performance numbers prior to their IPO, they will

[6] This last prediction requires the additional assumption that as the firm gets closer to its optimal scale of operations, its rate of adjustment toward this optimal scale gets smaller.

be able to show consistently superior performance for several years pre-IPO purely by manipulating these numbers.[7]

The analyses of Bhattacharya and Ritter (1983), Maksimovic and Pichler (2001), and Spiegel and Tookes (2007) also have interesting predictions for the dynamics of an IPO firm's market share relative to that of its product market competitors around its IPO. If the information gleaned by a firm's competitors at the time of its IPO actually allows them to compete more effectively against it (and this effect dominates the effect of the firm having easy access to the equity market after its IPO and thus being able to implement its project more effectively), then the firm's market share should decrease subsequent to its IPO. In contrast, if the effect of the firm's easy access to the equity market in fact dominates the negative effects of having to release sensitive information at the time of its IPO, the firm's market share should increase in the years following its IPO.

3. Data and Sample Selection

The primary data that we use in this study are from the Longitudinal Research Database (LRD), maintained by the Center of Economic Studies at the U.S. Census Bureau.[8] The LRD is a large micro database that provides plant-level information for firms in the manufacturing sector (SIC codes 2000 to 3999). In the census years (1972, 1977, 1982, 1987, 1992, 1997), the LRD covers the entire universe of manufacturing plants in the Census of Manufacturers (CM). In noncensus years, the LRD tracks approximately 50,000 manufacturing plants every year in the Annual Survey of Manufacturers (ASM), which covers all plants with more than 250 employees. In addition, it includes smaller plants that are randomly selected every fifth year to complete a rotating five-year panel. Therefore, all U.S. manufacturing plants with more than 250 employees are included in the LRD on a yearly basis from 1972 to 2000, and smaller plants with fewer than 250 employees are included in the LRD every census year and are also randomly included in the noncensus years, continuously for five years, as a rotating five-year panel.[9] Most of the data items reported in the LRD (e.g., the number of employees, employee compensation, capital expenditures, and total value of shipments) represent items that are also reported to the IRS, thus increasing the accuracy of the data.

[7] Another possible reason proposed in the literature for the decline in the operating performance of firms subsequent to their IPO is the reduction in stock ownership by the entrepreneur and other top mangers in the firm (which, in turn, reduces their incentives to expend effort to maximize firm value, for the reasons first outlined by Jensen and Meckling 1976). However, unlike the previous two theories, this "incentive" theory does not predict an increase in firm performance prior to the IPO, since managerial ownership does not increase (and often decreases) in the years immediately prior to a firm's IPO.

[8] See McGuckin and Pascoe (1988), who provide a detailed description of the Longitudinal Research Database (LRD) and the method of data collection.

[9] Given that a random sample of smaller plants is continuously present in our sample, our data are not substantially skewed toward larger firms; smaller firms are well represented in the data. The rotating sample of smaller plants is sampled by the Census Bureau each year in the noncensus years in order to minimize such a bias in the data.

The crucial advantage of using the LRD data relative to COMPUSTAT data in this study is that the LRD covers both public and private firms in the manufacturing industries. The comprehensive coverage of private firms and therefore the IPO firms in their private stage enables us to examine the product market determinants of the going-public decision.[10] Moreover, the panel format of the LRD (1972–2000) provides data on both firms remaining private and those going public, consistently through time. This allows us to examine the dynamics of the IPO firms' performance both pre- and post-IPO, benchmarked against their private peers. Another advantage of using the LRD for this study is that it enables us to construct precise measures of firms' product market performance. For example, relative product market performance measures such as total factor productivity, market share, and industry concentration are based on the entire sample of private and public firms available in our data (the LRD). These measures therefore provide more precise estimates compared with those constructed relative to only the public firms that are available on COMPUSTAT. In addition to product market measures from the LRD, we also use CRSP and I/B/E/S for constructing measures related to stock market liquidity and information asymmetry, respectively, which we discuss in detail later. Since the LRD provides plant-level information, we aggregate all plant-level measures to the firm level using a value-weighted approach.[11]

Our sample of IPOs is drawn from the Security Data Corporation's (SDC's) New Issues Database. As in most empirical studies on IPOs, we removed from our sample all IPOs related to equity carve-outs, American depository receipts, American depository shares, global deposit receipts, global deposit shares, units, trust receipts, and trust units. We also require that the primary industry of the firm going public is within the manufacturing sector (SIC codes 2000 to 3999) and that the firm is present on Compustat for the fiscal year of the IPO. Thus, our sample of IPOs from SDC comprises 2578 firms during the years 1972 to 2000. We first match this sample of IPO firms to the LRD using the LRD-COMPUSTAT bridge file for a span of five years around the IPO date.[12] Out of the 2578 firms, we matched 1315 firms to the LRD.[13] In addition, we also identified all public firms (as defined by CRSP)—i.e., firms that had an IPO prior to the start of our sample period (1972)—in the LRD by using the

[10] Unfortunately, due to the data limitations, we are unable to look at the ownership composition and capital structure of the firm before going public.

[11] For all variables we aggregate the plant-level measures using a value-weighted approach, in which the weights on the plants are the ratio of its sales to the total sales of the firm. As a robustness check, we also used the ratio of plant employment to firm employment as weights. The results obtained are similar in both cases. For firm age, we use the age of the earliest plant belonging to that firm.

[12] Matching a firm for five years around the IPO date ensures that at least one census year is included for the matching. Since the entire universe of the manufacturing plants is represented in census years, it allows us to completely identify all plants associated with the IPO firms. The LRD provides a permanent plant number (PPN) and a firm identifier (FID), both of which remain invariant through time. We then use these identifiers to track the plants and the firms forward and backward in time.

[13] The discrepancy in the number of IPOs between the LRD and SDC is mostly due to the incorrect industry classification of the firm in SDC.

same approach. In our analysis of the going-public decision, we eliminate these public firms from our sample. Thus, the final sample in our regression analysis contains all firms remaining private throughout the years 1972 to 2000 and firms that went public between 1972 and 2000.

Finally, in order to control for access to private financing prior to going public through an IPO, we obtain data on venture capital financing and bank loans and merge them with the LRD. Our sample of venture investments is drawn from VentureXpert, a database maintained by Thomson Reuters that contains round by round information for both the firms in which VCs invest as well as the venture capitalist (VC) firms themselves. After restricting our sample to those firms that received their first round of VC financing between 1970 and 2000, we merge the sample with the LRD. Our data on bank loans are drawn from Reuters Loan Pricing Corporation's (LPC's) DealScan database. DealScan is the primary source of bank loan data and has been used extensively by studies in the empirical banking literature.[14] This database provides borrower and lender identities as well as other detailed information on loan contract terms. Since the data from DealScan are at the loan facility level, we first aggregate the loans for each borrower to the annual level and then merge the aggregated data to the LRD.[15]

Table 1 presents the industry distribution at the two-digit SIC level of the firms that went public in our sample.[16] As can be seen from this table, our matched IPO sample is very much representative of U.S. IPOs in the manufacturing sector, with some concentration in electronics and precision instruments industries.

3.1 Measurement of total factor productivity (TFP)

Total factor productivity (TFP) is calculated from the LRD for each individual plant at the annual four-digit (SIC) industry level using the entire universe of plants in the LRD. The total factor productivity of the firm is then calculated as a weighted sum of plant total factor productivities (TFP) at the annual level. In particular, we estimate the TFP of firms separately depending on whether they use a capital-intensive or non-capital-intensive technology. We do this by determining whether a firm operates a large capital stock relative to its four-digit (SIC) industry peers, thus dividing each industry into capital and non-capital-intensive sectors. TFP, therefore, captures a firm's productivity relative to that of its industry peers with similar capital stock. We obtain measures of TFP at

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[14] DealScan provides market information on commercial loans and private placements filed with the Securities and Exchange Commission or obtained through direct research from banks. According to LPC, about 60% of the loan data are from SEC filings including 13Ds, 14Ds, 13Es, 10Ks, 10Qs, 8Ks, and Registration Statements. In addition, LPC supplements the loan data by contacting borrowers, lenders, and the credit industry. DealScan is updated on a daily basis with new deals constantly being added to the database.

[15] DealScan only provides data starting from 1987 and thus our bank loan data start then. We do not have information on bank loans during the period 1970–1986.

[16] For confidentiality purposes, we are unable to report the actual numbers for some of the industries. Hence, in some cases we report it as ND (not disclosed).

Table 1
Industry distribution of the going public sample

Two-digit SIC	Industry name	Number of IPO firms
20	Food and kindred products	50
21	Tobacco products	ND
22	Textile mill products	34
23	Apparel and other textile products	37
24	Lumber and wood products	27
25	Furniture and fixtures	24
26	Paper and allied products	24
27	Printing and publishing	43
28	Chemicals and allied products	83
29	Petroleum and coal products	ND
30	Rubber and miscellaneous plastics products	47
31	Leather and leather products	ND
32	Stone, clay, and glass products	34
33	Primary metal industries	110
34	Fabricated metal products	47
35	Industrial machinery and equipment	201
36	Electronic and other electric equipment	245
37	Transportation equipment	53
38	Instruments and related products	187
39	Miscellaneous manufacturing industries	ND

This table presents the two-digit-level SIC industry distribution of the sample of manufacturing firms in the LRD that went public during the period from 1972 to 2000. ND stands for "not disclosed," to comply with the U.S. Census Bureau's disclosure criteria.

the plant level by estimating a log-linear Cobb-Douglas production function for each industry, year, and capital-intensive sector. Firms belong to the capital-intensive sector of an industry when its ratio of capital stock relative to the industry is greater than the median value in that year.[17] Individual plants are indexed i; industries j; capital-intensive sectors k; for each year t in the sample:

$$\ln(Y_{ijkt}) = \alpha_{jkt} + \beta_{jkt}\ln(K_{ijkt}) + \gamma_{jkt}\ln(L_{ijkt}) + \delta_{jkt}\ln(M_{ijkt}) + \varepsilon_{ijkt}. \quad (1)$$

We use the LRD data to construct as closely as possible the variables in the production function. Output (Y) is constructed as plant sales (total value of shipments in the LRD) plus changes in the value of inventories for finished goods and work-in-progress. Since we appropriately deflate plant sales by the annual industry-specific price deflator, our measure is proportional to the actual quantity of output. Thus, the dispersion of TFP for firms in our sample almost entirely reflects dispersions in efficiency.

Labor input (L) is defined as production worker-equivalent man-hours. This is the product of production worker man-hours, and the ratio of total wages

[17] We thank an anonymous referee for suggesting that we estimate TFP conditional on the capital-intensiveness of the plant relative to its industry. We ran separate regressions in each four-digit (SIC) industry-year-capital-intensive sector to calculate TFP, and required that for each regression we have a minimum of thirty observations. In cases where this criterion was not satisfied, we calculated TFP by reestimating the regressions at the three-digit (SIC) industry-year-capital-intensive-sector level. As robustness checks, we also reestimated the production function using a dummy variable to indicate capital-intensiveness of a plant relative to its industry peers at the annual four-digit (SIC) industry level. As an alternative, we also calculated TFP by estimating the regressions at the annual four-digit (SIC) industry level without accounting for the degree of capital-intensiveness and also with value-added production function specifications and separate white- and blue-collar labor inputs, including nonproduction workers. In all cases we obtained qualitatively similar results.

and salaries to production worker wages. Values for the capital stock (*K*) are generated by the recursive perpetual inventory formula. We use the earliest available book value of capital as the initial value of net stock of plant capital (this is either the value in 1972, or the first year a plant appears in the LRD sample). These values are written forward annually with nominal capital expenditure (appropriately deflated at the industry level) and depreciated by the economic depreciation rate at the industry level obtained from the Bureau of Economic Analysis. Since values of all these variables are available separately for buildings and machinery, we perform this procedure separately for each category of assets. The resulting series are then added together to yield our capital stock measure. Finally, material input (*M*) is defined as expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased, adjusted for the change in the value of material inventories. All the variables are deflated using annual price deflators for output, materials, and investment at the four-digit SIC level from the Bartelsman and Gray NBER Productivity Database.[18] Deflators for capital stock are available from the Bureau of Economic Analysis.[19]

This measure of TFP is more flexible than the cash-flow measure of performance, as it does not impose the restriction of constant returns to scale and constant elasticity of scale. Also, since coefficients on capital, labor, and material inputs can vary by industry and year, this specification allows for different factor intensities in different industries. The TFP measure for each individual plant is the estimated residual of these regressions. Thus, it is the difference between the actual output produced by the plant compared with its "predicted output." This "predicted output" is what the plant should have produced, given the amount of inputs it used and the industry production technology in place. Hence, a plant that produces more than the predicted amount of output in any given year has a greater than average productivity for that year. Thus, TFP can be understood as the relative productivity rank of a plant within its industry in any given year. Since these regressions include a constant term, TFP contains only the idiosyncratic part of plant productivity.[20] Plant-level TFP measures are then aggregated to the firm level by a value-weighted approach, in which the weight on each plant is the ratio of its output (total value of shipments) to the total output of the firm. The firm-level TFP is winsorized at the 1st and 99th percentiles.

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[18] See Bartelsman and Gray (1996) for details.

[19] For a detailed description of the construction of TFP measures from LRD variables, see Lichtenberg and Siegel (1992).

[20] As a robustness check for our regression results, we use an alternative measure of productivity; namely, value added per worker, which is defined as total sales less materials cost of goods sold, divided by the number of workers. This measure has been used in McGuckin and Nguyen (1995) and Maksimovic and Phillips (2001). This measure does not have the desirable theoretical properties of TFP, but it does have familiar statistical properties, since it is not computed from a regression.

3.2 Measures of firm-specific, industry-specific, information asymmetry, and control variables

In this subsection we discuss the construction and measurement of various firm-specific product market variables as well as the control variables we use in our empirical analysis. The LRD contains detailed information at the plant level on the various production function parameters, such as total value of shipments, employment, labor costs, material costs, new capital investment for the purchase of buildings, machinery, other equipment, etc. Using this detailed information, we first construct the variables of interest at the plant level, and then aggregate the plant-level information to firm-level measures.

Capital stock is constructed via the perpetual inventory method, as discussed in Section 3.1. We measure age as the number of years since the birth of the firm as recorded in the Census data.[21] *Sales* is defined as the total value of shipments in thousands of dollars. *Capital expenditure* is the dollar value the firm spends on the purchase and maintenance of plant, machinery, and equipment, etc. *Materials cost* is the expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased. *Rental and administrative expenditure* is the rental payments or equivalent charges made during the year for the use of buildings, structures, and various pieces of office equipment. *Total wage* is the total payroll of firms. *Average wage* is the total wage over total employment. All dollar values in the LRD are in thousands of dollars (1998 real terms), and all firm-level measures are winsorized at the 1st and 99th percentiles.

To test *H1*, and also to control for firm size in other specifications, we define firm size (*SIZE*) as the natural logarithm of the capital stock of the firm.[22] We define firm age as the natural logarithm of age (*AGE*) and control for potential nonlinear effects of age using *(AGE SQUARE)*. As postulated in *H1*, we expect a positive relationship between *SIZE, AGE,* and the probability of going public. To test the effect of firm productivity on its decision to go public (*H8*), we calculate total factor productivity (*TFP*) as discussed in Section 3.1. This measure of TFP captures a firm's productivity level relative to that of its industry peers with similar capital stock. A firm with high productivity is one that is able to produce more output per unit of input. Empirically, we expect *TFP* to have a positive effect on a firm's decision to go public.

Capital intensity (*CAPINT*) is defined as a firm's capital stock over total employment. According to *H4*, since firms operating in more capital-intensive industries and those characterized by greater riskiness of cash flows are more

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[21] In order to properly construct the age variable for plants, we start from the census of 1962, which is the first year for which data are available from the Census Bureau. For plants that started prior to 1962, we use 1962 as the first year for that plant. Given the sampling scheme and scope of LRD, this measure is highly correlated with the actual age of the firm. Particularly, the relative age across firms, which is more relevant for the probability of going public, is captured very well by this measure.

[22] For robustness, we also rerun our regressions using log (employment) and log (sales) as proxies of firm size. Our results remain qualitatively unchanged using these alternative proxies.

likely to go public, *CAPINT* is expected to have a positive relationship with the probability of going public. In order to proxy for industry risk (*INDRSK*), we calculate the industry median of the five years' coefficient of variation of firm sales at the three-digit SIC level. We expect *INDRSK* to have a positive relationship to the probability of going public.

We define capital expenditure ratio (*CAPR*) as the firm's capital expenditure over capital stock. This measure captures the relative investment intensity of firms. We define sales growth (*SGTH*) as the average growth in sales over the past three years.[23] Based on *H9*, since firms with higher levels of output growth and higher levels of capital expenditures are more likely to go public, we expect positive relationships between *CAPR*, *SGTH*, and the probability of going public. Market share (*MSHR*) is defined as the firm's market share in terms of sales at the three-digit SIC level. We use the market share of the firm to capture the firm's industry leader position. Based on *H5*, a higher market share is expected to have a positive effect on the probability of going public. We construct the industry Herfindahl index (*HI*) based on the market share measure of each firm in the LRD. The Herfindahl index is calculated by summing up the square of each firm's market share (in sales) at the three-digit SIC level. A higher Herfindahl index means that the industry is more concentrated. According to our hypothesis *H6*, firms in more concentrated industries are more likely to go public. Hence, we expect a positive relationship between the industry Herfindahl index and the probability of going public. We define high-tech (*HTEK*) companies as those with the three-digit SIC codes 357, 366, 367, 372, 381, 382, and 384.[24] According to *H7*, since firms operating in industries where the value of confidentiality is greater (such as high-tech industries) are less likely to go public, *HTEK* is expected to have a negative relationship with the probability of going public.

The share turnover (*TOV*) measure and number of public firms listed in CRSP (*LIST*) are industry-level measures constructed from CRSP. These measures are constructed as proxies to test *H2* and *H3*, respectively. We use the mean of the share turnover across public firms in the same three-digit SIC industry to proxy for expected liquidity in that industry and expect it to have a positive effect on the probability of going public.[25] We use the number of firms already listed in CRSP in the same three-digit SIC industry to proxy for outsiders' ease of evaluation of firms in that industry. In general, the more firms already listed in an industry, the easier it is for outside investors to evaluate a firm in that

[23] As robustness checks, we also use alternative measures of sales growth, such as growth in firm sales over a one-year period and as a dummy variable that equals 1 if the firm had a high growth rate, where high growth rate is defined as the average sales growth over the last three years being above 25%, with each year's growth being at least 10%. Our results remain qualitatively similar.

[24] This definition is similar to that in Loughran and Ritter (2004).

[25] Stock market liquidity is a proxy for the cost of raising public capital. The higher the stock market liquidity in an industry, the lower the cost of raising capital through the public equity market, and the more likely the firms in that industry to go public. Microstructure models such as Kyle (1985) also suggest that the stock market liquidity is lower when the information asymmetry regarding the valuation of the firm's equity is greater.

industry. Therefore, this measure is expected to have a positive relationship with the probability of a firm going public from that industry.

To test *H2*, regarding the relationship between the extent of information asymmetry faced by a firm and the likelihood of its going public, we construct three different measures to proxy for information asymmetry, using analysts' forecasts from I/B/E/S. We use the industry average standard deviation in analysts' forecast (*STDEV*), the industry average analysts' forecast error (*FORERR*), and the industry average number of analysts following (*NUMA*) at the three-digit SIC level. The higher the standard deviation in analysts' forecasts, the higher the analysts' forecast error, and the fewer the analysts following in an industry, the greater the information asymmetry facing firms in that industry. We expect greater information asymmetry in an industry to have a negative relationship with the probability of firms from that industry going public.

Table 2 presents the summary statistics of firm characteristics for the firms that go public (have an IPO) during our sample period and for firms remaining private throughout our sample period. All reported statistics are firm-year observations, and for the sample of IPO firms only the years prior to the firm's IPO are included.[26] These basic comparisons show that firms going public during our sample period are on average more productive, larger, older, and invest more than firms that remain private. The average sales growth for firms that have an IPO is 14.5%, which is significantly higher than the sales growth of firms remaining private, which is around 4%. Moreover, the TFP of firms going public is on average 0.046, while that of private firms is −0.012, both of which suggest that firms going public are on average more productive and efficient and perform better than their industry peers.

Table 3 presents the summary statistics of firm characteristics for firms that received private financing versus those that did not. Panel A presents the results for those firms that received either venture capital financing or bank loans or both, panel B presents the results for those firms that received venture capital financing, and panel C presents the results for those firms that received bank loans. As can be seen from the results, in all three panels we find that firms that receive private funding are on average more productive, larger, older firms, with greater capital expenditure and market share. Moreover, the TFP and sales growth of such firms are significantly greater than those of firms not receiving private financing. These results suggest that firms that receive private financing are on average more productive and efficient and of better quality than those that do not receive private financing. Specifically, the TFP of firms receiving venture financing is 0.023 and that of firms receiving bank financing is 0.037, compared with the TFP of −0.013 of firms not receiving any private financing. Similarly, the sales growth of firms receiving venture financing is 10.6%, and that of firms receiving bank financing is 9.6%, compared with the sales growth

[26] In unreported results, we also tabulated the summary statistics of the IPO firms for all years before and after going public and found qualitatively similar results.

Table 2
Summary statistics—going public versus remaining private

	Firms going public			Firms remaining private			Test of differences	
	Mean	SD	Observation	Mean	SD	Observation	Mean difference *t*-test	Wilcoxon rank-sum test
Capital Stock	63,451.570	110,107.700	6401	5443.286	25,768.150	918,445	170.00***	96.06***
Total Employment	1295.147	1795.960	6401	150.792	448.210	918,445	190.00***	100.72***
Total Sales	168,558.700	274,834.900	6401	17,021.850	65,688.850	918,445	170.00***	100.20***
Market Share	0.024	0.066	6401	0.002	0.014	914,928	110.00***	84.70***
Capital Expenditure	5970.663	10,386.230	6401	554.584	2559.227	918,445	160.00***	94.73***
CAPEX Ratio	0.136	0.142	6060	0.122	0.178	677,601	6.32***	28.15***
Capital Intensity	43.664	48.830	6401	24.229	36.369	882,929	42.44***	52.13***
Age	7.048	6.047	6401	5.178	5.652	918,445	26.38***	31.49***
TFP	0.046	0.246	6361	-0.012	0.250	869,203	18.63***	22.43***
Sales Growth	0.145	0.338	5260	0.038	0.356	637,287	21.76***	27.09***
Percentage of Hi-tech	0.242	0.428	6401	0.049	0.215	918,445	70.88***	70.69***
Total Wage	38,131.420	55,686.820	6401	3948.162	13,190.770	918,445	200.00***	103.23***
Average Wage	29.447	10.246	6401	24.368	10.437	882,929	38.77***	39.75***
Materials Cost	95,429.530	160,667.400	6401	10,559.200	42,532.190	918,445	150.00***	95.48***
Rental and Admin. Exp.	7857.582	11,935.600	6401	775.621	2821.635	918,445	190.00***	101.72***

This table presents summary statistics for firms that went public and firms that remained private in the LRD between 1972 and 2000. The going-public firms are those firms in the manufacturing sector (SIC 2000–3999) that went public between 1972 and 2000 as recorded in SDC. The firms remaining private are all the firms in the LRD that did not have an IPO between 1972 and 2000, and which were not public prior to 1972. All statistics are firm-year observations, with the IPO sample being restricted to the years when the firms were private, prior to going public. *Capital Stock* is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets. *Total Employment* is the total number of employees in the firm. *Total Sales* is the total value of shipments in thousands of dollars. *Market Share* is the firm's market share in terms of sales in the same three-digit SIC industry. *Capital Expenditure* is the sum of new and used capital expenditures by the firms in thousands of dollars. *CAPEX Ratio* is capital expenditure over capital stock. *Age* is the number of years since the birth of the first plant of the firm as recorded in the Census data. *Capital Intensity* is the capital stock over total employment. *TFP* is the weighted average of plant-level total factor productivity at the four-digit SIC level. To calculate TFP one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed). *Sales Growth* is the average growth in sales in the past three years. *Percentage of Hi-tech* is the percentage of firms in the sample that are high technology firms (i.e., belonging to three-digit SIC codes 357, 366, 367, 372, 381, 382, 384). *Total Wage* is sum of total salaries and wages of the firm (in thousands of dollars). *Average Wage* is total wage over total employment. *Materials Cost* is the expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased in thousands of dollars. *Rental and Admin. Exp.* is the rental payments or equivalent charges made during the year for the use of buildings, structures, and various pieces of office equipment in thousands of dollars. All the dollar values are in real terms. The last two columns report the *t*-statistics and the *z*-statistics for the test of difference in means and the distribution between the sample of firms going public and the sample of firms remaining private, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Summary statistics—receiving private financing versus not receiving private financing

Panel A: Private funding is either venture capital financing or bank loan financing or both

	Firms receiving private funding			Firms without private funding			Test of differences	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean difference *t*-test	Wilcoxon rank-sum test
Capital Stock	56,733.100	101,116.700	24,355	4468.426	20,945.050	900,491	300.00***	158.17***
Total Employment	1115.013	1654.197	24,355	132.848	371.021	900,491	330.00***	176.00***
Total Sales	155,969.600	257,119.100	24,355	14,341.000	52,761.770	900,491	330.00***	184.00***
Market Share	0.020	0.058	24,355	0.002	0.012	896,989	180.00***	147.63***
Capital Expenditure	5357.999	9667.070	24,355	463.168	2120.283	900,491	290.00***	168.99***
CAPEX Ratio	0.124	0.137	21,328	0.122	0.179	662,333	2.06**	40.02***
Capital Intensity	45.468	53.179	24,162	23.779	35.756	865,155	91.50***	91.04***
Age	8.079	6.941	24,355	5.113	5.597	900,491	81.03***	79.73***
TFP	0.029	0.232	23,847	−0.013	0.251	851,717	25.39***	33.35***
Sales Growth	0.099	0.316	20,289	0.037	0.357	622,258	24.60***	33.25***
Percentage of Hi-tech	0.170	0.375	24,355	0.047	0.211	900,491	87.16***	86.80***
Total Wage	32,925.000	50,791.420	24,355	3407.431	10,725.610	900,491	340.00***	182.66***
Average Wage	29.542	9.837	24,162	24.261	10.425	865,155	77.78***	82.54***
Materials Cost	92,190.300	156,478.400	24,355	8950.408	35,116.480	900,491	300.00***	173.88***
Rental and Admin. Exp.	6859.895	10,956.700	24,355	661.405	2286.556	900,491	330.00***	181.47***

Panel B: Private funding is venture capital financing

	Firms receiving VC funding			Firms without private funding			Test of differences	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean difference *t*-test	Wilcoxon rank-sum test
Capital Stock	34,794.690	81,836.810	9898	4468.426	20,945.050	900,491	130.00***	69.25***
Total Employment	747.338	1402.324	9898	132.848	371.021	900,491	150.00***	87.05***
Total Sales	100,448.800	214,028.700	9898	14,341.000	52,761.770	900,491	150.00***	93.81***
Market Share	0.011	0.038	9898	0.002	0.012	896,989	74.21***	63.11***
Capital Expenditure	3550.667	8101.759	9898	463.168	2120.283	900,491	130.00***	86.46***
CAPEX Ratio	0.133	0.151	7979	0.122	0.179	662,333	5.48***	26.21***
Capital Intensity	35.284	44.864	9765	23.779	35.756	865,155	31.52***	34.61***
Age	6.990	6.467	9898	5.113	5.597	900,491	33.14***	35.21***
TFP	0.023	0.246	9523	−0.013	0.251	851,717	13.91***	18.59***
Sales Growth	0.106	0.361	7820	0.037	0.357	622,258	17.12***	19.34***
Percentage of Hi-tech	0.279	0.448	9898	0.047	0.211	900,491	110.00***	105.98***
Total Wage	22,130.650	42,709.300	9898	3407.431	10,725.610	900,491	160.00***	94.66***
Average Wage	30.229	10.438	9765	24.261	10.425	865,155	56.26***	56.58***
Materials Cost	56,869.770	127,317.600	9898	8950.408	35,116.480	900,491	130.00***	83.59***
Rental and Admin. Exp.	4546.744	9162.395	9898	661.405	2286.556	900,491	160.00***	93.76***

Table 3
(Continued)

Panel C: Private funding is bank loan financing

	Firms receiving bank loans			Firms without private funding			Test of differences	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean difference *t*-test	Wilcoxon rank-sum test
Capital Stock	74,521.740	112,760.400	16,578	4468.426	20,945.050	900,491	350.00***	161.87***
Total Employment	1425.364	1821.298	16,578	132.848	371.021	900,491	370.00***	170.49***
Total Sales	202,750.900	286,137.700	16,578	14,341.000	52,761.770	900,491	370.00***	175.39***
Market Share	0.026	0.067	16,578	0.002	0.012	896,989	210.00***	151.17***
Capital Expenditure	6923.807	10,759.810	16,578	463.168	2120.283	900,491	320.00***	161.58***
CAPEX Ratio	0.120	0.127	15,372	0.122	0.179	662,333	−1.16	34.69***
Capital Intensity	52.217	56.541	16,578	23.779	35.756	865,155	99.84***	97.84***
Age	8.735	7.107	16,578	5.113	5.597	900,491	82.11***	79.20***
TFP	0.037	0.224	16,428	−0.013	0.251	851,717	25.36***	32.96***
Sales Growth	0.096	0.287	14,297	0.037	0.357	622,258	19.61***	29.53***
Percentage of Hi-tech	0.110	0.312	16,578	0.047	0.211	900,491	37.50***	37.47***
Total Wage	42,125.500	56,102.970	16,578	3407.431	10,725.610	900,491	380.00***	173.20***
Average Wage	29.217	9.342	16,510	24.261	10.425	865,155	60.63***	67.25***
Materials Cost	120,991.400	174,806.500	16,578	8950.408	35,116.480	900,491	340.00***	169.94***
Rental and Admin. Exp.	8812.204	12,118.230	16,578	661.405	2286.556	900,491	370.00***	172.30***

This table presents summary statistics for firms that either received private financing (through venture capital financing, through bank loans, or through both) or those that did not receive any private financing in the LRD between 1972 and 2000. All firms are in the manufacturing sector (SIC 2000–3999). Those firms that received venture capital financing were identified as such from SDC's Venture Expert database, while those receiving bank loans were identified as such from LPC's DealScan database. Firms that did not receive any financing are all remaining firms present in the LRD between 1972 and 2000. In panel A, we define a firm to have received private financing if the firm received either venture capital financing or bank loan financing or both. In panel B, we define a firm to have received private financing if the firm received venture capital financing. In panel C, we define a firm to have received private financing if the firm received bank loans. All statistics are firm-year observations, restricted to the years when the firms were private. *Capital Stock* is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets. *Total Employment* is the total number of employees in the firm. *Total Sales* is the total value of shipments in thousands of dollars. *Market Share* is the firm's market share in terms of sales in the same three-digit SIC industry. *Capital Expenditure* is the sum of new and used capital expenditures by the firms in thousands of dollars. *CAPEX Ratio* is capital expenditure over capital stock. *Age* is the number of years since the birth of the first plant of the firm as recorded in the Census data. *Capital Intensity* is the capital stock over total employment. *TFP* is the weighted average of plant-level total factor productivity at the four-digit SIC level. To calculate TFP one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed). *Sales Growth* is the average growth in sales in the past three years. *Percentage of Hi-tech* is the percentage of firms in the sample that are high technology firms (i.e., belonging to three-digit SIC codes 357, 366, 367, 372, 381, 382, 384). *Total Wage* is sum of total salaries and wages of the firm (in thousands of dollars). *Average Wage* is total wage over total employment. *Materials Cost* is the expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased in thousands of dollars. *Rental and Admin. Exp.* is the rental payments or equivalent charges made during the year for the use of buildings, structures, and various pieces of office equipment in thousands of dollars. All the dollar values are in real terms. The last two columns report the *t*-statistics and the *z*-statistics for the test of difference in means and the distribution between the sample of firms that received private funding and those that did not, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

of 3.7% for firms that did not receive any private financing. Both these results therefore suggest that it is the better-quality firms that are able to attract private financing prior to going public. Finally, the results also show that firms that receive bank loans are larger than those that receive venture capital financing.[27]

4. Relationship between Product Market Characteristics and the Going-Public Decision

In this section, we analyze the determinants of the going-public decision, with emphasis on the product market characteristics of the firm, using a large sample of private firms from the U.S. Census Bureau's Longitudinal Research Database (LRD). Prior to going public, a firm's access to private funding, such as venture financing or bank loan financing, may influence its decision to go public. This may be due to two possible reasons. First, some firms may be better than others in terms of the intrinsic quality of their projects, and such higher-quality firms may have a better chance of attracting private financing. We will refer to the above effect as "screening" or "selection." Second, firms with greater access to private financing can invest more, have larger capital stock, and may be able to grow faster than their peers, possibly by garnering a larger market share in their industry. We will refer to this second effect (broadly) as "monitoring" or "treatment." Clearly, both effects may have an important positive impact on a firm's going-public decision, and it would be interesting to distinguish between the above two effects to the extent possible.[28,29] To address the above influence of private financing on the going-public decision, we first directly control, in Section 4.1, for such private funding received by firms prior to going public and analyze its impact on the going-public decision. In Section 4.2, we control for the possible selection effect of private funding using an instrumental variables framework, where we instrument the probability of firms receiving such private funding prior to going public; such a control is lacking in previous studies of the going-public decision, such as Pagano, Panetta, and Zingales (1998).

4.1 Determinants of the going-public decisions of firms

In this section, we analyze the going-public decisions of firms after directly controlling for access to private funding (*PF*): either venture capital financing

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[27] As can be seen from the results in panels B and C, firms that received bank loans are larger compared with firms that received venture financing. This is consistent with the fact that banks are usually willing to lend only to more established firms. It is also possible that DealScan, our source for bank loan data, may not have comprehensive coverage of loans to very small firms. DealScan is, however, the best source of historical bank loan data and is one of the most widely used databases in the academic banking literature.

[28] We thank an anonymous referee for much of this discussion, and for suggesting that we attempt to distinguish between these two effects.

[29] The theoretical literature in venture capital financing has argued that venture financing can considerably enhance the probability of success for firms receiving such financing (see, e.g., Repullo and Suarez 2004). On the empirical side, Chemmanur, Krishnan, and Nandy (2008) show that venture-financed firms have greater TFP than non-venture-financed firms and further, firms backed by higher reputation venture capitalists have a significantly greater probability of exiting through an IPO as opposed to an acquisition or a write-off.

or bank loan financing or both.[30] On the basis of the hypotheses developed in Section 2.1, we estimate the following maximum likelihood dynamic probit model of the probability of going public.[31] In the following specifications, individual firms are indexed *i*; industries *j*; for each year *t*, in the sample:

$$\begin{aligned} Pr(IPO_{it} = 1) = F(&\beta_1 SIZE_{i,t-1} + \beta_2 SGTH_{i,t-1} + \beta_3 MSHR_{i,t-1} \\ &+ \beta_4 TFP_{i,t-1} + \beta_5 CAPINT_{i,t-1} + \beta_6 AGE_{i,t-1} \\ &+ \beta_7 CAPR_{i,t-1} + \beta_8 INDRSK_{j,t-1} + \beta_9 HI_{j,t-1} \\ &+ \beta_{10} TOV_{j,t-1} + \beta_{11} HTEK_{i,t-1} + \beta_{12} LIST_{j,t-1} \\ &+ \beta_{13} STDEV_{j,t-1} + \beta_{14} FORER_{j,t-1} + \beta_{15} NUMA_{j,t-1} \\ &+ \beta_{16} PF_{i,t-1} + \beta_{17} PF^{*}TFP_{i,t-1} + \beta_{18} PF^{*}SGTH_{i,t-1} \\ &+ \beta_{19} PF^{*}SIZE_{i,t-1} + \beta_{20} PF^{*}HI_{i,t-1} + \beta_{21} SP500_{t-1}), \quad (2) \end{aligned}$$

where *IPO* is a dummy variable that equals 1 if the firm goes public in year *t*, and 0 if the firm remains private.[32] $F(\cdot)$ is the cumulative distribution function of a standard normal variable, *PF* is the private funding variable as defined above, and *SP500* is the annual return on Standard & Poor's 500 Index.[33] All other variables are as described in the previous section. At any time *t*, the sample includes all firms that are private at that point in time, and the firms that go public (had an IPO) in that year. After a firm goes public, it is dropped from the sample.

Table 4 presents the maximum likelihood estimates of the probit model in four panels. In each of the four panels, the analysis is presented in three separate modules, with each module differing based only on the definition of the private funding dummy variable. In the first module (comprising *Reg*1 and *Reg*2), we define the private funding dummy to equal 1 if the firm received either venture capital financing or bank loans or both, and 0 otherwise. In the second module (comprising *Reg*3 and *Reg*4), we define the private funding dummy to equal

[30] The private funding variable is a dummy variable that takes the value of 1 if the firm is still private and has received either venture financing or a bank loan in any prior year, and is 0 otherwise. The variable is always equal to zero for firms that do not ever receive private funding during our sample period. For firms that do receive either venture funding or bank loans, it is zero in all years prior to receiving such private funding and it equals 1 in the years following it. Note that our sample includes only private firms, so that firms going public drop out of the sample for all years after their IPO.

[31] In unreported tests, we have also analyzed the going-public decision using a Cox proportional hazard model specification, obtaining qualitatively similar results. However, when using panel data, hazard models are equivalent to dynamic probit models: see, e.g., Allison (1984) or Shumway (2001). Moreover, as pointed out by Heckman and Singer (1984), hazard rate estimations are quite sensitive to unobserved firm-level heterogeneity, which leads us to focus on probit estimations in this article. We thank an anonymous referee for bringing this to our attention.

[32] Note that for firms that remain private throughout our sample, this dummy variable is always equal to zero.

[33] It is a well-known stylized fact that the IPO market exhibits cyclical patterns over time. To control for this time-varying effect of the equity market conditions, we use calendar year dummies. Many theoretical and empirical papers argue that this cyclical pattern is partly due to overall market performance. Hence, in alternate specifications, we use the S&P500 annual return as a control. Note that, since our calendar year dummies already capture the annual stock market performance component, we do not use the S&P500 annual return when we use calendar year dummies.

1 if the firm received private equity (venture capital financing) and 0 otherwise. In the third module (comprising *Reg5* and *Reg6*), we define the private funding dummy to equal 1 if the firm received private debt (bank loans) and 0 otherwise.[34] In panel A, the explanatory variables are limited to firm-specific variables. In panel B, the firm-specific variables are supplemented by industry characteristics. In panel C, information asymmetry proxies as well as the firm-specific and industry variables from panels A and B are included. One can think of panel C as incorporating the full regression model of the firm's decision to go public, as hypothesized in Section 2.1. Finally, in panel D, we analyze the going-public decision, allowing for interactions between sales growth and two other firm-specific variables (namely, *TFP* and *Size*) and between sales growth and one industry characteristic—namely, the Herfindahl index (we study additional interactions between firm-specific variables and industry characteristics in our robustness tests, presented in Table 8 and discussed in Section 4.4). The methodology adopted in our regression framework throughout this article is consistent with that suggested by Petersen (2009), who advocates using fixed effects and adjusting the standard errors for correlations within firm clusters.

From panel A, we can see that all the firm-specific product market variables that we include in our specifications are significant determinants of a firm's decision to go public. Consistent with *H1*, *SIZE* has a positive effect on the probability of going public: the coefficient on *SIZE* is positive and significant at the 1% level in all specifications. Consistent with *H8*, *TFP* has a positive effect on the probability of going public: the coefficient on *TFP* is also positive and significant either at the 1% or 5% level in all specifications. Consistent with *H9*, *CAPR* and *SGTH* both have significantly positive effects on the probability of going public. Consistent with *H5*, *MSHR* is also significantly positively related to the going-public decision. We find that the *HTEK* dummy is significantly positively related to the probability of going public, which is inconsistent with *H7*, suggesting that high-tech firms have a higher probability of going public.[35] Regressions 2, 4, and 6 in panel A show the effects of *CAPINT* and *AGE*. Due to a multi-collinearity problem among *SIZE*, *CAPINT*, and *AGE*, we do not include *SIZE* as a control in these regressions. Consistent with *H4*, the estimate on *CAPINT* is positive and significant, implying that the more capital intensive the firm, the more likely it is to go public. We find weak support for hypothesis *H1* when industry and year fixed effects are omitted (*AGE* is significant only in *Reg2* and *Reg4*); in other specifications *AGE*, though positive, is statistically insignificant. While the first specification of each module in panel A includes industry and year fixed effects, the second specification of each module uses the

[34] Due to space limitations we show only two regression specifications for each module. Results from other regression specifications are qualitatively similar and can be obtained from the authors upon request.

[35] One caveat to this result is that our high-tech industries are all within the manufacturing sector. Recall that service-oriented high-tech industries, such as Internet firms, are not included in our sample.

Table 4
Determinants of the going-public decision

	Private financing (venture capital or bank loan)		Private equity (venture capital only)		Private debt (bank loan only)	
	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
Panel A: Effect of firm-specific variables						
Size	0.205***		0.223***		0.212***	
	[0.010]		[0.010]		[0.014]	
Sales Growth	0.409***	0.366***	0.392***	0.376***	0.378***	0.345***
	[0.040]	[0.031]	[0.039]	[0.029]	[0.054]	[0.043]
Market Share	0.906***	2.356***	1.037***	2.692***	0.939**	2.237***
	[0.290]	[0.237]	[0.279]	[0.231]	[0.391]	[0.279]
TFP	0.152**	0.119**	0.173***	0.135***	0.247***	0.194***
	[0.064]	[0.050]	[0.061]	[0.047]	[0.080]	[0.064]
Capital Intensity		0.102***		0.127***		0.111***
		[0.014]		[0.014]		[0.019]
Ln(Age)		0.088***		0.139***		0.013
		[0.022]		[0.022]		[0.027]
CAPEX Ratio	0.452***	0.197***	0.464***	0.214***	0.337**	0.179*
	[0.095]	[0.074]	[0.094]	[0.071]	[0.142]	[0.107]
Hi-tech Dummy	0.314***	0.547***	0.357***	0.608***	0.346***	0.626***
	[0.060]	[0.037]	[0.059]	[0.035]	[0.078]	[0.045]
Private Funding (PF)	1.229***	1.024***	0.858***	0.716***	2.557***	1.242***
	[0.215]	[0.043]	[0.275]	[0.058]	[0.355]	[0.056]
*PF*TFP*	0.066	0.121	0.164	0.230	−0.261	−0.238
	[0.157]	[0.133]	[0.197]	[0.165]	[0.222]	[0.199]
*PF*Sales Growth*	−0.121	−0.053	−0.036	0.016	−0.138	−0.126
	[0.101]	[0.091]	[0.133]	[0.125]	[0.147]	[0.129]
*PF*Size*	−0.041*		−0.035		−0.146***	
	[0.021]		[0.028]		[0.033]	
SP500		0.556***		0.604***		0.119
		[0.089]		[0.089]		[0.136]
Industry dummies	Yes	No	Yes	No	Yes	No
Year dummies	Yes	No	Yes	No	Yes	No
Observations	474,096	498,644	474,096	498,644	199,018	203,495
Pseudo *R*-square	0.25	0.16	0.22	0.11	0.26	0.17
Panel B: Combined effect of firm-specific variables and industry characteristics						
Size	0.187***		0.211***		0.187***	
	[0.009]		[0.009]		[0.012]	
Sales Growth	0.394***	0.369***	0.379***	0.365***	0.363***	0.338***
	[0.040]	[0.033]	[0.039]	[0.031]	[0.053]	[0.045]
Market Share	1.163***	3.165***	1.149***	3.422***	1.122***	2.992***
	[0.298]	[0.276]	[0.281]	[0.284]	[0.402]	[0.412]
TFP	0.149**	0.123**	0.174***	0.146***	0.244***	0.214***
	[0.064]	[0.052]	[0.061]	[0.049]	[0.077]	[0.066]
Capital Intensity		0.104***		0.123***		0.137***
		[0.016]		[0.015]		[0.022]
Ln(Age)		0.009		0.025		0.000
		[0.027]		[0.026]		[0.031]
CAPEX Ratio	0.467***	0.322***	0.476***	0.328***	0.375***	0.227**
	[0.094]	[0.078]	[0.094]	[0.075]	[0.135]	[0.113]
Hi-tech Dummy	0.475***		0.512***		0.511***	
	[0.043]		[0.041]		[0.054]	
Industry Risk	0.412	0.189	0.512*	0.366	0.986***	0.781*
	[0.297]	[0.356]	[0.284]	[0.342]	[0.343]	[0.404]
Herfindahl Index	0.531***	0.177	0.449***	0.045	0.329	−0.105
	[0.169]	[0.198]	[0.168]	[0.199]	[0.266]	[0.297]
Turnover	0.074***	0.086***	0.069***	0.081***	0.069***	0.081***
	[0.017]	[0.016]	[0.017]	[0.015]	[0.017]	[0.017]
Private Funding (PF)	0.951***	1.177***	0.662***	0.824***	1.174***	1.468***
	[0.064]	[0.061]	[0.091]	[0.087]	[0.088]	[0.087]
*PF*TFP*	0.084	0.112	0.189	0.199	−0.308	−0.240
	[0.161]	[0.138]	[0.206]	[0.171]	[0.238]	[0.213]

(*continued overleaf*)

Table 4
(Continued)

	Private financing (venture capital or bank loan)		Private equity (venture capital only)		Private debt (bank loan only)	
	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
*PF*Sales Growth*	−0.099	−0.036	−0.012	0.014	−0.130	−0.013
	[0.105]	[0.091]	[0.140]	[0.123]	[0.166]	[0.144]
*PF*Herfindahl Index*	−1.497***	−1.707***	−1.748**	−1.465*	−1.722**	−2.125***
	[0.490]	[0.479]	[0.832]	[0.801]	[0.691]	[0.716]
Industry dummies	No	Yes	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	454,213	449,585	454,213	449,585	195,229	193,714
Pseudo R-square	0.24	0.20	0.21	0.15	0.24	0.21
Panel C: Combined effect of firm-specific variables, industry characteristics, and information asymmetry variables						
Size	0.194***		0.217***		0.194***	
	[0.010]		[0.010]		[0.013]	
Sales Growth	0.401***	0.362***	0.388***	0.372***	0.369***	0.350***
	[0.042]	[0.032]	[0.041]	[0.030]	[0.054]	[0.042]
Market Share	0.636	2.518***	0.755**	3.043***	0.339	1.936***
	[0.417]	[0.364]	[0.365]	[0.326]	[0.603]	[0.525]
TFP	0.121*	0.099*	0.145**	0.120**	0.226***	0.184***
	[0.064]	[0.052]	[0.061]	[0.049]	[0.076]	[0.065]
Capital Intensity		0.084***		0.109***		0.113***
		[0.014]		[0.014]		[0.019]
Ln(Age)		0.010		0.056**		−0.012
		[0.024]		[0.023]		[0.027]
CAPEX Ratio	0.456***	0.254***	0.466***	0.277***	0.364***	0.236**
	[0.100]	[0.074]	[0.099]	[0.071]	[0.141]	[0.104]
Hi-tech Dummy	0.223**		0.254***		0.048	
	[0.091]		[0.089]		[0.119]	
Industry Risk	0.235	0.708***	0.312	0.937***	0.537	1.144***
	[0.427]	[0.213]	[0.412]	[0.192]	[0.497]	[0.227]
Herfindahl Index	0.224	0.464**	0.319	0.516***	−0.175	0.399
	[0.261]	[0.190]	[0.254]	[0.180]	[0.371]	[0.251]
Turnover	0.063***	0.100***	0.054**	0.106***	0.048**	0.082***
	[0.022]	[0.007]	[0.022]	[0.006]	[0.024]	[0.008]
Number of Firms Listed in CRSP	0.000		0.001		0.001**	
	[0.001]		[0.001]		[0.001]	
Std. Dev. of Analysts Forecasts	−0.030	−0.030**	−0.029	−0.041**	−0.012	−0.103*
	[0.025]	[0.014]	[0.023]	[0.017]	[0.023]	[0.053]
Analysts Forecast Error	−0.001	−0.009	−0.002	−0.012	−0.005	0.008
	[0.006]	[0.008]	[0.011]	[0.009]	[0.029]	[0.017]
Number of Analysts	0.003	0.011**	0.002	0.012***	0.007	0.000
	[0.007]	[0.005]	[0.007]	[0.004]	[0.009]	[0.006]
Private Funding (PF)	0.805***	1.068***	0.502***	0.815***	1.029***	1.240***
	[0.048]	[0.043]	[0.064]	[0.056]	[0.067]	[0.057]
*PF*TFP*	0.081	0.143	0.213	0.260	−0.346	−0.204
	[0.165]	[0.142]	[0.211]	[0.181]	[0.244]	[0.208]
*PF*Sales Growth*	−0.133	−0.078	−0.085	−0.041	−0.130	−0.111
	[0.105]	[0.088]	[0.139]	[0.118]	[0.165]	[0.126]
SP500		0.481***		0.562***		0.088
		[0.111]		[0.112]		[0.145]
Industry dummies	Yes	No	Yes	No	Yes	No
Year dummies	Yes	No	Yes	No	Yes	No
Observations	376,164	376,547	376,164	376,547	181,124	184,603
Pseudo R-square	0.24	0.14	0.21	0.09	0.25	0.14
Panel D: Combined effect of firm-specific variables, industry characteristics, and interactions						
Size	0.191***	0.201***	0.215***	0.224***	0.197***	0.196***
	[0.009]	[0.010]	[0.009]	[0.010]	[0.013]	[0.014]
Sales Growth	0.396***	0.478***	0.396***	0.485***	0.322*	0.408**
	[0.134]	[0.136]	[0.139]	[0.141]	[0.176]	[0.173]

(*continued overleaf*)

Table 4
(Continued)

	Private financing (venture capital or bank loan)		Private equity (venture capital only)		Private debt (bank loan only)	
	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
Market Share	0.695**	0.806**	0.847***	0.911***	0.384	0.686
	[0.315]	[0.334]	[0.299]	[0.314]	[0.502]	[0.505]
TFP	0.184***	0.183***	0.214***	0.213***	0.216***	0.216***
	[0.064]	[0.064]	[0.064]	[0.064]	[0.082]	[0.083]
CAPEX Ratio	0.541***	0.482***	0.550***	0.489***	0.427***	0.367***
	[0.089]	[0.095]	[0.088]	[0.094]	[0.129]	[0.137]
Industry Risk	1.432***	0.736**	1.503***	0.873***	1.957***	1.235***
	[0.247]	[0.353]	[0.231]	[0.335]	[0.268]	[0.402]
Herfindahl Index	0.256	−0.084	0.300*	−0.045	0.075	−0.511
	[0.170]	[0.231]	[0.162]	[0.220]	[0.270]	[0.348]
Turnover	0.117***	0.086***	0.115***	0.082***	0.107***	0.077***
	[0.014]	[0.017]	[0.013]	[0.017]	[0.014]	[0.019]
Private Funding (PF)	0.876***	0.820***	0.635***	0.538***	1.005***	1.012***
	[0.044]	[0.044]	[0.056]	[0.057]	[0.062]	[0.064]
*Sales Growth*TFP*	−0.107	−0.122	−0.117	−0.130	−0.095	−0.111
	[0.110]	[0.113]	[0.109]	[0.112]	[0.145]	[0.152]
*Sales Growth*Size*	0.000	−0.012	0.000	−0.012	0.010	−0.002
	[0.015]	[0.016]	[0.016]	[0.016]	[0.021]	[0.021]
*Sales Growth*Herfindahl Index*	0.008	0.141	0.056	0.184	−0.502	−0.498
	[0.276]	[0.353]	[0.266]	[0.343]	[0.542]	[0.588]
Industry dummies	No	Yes	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	454,213	454,213	454,213	454,213	195,229	194,180
Pseudo *R*-square	0.23	0.24	0.20	0.22	0.23	0.25

This table presents the effects of firm-specific variables, industry characteristics, and information asymmetry variables on a firm's decision to go public using a sample of private firms from the LRD. The effect of the variables on the probability of going public is estimated using a probit model. The base model is $Pr(IPO_{ijt} = 1) = F(\beta_1 SIZE_{i,t-1} + \beta_2 SGTH_{i,t-1} + \beta_3 MSHR_{i,t-1} + \beta_4 TFP_{i,t-1} + \beta_5 CAPINT_{i,t-1} + \beta_6 AGE_{i,t-1} + \beta_7 CAPR_{i,t-1} + \beta_8 INDRSK_{j,t-1} + \beta_9 HI_{j,t-1} + \beta_{10} TOV_{j,t-1} + \beta_{11} HTEK_{i,t-1} + \beta_{12} LIST_{j,t-1} + \beta_{13} STDEV_{j,t-1} + \beta_{14} FORERR_{j,t-1} + \beta_{15} NUMA_{j,t-1} + \beta_{16} SP500_{t-1} + \beta_{17} PF_{j,t-1})$, where $F(\cdot)$ is the cumulative distribution function of a standard normal variable. The dependent variable is 0 if the firm is private and 1 in the year of the IPO. *Size* is the lagged value of logarithm of capital stock; *Sales Growth (SGTH)* is the average growth in sales in the past three years; *Market Share (MSHR)* is the lagged value of a firm's market share in terms of total value of shipment in its three-digit SIC industry; *TFP* is the lagged value weighted average of plant-level total factor productivity at the four-digit SIC level, in which one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed); *Capital Intensity (CAPINT)* is the lagged value of capital stock per worker; *Ln(Age)* is the natural logarithm of firm age; *CAPEX Ratio (CAPR)* is the lagged value of capital expenditures over capital stock; *Hi-tech dummy (HTEK)* is 1 if the firm has a three-digit SIC code of 357, 366, 367, 372, 381, 382, 384, and 0 otherwise; *Private Funding (PF)* is a dummy variable that signifies if the firm received private financing, either in the form of venture capital financing and/or in the form of bank loan financing. In *Reg1* and *Reg2*, *PF* is one if the firm received either venture capital and/or loan financing; in *Reg3* and *Reg4*, *PF* is one if the firm received venture capital financing only; and in *Reg5* and *Reg6*, *PF* is one if the firm received bank loan financing only; *Industry Risk (INDRSK)* is the one-year lagged median of the five-year standard deviation of sales at the three-digit SIC level of all the firms covered in the LRD that year; *Herfindahl Index (HI)* is the lagged value of Herfindahl index at the three-digit SIC level; *LIST* is the total number of firms in the same three-digit SIC that are listed in the CRSP in the prior year. *Turnover (TOV)* is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the three-digit SIC level in the prior year. *NUMA* is the lagged three-digit SIC level mean of the number of analysts covering firms in an industry. *FORERR* is the lagged three-digit SIC level mean of average analysts forecast errors across firms in the industry. *STDEV* is the lagged three-digit SIC level mean of the standard deviation in analysts' forecast of EPS. *SP500* is the prior year's annual return of S&P's 500 Index. All dollar values are in real terms. All observations are firm year observations. Panel A reports the effect of firm-specific product market variables on the decision to go public; panel B reports the effect of firm-specific variables along with industry-specific characteristics on the decision to go public; panel C reports the effect of firm-specific variables along with industry-specific characteristics and asymmetric information variables on the decision to go public; and panel D reports the effect of the interactions between the firm-specific and industry-specific variables on the decision to go public. Calendar year and industry dummies are included in some specifications as indicated. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

SP500 variable to control for market fluctuations instead of year dummies. As expected, the coefficient on *SP500* is positive and significant in two regressions, implying that firms are more likely to go public if the stock market has achieved a higher level of return.

Our control for private funding, *PF*, is positive and significant in all specifications, implying that firms that receive private funding (either venture capital or bank loans or both) are more likely to go public. As discussed before, access to private funding may enable firms to build up more capital stock and thus allow them to grow faster, thereby increasing their probability of going public. However, even though access to private funding is an important determinant of going public, it is crucial to note that, even after directly controlling for it, the various firm-specific, industry-specific, and information asymmetry variables arising from our theoretical hypotheses continue to be significant determinants of firms' going-public decisions (we discuss our results on the effects of industry and information asymmetry variables on the going-public decision below). In addition, we also include terms to capture the interactions of *TFP*, *SGTH*, and *SIZE* with *PF* to identify any additional marginal effects of these firm-specific variables with private funding, and we find that in most cases there are no significant interaction effects. We do find some evidence suggesting that firms with larger size that have access to private funding have a marginally lower probability of going public compared with firms of similar size but no private funding. This may imply that already large firms that receive private funding have less need to go public and raise further capital, since their capital requirements have already been met by the amount raised through private funding. In summary, the results in panel A strongly support our hypotheses that larger firms, those that are more productive, have higher sales growth, higher capital expenditures, and larger market shares, are more likely to go public after directly controlling for their access to private funding.

Our panel B regressions include industry-specific characteristics such as industry risk, industry concentration, and the average liquidity of listed stocks (turnover) in the industry in addition to the firm-specific variables in panel A. Comparing *Reg1* in panel B with that in panel A, we see that the coefficients on the firm-specific variables have similar magnitudes, direction, and significance, in both regressions. In addition, in panel B, we find that the impact of industry concentration and industry turnover (*Herfindahl Index* and *TOV*) on the going-public decision are positive and statistically significant, being consistent with hypotheses *H2* and *H6,* respectively. We also find weak evidence that industry risk (*INDRSK*) is positively associated with the decision to go public. Our finding that greater industry concentration leads to a higher probability of an IPO is also related to our hypothesis *H7,* since the value of confidentiality in concentrated industries may be less.[36] Our control for private funding, *PF*, is

[36] These results are also consistent with those of Hou and Robinson (2006), who show that expected returns are lower in more concentrated industries.

positive and significant in all specifications as before. In panel B, we introduce an additional interaction term relative to panel A—namely, between *PF* and industry concentration, as measured by the *Herfindahl Index (HI)*. The results show a significantly negative effect for the interaction term *PF*HI*, suggesting that conditional on receiving private financing, firms in more concentrated industries are marginally less likely to go public. This suggests that in concentrated industries, access to private financing reduces firms' need to go public. This may be because the capital requirements of these firms have already been met through the availability of private financing.

The regressions in Table 4, panel C, include information asymmetry variables along with the firm-specific and industry-specific variables from panels A and B. We find weak support for *LIST*, which proxies outsiders' ease of evaluation of firms, with a positive and significant coefficient in the bank loan sample. This is consistent with *H3*, suggesting that firms operating in industries that are easier for outside investors to evaluate are more likely to go public. All regressions in panel C also include the three proxies for information asymmetry that we discussed earlier.[37] Consistent with *H2*, the coefficient on *STDEV* is negative and significant, which implies that the greater the information asymmetry facing firms in an industry, the less likely they are to go public.[38] The coefficient on the number of analysts, *NUMA*, is positive and significant, also consistent with *H2,* suggesting that firms facing a smaller extent of information asymmetry are more likely to go public. Most of the other explanatory variables, such as *PF*, *TFP*, *SGTH*, *MSHR*, *CAPINT*, and *AGE,* continue to maintain similar levels of magnitude and significance as in the results in the previous panels, with *PF*, *TFP*, and *SGTH* being significant in all specifications. Consistent with *H4*, the coefficients on *CAPINT* across various specifications are positive and significant, while the coefficient on *AGE* is significant only in *Reg4*. The coefficients of the other variables follow a similar pattern as before, with the Herfindahl index being significant in specifications in which the industry dummies are omitted.

Panel D in Table 4 presents a robustness check after introducing interaction terms between *SGTH* and two other firm-specific variables, *TFP* and *SIZE*, and one industry variable, the *Herfindahl Index.* The results from panel D show that these interaction terms are mostly insignificant and do not have any additional marginal impact on the going-public decision once we control for *SGTH* in the regressions. *SGTH* by itself continues to be positive and highly significant across all specifications, consistent with *H9,* suggesting that firms that have higher growth rates are more likely to go public earlier.

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[37] The information asymmetry proxies are constructed from I/B/E/S and start only from 1976. Therefore, our regressions in panel C that use these information asymmetry measures are based on the sample between 1976 and 2000, instead of our complete sample.

[38] However, once industry and year fixed effects are introduced, we lose significance on *STDEV* and *NUMA*, which is not surprising, given that these information asymmetry variables are measured at the industry level.

In summary, our regression results in Table 4 are generally consistent with the hypotheses presented in Section 2.1. We find that larger, more capital intensive firms, those with higher total factor productivity, those with higher growth in output (sales), those with higher capital expenditure ratios, and those with higher market share are more likely to go public. Further, firms that operate in more concentrated industries, those in more risky industries, and those that operate in industries characterized by higher liquidity of already listed firms and by less information asymmetry are more likely to go public. Making use of data on private funding (bank and/or venture capital), we directly control for the effect of private funding on the going-public decision and demonstrate that, although access to private funding is an important factor that affects a firm's going-public decision, it does not negate the effects of the various firm-specific, industry, and information asymmetry variables that we discussed before as important determinants of the going-public decision. These variables continue to be significant even after directly controlling for access to private funding.

While some of our results agree with those in Pagano, Panetta, and Zingales (1998), to the best of our knowledge, our findings on total factor productivity, market share of the firm, industry risk and industry concentration, industry liquidity, and asymmetric information are completely new to the literature. Ours is the first article in the literature that documents that TFP, sales growth, and market share of a firm are important determinants of the going-public decision after controlling for the effects of a firm's access to private funding before the IPO. Ours is also the first article to show that firms in industries associated with higher risk, higher concentration, higher liquidity, and less information asymmetry tend to go public earlier. Our results are also economically significant: a one-unit increase in TFP leads to an 11% increase in the sample average probability of an IPO. Similarly, a unit increase in sales growth leads to roughly a 20% increase in the sample average probability of an IPO, while a unit increase in market share leads to a 54% increase in the sample average probability of going public.

Consistent with Pagano, Panetta, and Zingales (1998), we show that size and capital expenditure are also important determinants of the going-public decision. A unit increase in size leads to an increase in the sample average probability of an IPO by 12%; a similar increase in capital expenditure increases the probability of going public by 26%. Contrary to the results in Helwege and Packer (2003), but consistent with those of Boehmer and Ljungqvist (2004) (who study a sample of German IPOs), we document that more mature (older) firms have a higher probability of going public.[39]

[39] Unlike Helwege and Packer (2003), our sample of private firms is the universe of all private manufacturing firms in the United States, while the sample of private firms in Helwege and Packer (2003) is the small number of much older and larger private firms that have issued corporate debt prior to going public. Thus, compared with their sample, our sample of private firms is much more representative of the U.S. economy.

4.2 Two-stage analysis of the going-public decision

4.2.1 First stage: the probability of receiving private funding. In this section, we allow for the possibility that our observed access to private funding may be capturing unobserved firm quality and thus we need to account for the potential endogeneity between access to private funding and the going-public decision of the firm. To address this concern, we employ an instrumental variables framework, in which we instrument the probability of receiving private funding in the first stage. Using this predicted probability as a control variable, we then analyze the determinants of the going-public decision in the second stage.[40]

In the first stage, we run a panel regression in which the dependent variable is a dummy that takes the value of 1 if the firm is still private and has received either venture financing or bank loans in any prior year, and is 0 otherwise.[41] In our first-stage regression, the independent variables include firm-level characteristics that could affect the probability of receiving private financing, such as prior TFP, firm size, sales growth, firm age, market share, capital expenditure ratio, and whether the firm operates in a high-tech industry or not; it also includes industry-level characteristics such as the industry Herfindahl index. Further, in addition to calendar year dummies and industry fixed effects, we also include three instruments that are correlated with the demand or supply of private financing (such as venture funding) but are independent of the future performance of firms. These instruments are: the increase in National Science Foundation (NSF) applied and basic research grants, the capital gains tax rate, and the AAA spread. Our intuition for these instruments is as follows. An increase in NSF research grants could lead to an increase in the establishment of new entrepreneurial firms that may then potentially seek private funding; thus, this instrument affects the demand for private financing. The capital gains tax rate (which we include following Gompers and Lerner 2000) affects the ability of private financiers such as venture capitalists to secure commitments from investors, thus impacting their ability to invest in private firms. Increases in the capital gains tax rates will therefore be associated with lower commitments from investors, resulting in smaller investments by private financiers. Similarly, the AAA spread, which is the spread of AAA bonds over five-year Treasury bonds, captures the investment alternatives available to investors who may invest in such private funds. An increase in the spread may therefore lead to a decline in commitments to VC and other private funds, thus lowering the overall availability of such financing. These instruments provide us with a

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[40] As in the previous section, we also separately conducted the two-stage analysis using as a proxy for private funding: (1) only the venture financing data for all years from 1970; and (2) only the bank loan data starting from 1987. In both cases we obtain qualitatively similar results to those reported here, which are based on a firm obtaining either venture financing or bank loans.

[41] The dependent variable is always equal to 0 for firms that do not ever receive private financing during our sample period. For firms that do receive either venture funding or bank loans, it is 0 in all years prior to receiving such private financing, and it equals 1 in the years following it. Note that our sample includes only private firms, so that firms going public drop out of the sample for all subsequent years.

Table 5
The probability of receiving private funding

	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*
Capital Gains Tax Rate	−0.009***	−0.009***	−0.010***	−0.012***	−0.009***
	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
AAA Spread	0.023	0.017	0.017	−0.067***	0.024
	[0.030]	[0.030]	[0.029]	[0.011]	[0.030]
Increase in NSF Research Grants	0.481***	0.479***	0.485***	0.548***	0.477***
	[0.021]	[0.020]	[0.020]	[0.018]	[0.020]
Size	0.293***	0.294***	0.299***	0.301***	0.291***
	[0.010]	[0.010]	[0.010]	[0.009]	[0.009]
TFP	0.224***	0.224***	0.216***	0.201***	0.229***
	[0.036]	[0.036]	[0.037]	[0.036]	[0.037]
Sales Growth	0.079**	0.077**	0.115***	0.100***	0.086***
	[0.033]	[0.032]	[0.032]	[0.032]	[0.033]
Market Share	1.563***	1.549***	1.232***	1.374***	1.531***
	[0.354]	[0.355]	[0.357]	[0.346]	[0.330]
Ln(Age)	0.117	−0.050**	−0.068***	−0.108	0.11
	[0.101]	[0.021]	[0.021]	[0.094]	[0.100]
Ln(Age) Squared	−0.038			0.028	−0.038
	[0.025]			[0.023]	[0.025]
Herfindahl Index	0.765***	0.760***	0.455***	0.745***	0.611***
	[0.146]	[0.146]	[0.151]	[0.144]	[0.133]
CAPEX Ratio	0.569***	0.566***	0.613***	0.616***	0.567***
	[0.057]	[0.057]	[0.056]	[0.057]	[0.057]
Hi-tech Dummy	0.767***	0.767***		0.765***	0.879***
	[0.061]	[0.061]		[0.059]	[0.037]
Industry fixed effects	Yes	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	No	Yes
Observations	511,112	511,112	511,112	511,112	511,112
Pseudo R-square	0.33	0.33	0.32	0.31	0.32

This table reports the results on the probability of private firms receiving financing from private sources such as venture capital or bank loans. It presents the results of the first stage of the two-stage instrumental variables analysis of the going-public decision. The dependent variable is whether a firm receives either VC financing or bank loans or both in a given year (*Funding Dummy*). The independent variables in these regressions are: *Capital Gains Tax Rate,* which is the capital gains tax rate in the current year; *AAA Spread,* which is the spread of AAA bonds over five-year Treasury bonds in the current year; *Increase in NSF Research Grants*, which is the average of the past five-year increase in the real National Science Foundation research grants for both applied and basic research; *Size* is the lagged value of logarithm of capital stock; *Sales Growth* is the average growth in sales in the past three years; *Market Share* is the lagged value of a firm's market share in terms of total value of shipment in its three-digit SIC industry. *TFP* is the lagged value weighted average of plant-level total factor productivity at the four-digit SIC level, in which one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed). *Ln(Age)* is the natural logarithm of firm age; *Ln(Age) Squared* is the natural logarithm of firm age squared; *CAPEX Ratio* is the lagged value of capital expenditures over capital stock; *Hi-tech Dummy* is 1 if the firm has a three-digit SIC code of 357, 366, 367, 372, 381, 382, 384, and 0 otherwise; *Herfindahl Index* is the lagged value of Herfindahl index in the three-digit SIC industry level, the higher the Herfindahl index, the more concentrated the industry. Based on these first-stage regressions we predict the probability of receiving private financing for the firms in our sample; we then use this predicted probability of private financing as a control variable in our second-stage regressions analyzing the going-public probability of a firm. Calendar year and industry dummies are included in some specifications as indicated. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

certain degree of exogenous variation both in the demand for, and the supply of, private funds; in other words, they affect the selection of firms receiving private financing but do not directly affect the going-public decisions of firms.

The results from our first-stage regressions are presented in Table 5. They show that prior TFP, firm size, sales growth, firm market share, the level of firm capital expenditure, the industry Herfindahl index, and the high-tech dummy are all positive and highly significant determinants of firms receiving private funding. Similarly, firm age is a negative and significant determinant of receiving such financing. Finally, with regard to our instruments, we find that, consistent with our expectations, the first instrument—namely, the increase in NSF research grants—is positive and significant, suggesting that greater-funded research may lead to an increase in entrepreneurial firm formation, thus leading to greater demand for private funds. Our second instrument—namely, the capital gains tax rate—is negative and significant, indicating that an increase in the tax rate leads to a fall in committed capital to private financiers, thus decreasing the probability of firms receiving such private financing. Finally, our third instrument, the AAA spread, is negative and significant in some specifications, suggesting that the availability of funds is an important variable affecting the probability of a firm receiving private financing.

Overall, our results show that more efficient and better-quality firms, as proxied by TFP, with greater market shares and operating in more concentrated industries are more likely to have access to private financing. Based on these first-stage estimates, we predict the probability of receiving private financing for all firms in the LRD for each year, labeling it *Predicted Private Funding (PPF)*. We then use this as a control variable for selection effects correlated with firm quality in our second-stage regressions on the going-public decisions of firms.[42]

4.2.2 Second stage: the going-public decision of firms. In this section, we repeat our analysis of Section 4.1 using the predicted probability of receiving private financing as a control, as discussed above. In Table 6 we present the maximum likelihood estimates of the full probit model incorporating firm-specific, industry-specific, and information asymmetry variables corresponding to panel C in Table 4.[43]

Our results from the second-stage regressions show that the firm-specific, industry-specific, and information asymmetry variables continue to be significant determinants of the going-public decision and remain qualitatively unchanged from results presented in Table 4, even after controlling for the "screening" or "selection" effects of access to private funding. Thus, TFP, sales growth, market share, capital expenditure, firm size, the high-tech dummy, Herfindahl index, industry risk, and lower information asymmetry (as proxied by lower standard deviation of analysts' forecasts or by larger analyst coverage) continue to positively and significantly affect the probability of a firm going

[42] As our results in Table 5 show, access to private financing is correlated with better firm-specific attributes such as higher sales growth. Thus, by using the probability of receiving private financing as a control variable in the second stage, we are controlling for selection effects correlated with firm quality.

[43] We present only the results corresponding to the full model (panel C of Table 4) due to space limitations. Results for regressions corresponding to panels A, B, and D of Table 4 are qualitatively similar to those in Table 4 and are available from the authors upon request.

Table 6
Two-stage analysis of the going-public decision

	Combined effect of firm-specific variables, industry characteristics, and information asymmetry variables					
	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
Size	0.238***	0.193***	0.249***			
	[0.013]	[0.010]	[0.015]			
Sales Growth	0.425***	0.414***	0.433***	0.365***	0.348***	0.365***
	[0.044]	[0.043]	[0.047]	[0.034]	[0.033]	[0.035]
Market Share	1.153***	0.690*	0.991**	0.849*	1.306***	1.052**
	[0.334]	[0.374]	[0.406]	[0.447]	[0.444]	[0.468]
TFP	0.185***	0.147**	0.153**	0.096*	0.111**	0.098*
	[0.070]	[0.068]	[0.072]	[0.052]	[0.050]	[0.052]
Capital Intensity				0.031*	0.042***	0.035**
				[0.017]	[0.015]	[0.017]
Ln(Age)				−0.015	0.001	−0.012
				[0.027]	[0.025]	[0.027]
CAPEX Ratio	0.518***	0.329***	0.519***	0.212***	0.124	0.216***
	[0.097]	[0.095]	[0.103]	[0.082]	[0.079]	[0.082]
Hi-tech Dummy		0.411***	0.329***		0.257***	0.051
		[0.060]	[0.090]		[0.065]	[0.090]
Industry Risk	0.403	0.138	0.426	−0.001	−0.393	−0.278
	[0.381]	[0.257]	[0.395]	[0.401]	[0.271]	[0.442]
Herfindahl Index	0.223	0.365*	0.395	0.048	0.364*	0.180
	[0.205]	[0.218]	[0.254]	[0.245]	[0.208]	[0.259]
Turnover	0.058***	0.071***	0.058***	0.043*	0.036**	0.032
	[0.020]	[0.011]	[0.021]	[0.023]	[0.015]	[0.026]
Number of Firms Listed in CRSP	0.002***	0.001***	0.001*		0.001	0.001
	[0.000]	[0.000]	[0.001]		[0.000]	[0.001]
Std. Dev. of Analysts Forecasts		−0.031*	−0.036	−0.028	−0.021*	−0.027
		[0.018]	[0.027]	[0.020]	[0.011]	[0.020]
Analysts Forecast Error		−0.019	−0.003	−0.001	−0.009	−0.001
		[0.013]	[0.012]	[0.002]	[0.009]	[0.002]
Number of Analysts		−0.002	0.001	0.016**	0.011**	0.015**
		[0.005]	[0.007]	[0.006]	[0.005]	[0.006]
Predicted Private Funding (PPF)	−0.230	0.305	−0.503	2.963***	2.341***	2.802***
	[0.275]	[0.186]	[0.308]	[0.202]	[0.174]	[0.224]
*PPF*TFP*	0.165	0.203	0.370	−0.083	−0.066	−0.077
	[0.374]	[0.307]	[0.379]	[0.326]	[0.272]	[0.322]
*PPF*Sales Growth*	−0.363	−0.408	−0.394	−0.695***	−0.402*	−0.689***
	[0.313]	[0.262]	[0.327]	[0.266]	[0.226]	[0.267]
SP500		0.390***			0.332***	
		[0.108]			[0.103]	

Table 6
(Continued)

Industry fixed effects	Yes	No	Yes	Yes	No	Yes
Year fixed effects	Yes	No	Yes	Yes	No	Yes
Observations	453,570	379,559	376,164	373,162	376,547	373,162
Pseudo R-square	0.21	0.16	0.2	0.16	0.12	0.16

This table presents the results of the second stage of the two-stage instrumental variables analysis of the going-public decision, in which the probability of receiving private financing is instrumented in the first stage, in Table 5. As before, the effects of firm-specific variables, industry characteristics, and information asymmetry variables on a firm's decision to go public are considered using a sample of private firms from the Longitudinal Research Database (LRD). The effect of the variables on the probability of going public is estimated by a probit model. The base model is $Pr(IPO_{ijt} = 1) = F(\beta_1 SIZE_{i,t-1} + \beta_2 SGTH_{i,t-1} + \beta_3 MSHR_{i,t-1} + \beta_4 TFP_{i,t-1} + \beta_5 CAPINT_{i,t-1} + \beta_6 AGE_{i,t-1} + \beta_7 CAPR_{i,t-1} + \beta_8 INDRSK_{j,t-1} + \beta_9 HI_{j,t-1} + \beta_{10} TOV_{j,t-1} + \beta_{11} HTEK_{i,t-1} + \beta_{12} LIST_{j,t-1} + \beta_{13} STDEV_{j,t-1} + \beta_{14} FORERR_{j,t-1} + \beta_{15} NUMA_{j,t-1} + \beta_{16} SP500_{t-1} + \beta_{17} PPF_{j,t-1})$, where $F(\cdot)$ is the cumulative distribution function of a standard normal variable. The dependent variable is 0 if the firm is private and 1 in the year of the IPO. *Size* is the lagged value of logarithm of capital stock; *Sales Growth (SGTH)* is the average growth in sales in the past three years; *Market Share (MSHR)* is the lagged value of a firm's market share in terms of total value of shipment in its three-digit SIC industry; *TFP* is the lagged value weighted average of plant-level total factor productivity at the four-digit SIC level, in which one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed); *Capital Intensity (CAPINT)* is the lagged value of capital stock per worker; *Ln(Age)* is the natural logarithm of firm age; *CAPEX Ratio (CAPR)* is the lagged value of capital expenditures over capital stock; *Hi-tech dummy (HTEK)* is 1 if the firm has a three-digit SIC code of 357, 366, 367, 372, 381, 382, 384, and 0 otherwise; *Industry Risk (INDRSK)* is the one-year lagged median of the five-year standard deviation of sales at the three-digit SIC level of all the firms covered in the LRD that year; *Herfindahl Index (HI)* is the lagged value of Herfindahl index at the three-digit SIC level; *LIST* is the total number of firms in the same three-digit SIC that are listed in the CRSP in the prior year. *Turnover (TOV)* is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the three-digit SIC level in the prior year. *NUMA* is the lagged three-digit SIC level mean of the number of analysts covering firms in an industry. *FORERR* is the lagged three-digit SIC level mean of average analysts' forecast errors across firms in the industry. *STDEV* is the lagged three-digit SIC level mean of the standard deviation in analysts' forecast of EPS; *Predicted Private Funding (PPF)* is the predicted probability of receiving private financing as estimated in Table 3; *SP500* is the prior year's annual return of S&P's 500 Index. All dollar values are in real terms. All observations are firm year observations. We report the effect of firm-specific variables along with industry-specific characteristics and asymmetric information variables on the decision to go public. Calendar year and industry dummies are included in some specifications as indicated. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

public. In Table 6, our control for firm quality from the first stage, *PPF*, is positive and significant in some specifications, while being insignificant in others. These results suggest that although the screening aspect of access to private funding has some effect on the going-public decisions of firms, it does not by itself completely determine the decision to go public. The results also show that in most cases there are no significant interaction effects between *PPF* and other firm-specific variables. We do find some evidence suggesting that firms with higher sales growth that had access to private financing have a marginally lower probability of going public compared with firms with similar sales growth but no private financing. This suggests that those firms that are still at an early stage of an innovative project (characterized by high sales growth) and have successfully obtained private financing will delay their going-public decision, perhaps because for such firms the cost of revealing proprietary information is prohibitively higher (consistent with *H7*).

In summary, our regression results in Table 6 are very similar to our earlier results presented in Table 4 and are consistent with the hypotheses we discussed in Section 2.1. Making use of data on venture capital and bank loans, we are able to control for the selection aspect of access to private funding and demonstrate that, while such selection affects the going-public decisions of firms to some degree, the various firm-specific, industry-specific, and information asymmetry variables that we discussed earlier are important determinants of the going-public decision even after controlling for such selection effects.

4.3 The going-public decision and changes in subsequent industry concentration

In this section, we test our hypothesis *H10*, which suggests that as more firms in an industry go public, the concentration of the industry increases. Sutton (1991) argues that barriers to entry are endogenous to the number of firms in the industry and not a predetermined causal factor for the number of firms in an industry. In this context, he argues that firms are likely to use R&D and other sunk costs to keep competitors out of their industry. As our previous results show, private firms that make larger investments in capital expenditure including R&D have a significantly greater probability of going public. After going public, these firms have access to cheaper capital, which may lead them to make greater investments in R&D and other sunk costs, thereby further increasing barriers to entry and resulting in greater industry concentration.

In order to test if the going-public decision of a firm indeed affects subsequent industry concentration, for each year in our sample, we calculate the change in the Herfindahl index for each industry over the subsequent two (or three, depending on the specification) years. We then regress this measure on the percentage of firms going public in that industry over the prior three years as well as on other industry characteristics (as controls).[44] Table 7 presents our

[44] We obtain qualitatively similar results when using the percentage of IPOs in an industry over the previous two years or the previous year, with somewhat diminished levels of significance.

Table 7
Effect of firms going public in an industry on industry concentration

	Effect of firms going public in an industry on future change in industry herfindahl index							
	Δ Herfindahl over next two years	Δ Herfindahl over next two years	Δ Herfindahl over next two years	Δ 3-Year average Herfindahl over next two years	Δ Herfindahl over next three years	Δ Herfindahl over next three years	Δ Herfindahl over next three years	Δ 3-Year average Herfindahl over next three years
Pct. of IPO in Last 3 Years (PS3IPO3)	0.366**	0.347*	0.290*	0.359***	0.622***	0.542*	0.429*	0.618***
	[0.157]	[0.181]	[0.154]	[0.130]	[0.199]	[0.303]	[0.237]	[0.227]
Industry Risk		−0.082**	−0.013			−0.098*	−0.029	
		[0.039]	[0.039]			[0.055]	[0.051]	
Turnover		−0.003	−0.008			−0.004	−0.003	
		[0.004]	[0.005]			[0.006]	[0.008]	
Number of Analysts		0.000				0.001		
		[0.000]				[0.001]		
Analysts Forecast Error		0.000				0.000		
		[0.000]				[0.000]		
Std. Dev. of Analysts Forecasts		0.001**				0.001***		
		[0.000]				[0.000]		
Ln (Industry Capital Intensity)		−0.002	−0.001			−0.004	−0.004*	
		[0.002]	[0.002]			[0.003]	[0.002]	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	No	Yes	Yes	No	No	Yes
Observations	3785	2341	3373	3500	3640	2230	3241	3360
Adjusted *R*-square	0.008	0.018	0.010	0.016	0.012	0.025	0.014	0.033

This table presents the effect of firms going public in an industry on future changes in industry concentration. The effect of IPO activity on the changes of industry composition is estimated based on the following panel regression specification: $\Delta HI_{i,(t,t+3)} = \alpha + \beta_1 PS3IPO3_{i,t} + \beta_2 INDRSK_{i,t} + \beta_3 TOV_{i,t} + \beta_4 NUMA_{i,t} + \beta_5 STDEV_{i,t} + \beta_6 FORERR_{i,t} + \beta_7 INDCAPINT_{i,t} + \varepsilon_{it}$. All observations are industry year observations, where industry is defined at the three-digit SIC level. The dependent variable Δ*HI* is the change in the industry Herfindahl index over the next two or three years, in alternate regression specifications. *Pct. of IPO in Last 3 Years* (*PS3IPO3*) is the percentage of firms in the industry that went public in the last three years; *Industry Risk (INDRSK)* is the median of the five-year standard deviation of sales at the three-digit SIC level of all the firms covered in the Longitudinal Research Database (LRD) that year; *Turnover (TOV)* is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the three-digit SIC level in the current year; *Number of Analysts* (*NUMA*) is the three-digit SIC level mean of the number of analysts covering firms in an industry. *Analysts Forecast Error* (*FORERR*) is the three-digit SIC level mean of average analysts forecast errors across firms in the industry; *Std. Dev. of Analysts Forecasts* (*STDEV*) is the three-digit SIC level mean of the standard deviation in analysts forecast of EPS; *Ln (Industry Capital Intensity)* (*INDCAPINT)* is the natural logarithm of median capital intensity at the three-digit SIC level. All regression specifications are OLS regressions with calendar year fixed effects and industry fixed effects as indicated. Heteroskedasticity-corrected clustered robust standard errors, clustered on industry, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% percent levels, respectively.

results, which show that the percentage of IPOs over the last three years in an industry is a positive and significant determinant of subsequent changes in the concentration of that industry, thus supporting our hypothesis *H10*. The result is robust and holds also in alternative specifications in which we use changes in the Herfindahl index over the next two years as the dependent variable. These results also hold if we calculate the change in the industry concentration as a three-year moving average change in the future Herfindahl index. In addition, this result is also robust to including year and industry fixed effects. In some specifications, we include other industry characteristics such as industry risk, level of information asymmetry, and industry capital intensity. We find weak evidence that decreases in industry risk lead to an increase in the future Herfindahl index, while an increase in information asymmetry leads to an increase in the future Herfindahl index.

Overall, our results in Table 7 strongly support *H10*. To the best of our knowledge, these results are the first empirical evidence showing how the going-public decision of firms in an industry affects the creation of barriers to entry in that industry through investments in capital expenditures such as R&D. The above evidence supports Sutton's (1991) argument regarding the potential endogeneity of industry concentration.

4.4 Robustness tests: effect of firms going public in prior years, interactions between firm-specific variables and industry characteristics, and test of whether firm size is the sole determinant of the going-public decision

In this section (Table 8), we present three robustness tests of our earlier results on the going-public decision. First (in panel A), we analyze how the going-public decisions of firms in an industry in a given year affect the going-public decisions of firms in the same industry in subsequent years (potentially by affecting the concentration of their industry, as we showed in the previous section). Second (in panel B), we analyze how the interactions between two important industry characteristics, namely industry concentration and industry capital intensity, with firm-specific measures such as TFP and sales growth affect the going-public decisions of firms. Third (in panel C), we analyze whether firm size by itself is completely driving our results, since firm size may be correlated with the other firm-specific variables that we showed in Table 4 to affect a firm's going-public decision. As in Table 4, we make use of a maximum likelihood dynamic probit model to estimate a firm's probability of going public.

In panel A of Table 8, we first show that, unconditionally, the probability of firms going public in any industry in a given year is positively affected by the percentage of firms going public in that industry over the previous two years (or three years, in other specifications).[45] Thus, the coefficient of the

[45] This result is consistent with previous research on IPOs that has shown that more firms tend to go public in "hot" IPO markets (see Ritter 1984), where several firms from an industry go public within a short period of time.

Table 8
Robustness tests: effect of firms going public in prior years, interactions between firm-specific and industry variables, and test of whether firm size is the sole determinant of the going-public decision

Panel A: Effect of firms going public in prior years

	Reg1	*Reg2*	*Reg3*	*Reg4*
Size	0.182***	0.185***	0.183***	0.186***
	[0.011]	[0.011]	[0.011]	[0.011]
Sales Growth	0.366***	0.367***	0.367***	0.369***
	[0.039]	[0.039]	[0.039]	[0.039]
Market Share	−0.219	−0.167	−0.218	−0.076
	[0.433]	[0.421]	[0.441]	[0.419]
TFP	0.144**	0.147**	0.146**	0.150**
	[0.059]	[0.059]	[0.059]	[0.059]
CAPEX Ratio	0.450***	0.455***	0.451***	0.458***
	[0.094]	[0.094]	[0.094]	[0.095]
Industry Risk	1.037***	1.025***	0.993***	0.972***
	[0.270]	[0.272]	[0.273]	[0.279]
Herfindahl Index	0.399*	0.699***	0.392*	0.774***
	[0.213]	[0.216]	[0.215]	[0.219]
Turnover	0.084***	0.078***	0.083***	0.074***
	[0.016]	[0.016]	[0.016]	[0.016]
Std. Dev. of Analysts Forecasts	−0.046*	−0.045*	−0.044*	−0.043*
	[0.026]	[0.025]	[0.026]	[0.025]
Analysts Forecast Error	−0.001	−0.001	−0.001	−0.001
	[0.003]	[0.003]	[0.003]	[0.003]
Number of Analysts	−0.007	−0.009*	−0.007	−0.009*
	[0.005]	[0.005]	[0.005]	[0.005]
Predicted Private Funding (PPF)	1.235***	1.129***	1.191***	1.040***
	[0.197]	[0.201]	[0.201]	[0.207]
Pct. of IPO in Last 2 Years (PS3IPO2)	5.671***	11.321***		
	[0.906]	[1.647]		
Pct. of IPO in Last 3 Years (PS3IPO3)			4.478***	9.785***
			[0.799]	[1.420]
Herfindahl Index PS3IPO2*		−42.799***		
		[11.563]		
Herfindahl Index PS3IPO3*				−39.296***
				[9.946]
Year fixed effects	Yes	Yes	Yes	Yes
Observations	376,176	376,176	376,176	376,176
Pseudo *R*-square	0.19	0.19	0.19	0.19

Panel B: Interactions between firm-specific and product market variables

	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
Size	0.183***		0.183***	0.178***		0.177***
	[0.010]		[0.011]	[0.010]		[0.010]
Sales Growth	0.560***	0.418***	0.573***	0.361***	0.296***	0.362***
	[0.051]	[0.047]	[0.055]	[0.045]	[0.037]	[0.052]
Market Share	0.067	0.577	−0.482	0.142	0.618	−0.38
	[0.348]	[0.379]	[0.437]	[0.343]	[0.378]	[0.431]
TFP	0.195**	0.114	0.186*	0.224***	0.158***	0.214**
	[0.094]	[0.077]	[0.098]	[0.072]	[0.057]	[0.085]
Capital Intensity		0.027*			0.02	
		[0.014]			[0.014]	
Ln(Age)		0.096			0.095	
		[0.184]			[0.184]	
Ln(Age) Squared		−0.026			−0.026	
		[0.044]			[0.043]	

(*continued overleaf*)

Table 8
(Continued)

	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
CAPEX Ratio	0.447***	0.208***	0.434***	0.462***	0.211***	0.451***
	[0.089]	[0.077]	[0.094]	[0.088]	[0.077]	[0.093]
Industry Risk	1.136***	−0.149	1.300***	1.198***	−0.114	1.372***
	[0.259]	[0.302]	[0.266]	[0.255]	[0.300]	[0.262]
Herfindahl Index	0.243	0.349**	0.462**	0.213	0.304*	0.446**
	[0.158]	[0.145]	[0.208]	[0.168]	[0.156]	[0.218]
Turnover	0.093***	0.053***	0.091***	0.094***	0.054***	0.092***
	[0.014]	[0.016]	[0.015]	[0.014]	[0.016]	[0.015]
Std. Dev. of Analysts Forecasts			−0.042*			−0.046*
			[0.024]			[0.025]
Analysts Forecast Error			−0.001			−0.002
			[0.003]			[0.006]
Number of Analysts			−0.005			−0.006
			[0.005]			[0.005]
Predicted Private Funding (PPF)	1.459***	3.339***	1.473***	1.474***	3.340***	1.488***
	[0.188]	[0.172]	[0.194]	[0.187]	[0.171]	[0.192]
*High Capital Intensity*TFP*	−0.055	−0.016	−0.071			
	[0.118]	[0.097]	[0.121]			
*High Capital Intensity*Sales Growth*	−0.323***	−0.186***	−0.354***			
	[0.066]	[0.059]	[0.069]			
*High Herfindahl*TFP*				−0.77	−0.685*	−0.904
				[0.484]	[0.385]	[0.756]
*High Herfindahl*Sales Growth*				0.091	0.192	0.016
				[0.271]	[0.214]	[0.404]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	454,213	449,585	376,176	454,213	449,585	376,176
Pseudo R-square	0.19	0.15	0.19	0.19	0.15	0.18

Panel C: Test of whether firm size is sole determinant of the going-public decision

	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
Size	0.247***	0.243***	0.235***	0.246***	0.243***	0.220***
	[0.015]	[0.014]	[0.011]	[0.015]	[0.014]	[0.013]
Sales Growth	0.434***	0.435***	0.416***	0.440***	0.435***	0.427***
	[0.047]	[0.047]	[0.045]	[0.047]	[0.047]	[0.046]
Market Share	1.133***	1.615**	0.973***			0.965***
	[0.328]	[0.712]	[0.307]			[0.319]
TFP	0.150**	0.147*	0.132*	0.148*	0.149**	0.149**
	[0.076]	[0.076]	[0.072]	[0.076]	[0.076]	[0.075]
CAPEX Ratio	0.507***	0.506***	0.478***	0.489***	0.507***	0.479***
	[0.097]	[0.097]	[0.095]	[0.097]	[0.097]	[0.094]
Hi-tech Dummy	0.468***	0.470***	0.413***	0.425***	0.467***	0.606***
	[0.069]	[0.069]	[0.059]	[0.068]	[0.069]	[0.049]
Herfindahl Index	0.343*	0.233	0.305	0.392**	0.259	0.385**
	[0.201]	[0.191]	[0.199]	[0.193]	[0.189]	[0.165]
Predicted Private Funding (PPF)	−0.313	−0.329		−0.043	−0.322	0.208
	[0.279]	[0.279]		[0.261]	[0.278]	[0.246]
*PPF*TFP*	−0.160	−0.146		−0.178	−0.148	−0.253
	[0.449]	[0.449]		[0.440]	[0.448]	[0.436]
*PPF*Sales Growth*	−0.330	−0.305		−0.415	−0.293	−0.383
	[0.360]	[0.359]		[0.352]	[0.358]	[0.342]
*Size90*TFP*	0.231*	0.233*	0.200*	0.242*	0.230*	0.232*
	[0.137]	[0.136]	[0.119]	[0.136]	[0.135]	[0.139]
*Size90*Sales Growth*	0.003	−0.011	−0.057	−0.011	−0.016	0.016
	[0.084]	[0.084]	[0.076]	[0.084]	[0.084]	[0.083]

(*continued overleaf*)

Table 8
(Continued)

	Reg1	*Reg2*	*Reg3*	*Reg4*	*Reg5*	*Reg6*
*Size90*Market Share*		−0.581			0.998***	
		[0.752]			[0.333]	
*Size90*Herfindahl Index*	−0.285		−0.288	−0.135		−0.279
	[0.324]		[0.324]	[0.305]		[0.313]
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	474,096	474,096	474,096	474,096	474,096	474096
Pseudo R-square	0.21	0.21	0.21	0.21	0.21	0.2

Panel A analyzes the effects of firms going public in the same industry in prior years on firm's going-public decision. Panel B analyzes the interaction between two firm-specific variables, *TFP* and *Sales Growth*, respectively, with two industry variables, capital intensity and industry concentration (Herfindahl index) on the going-public decision. Panel C studies whether firm size by itself is the sole determinant of the decision to go public. The effect of the variables on the probability of going public is estimated by a probit model as before. *PS3IPO2* and *PS3IPO3* are the percentage of firms that have gone public in the same three-digit SIC during the last two years and last three years, respectively; *Size* is the lagged value of logarithm of capital stock; *Size90* is a dummy variable that equals 1 if the firm belongs to the top decile of firm size; *Sales Growth (SGTH)* is the average growth in sales in the past three years; *Market Share (MSHR)* is the lagged value of a firm's market share in terms of total value of shipment in its three-digit SIC industry; *TFP* is the lagged value weighted average of plant-level total factor productivity at the four-digit SIC level, in which one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed); *Ln(Age)* is the natural logarithm of firm age; *Ln(Age) Squared* is the natural logarithm of firm age squared; *CAPEX Ratio (CAPR)* is the lagged value of capital expenditures over capital stock; *Capital Intensity (CAPINT)* is the lagged value of capital stock per worker; *High Capital Intensity* is a dummy variable that equals 1 if the firm's *CAPINT* is greater than the median value in the sample; *Hi-tech dummy (HTEK)* is 1 if the firm has a three-digit SIC code of 357, 366, 367, 372, 381, 382, 384, and 0 otherwise; *Predicted Private Funding (PPF)* is the predicted probability of receiving private financing as estimated in Table 3; *Industry Risk (INDRSK)* is the one-year lagged median of the five-year standard deviation of sales at the three-digit SIC level of all the firms covered in the LRD that year; *Herfindahl Index (HI)* is the lagged value of Herfindahl index at the three-digit SIC level; *High Herfindahl* is a dummy variable that equals 1 if the firm's *HI* is greater than the median value in the sample; *Turnover (TOV)* is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the three-digit SIC level in the prior year. *Number of Analysts (NUMA)* is the lagged 3-digit SIC level mean of the number of analysts covering firms in an industry. *Analysts Forecast Error (FORERR)* is the lagged three-digit SIC level mean of average analysts' forecast errors across firms in the industry. *Std. Dev. of Analysts Forecasts (STDEV)* is the lagged three-digit SIC level mean of the standard deviation in analysts' forecast of EPS. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

percentage of firms in the industry going public in the previous two (or three) years is positive and significant in our probit regression of the going-public decision. The marginal effect of this variable in concentrated industries is, however, negative and significant. This result is consistent with the results from our previous section showing that, as the number of firms in an industry going public in an industry increases, the concentration of that industry increases in subsequent years. Thus, while unconditionally firms in concentrated industries have a greater probability of going public compared with firms in competitive industries as per *H6* and *H7*, the incremental probability of going public for firms in concentrated industries goes down once a significant percentage of firms from such industries have gone public.

In panel B of Table 8, we analyze the interactions between the two industry variables—namely, industry concentration and industry capital intensity—with the two firm-specific measures, TFP and sales growth. As shown in Table 4, sales growth by itself has a significantly positive effect on the decision to go public. However, the interaction term between sales growth and capital intensity has a significantly negative effect on the going-public decision, suggesting that more capital-intensive firms with greater sales growth have a marginally lower probability of going public. This implies that sales growth is not as significant a determinant of the going-public decision in high capital-intensive industries even though its overall effect is still positive. The other three interaction terms—namely, the interaction between capital intensity and TFP, industry concentration and sales growth, and industry concentration and TFP—remain mostly insignificant.

In panel C of Table 8, we investigate whether the results we have shown so far on the going-public decision are in fact completely driven by firm size alone. As our results in Table 4 show, firms with greater productivity, sales growth, market share, and industry concentration have a greater probability of going public. One possible explanation here is that all such firm attributes are potentially correlated with the firm's current and future funding needs, and therefore with firm size.[46] In order to test whether firm size is the primary factor driving our results, we first construct a dummy variable based on size deciles, *Size90*, which takes the value of 1 if the firm belongs to the highest decile of firm size and 0 otherwise.[47] We then repeat our tests on the going-public decision by incorporating interaction terms between *Size90* and firm-specific variables such as TFP, sales growth, market share, and the Herfindahl index into our maximum likelihood dynamic probit model of the probability of going public. Our intuition here is that, if size were the sole driver of our results, then the positive and significant effect of the other firm-specific and industry variables on the going-public decision that we documented earlier should be wiped away by the inclusion of these interaction terms, which should have positive coefficients and be significantly related themselves to the going-public decision.[48] Our results in panel C show that, with the exception of *Size90*TFP* (which is marginally significant at the 10% level), all the above interaction terms turn out to be insignificant, while the original variables themselves continue to retain levels of magnitude and significance as in the regressions presented in Table 4. Thus, although size is clearly an important factor influencing the

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[46] Special thanks to the editor, Mathew Spiegel, for suggesting this robustness test.

[47] In unreported robustness tests, we also constructed two other variables, indicating whether a firm was in the top two *(Size80)* or top three *(Size70)* size deciles, and we used them in our analyses, instead of *Size90*. In both cases, we obtained qualitatively similar results to the ones presented here.

[48] This is the extreme outcome when size is the sole driver of our earlier results. In contrast, if firm size systematically increases the impact on the going-public decision of all the other firm-specific variables, then we should observe a positive and significant marginal effect on all the interaction terms, suggesting that such effects are heightened as firm size increases.

going-public decisions of firms, it is not the sole determinant of the going-public decision.[49] Recall also that we show in Table 4 that firm-specific attributes such as TFP, sales growth, market share, and industry concentration all positively affect the going-public decision even after controlling for firm size, consistent with the predictions of the theoretical models underlying our hypotheses, *H5*, *H6*, *H8*, and *H9*.

In summary, in all three panels of Table 8, the original results from Table 4 broadly continue to hold for the firm-specific and industry characteristics that affect the going-public decision, after controlling for access to private funding and the interactions between important firm-specific and industry variables.[50] Further, while firm size is indeed an important determinant of the going-public decision, we have shown that it is not the sole determinant of this decision.

5. Analysis of the Dynamics of Firm Characteristics Before and After the IPO

In this section, we analyze the dynamic pattern of various firm-specific product market characteristics around the IPO date. While there are empirical papers in the IPO literature (such as Jain and Kini 1994; Mikkelson, Parch, and Shah 1997) that look at the operating performance of firms subsequent to their IPO, there has been no extensive study of firm performance in the years prior to the IPO. Using a unique sample of data from the LRD of the U.S. Census Bureau, in this article, we analyze, for the first time in the literature, the dynamic pattern of firm productivity and other product market firm characteristics from five years prior to the IPO to five years after the IPO.[51] While, in our univariate analysis (reported only in Figures 1–6, due to space limitations), we study the various product market characteristics of only the firms that went public, in our multivariate analysis we analyze the dynamic aspects of various product market variables of firms that went public using the firms that remained private throughout our sample period as a benchmark.

As discussed in Section 2.2, there are various theories that provide interesting implications for the dynamics of various firm characteristics around the IPO. In this section, we empirically investigate the dynamics of various firm characteristics before and after the IPO. To study the dynamics of firm performance, we employ a regression framework of the following specification:

$$\Upsilon_{it} = \alpha_t + \beta_i + \gamma X_{it} + \sum_{s=1}^{5} \delta_s Before_{it}^{s} + \sum_{s=1}^{5} \lambda_s After_{it}^{s} + \varepsilon_{it}, \qquad (3)$$

[49] The positive significance of *Size90***TFP*, however, does show that the impact of TFP on the going-public decision is greater for larger firms. However, as mentioned before, it does not eliminate the significance of TFP by itself.

[50] For all these robustness tests, we have also run the regressions using the direct private funding (*PF*) variable instead of the predicted private funding (*PPF*) variable. In all cases our results remain qualitatively unchanged from those presented here.

[51] The results are robust to the choice of this five-year window on each side of the IPO. We obtain similar results when considering seven-year and three-year windows as well.

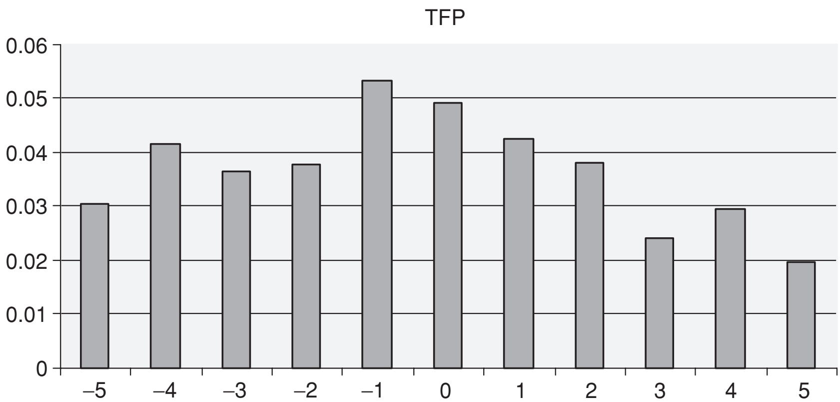

Figure 1
Dynamic pattern of TFP around the IPO

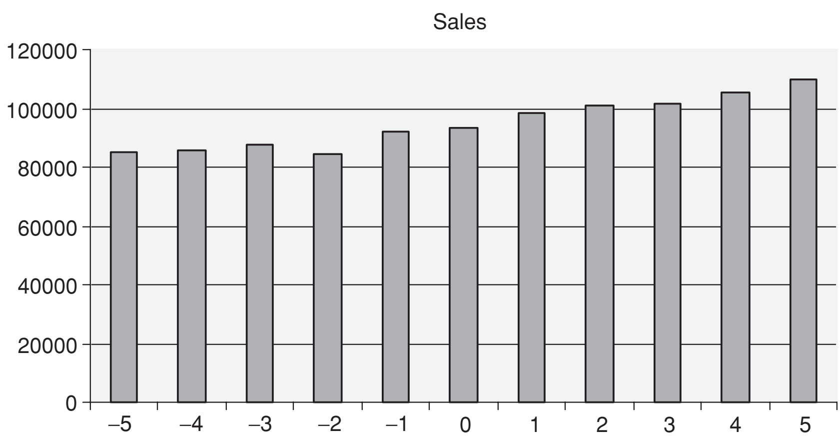

Figure 2
Dynamic pattern of sales around the IPO

where Y_{it} is the variable of interest (e.g., TFP, sales, capital expenditures, etc.); X_{it} is a control for firm size that is time varying; $Before^{s}{}_{it}$ is a dummy variable equal to 1 if the firm goes public and the observation is s years prior to the IPO, where $s = 1, 2, 3, 4$, or 5 years; and $After^{s}{}_{it}$ is a dummy variable equal to 1 if the firm goes public and the observation is s years after the IPO, where $s = 1, 2, 3, 4$, or 5 years; i indexes firms; t indexes years; and β_i are firm fixed effects. Note that the benchmark (or control sample) in our analysis is the set of firms that remained private throughout. For the firms that remained private throughout our sample, the $Before^{s}{}_{it}$ and $After^{s}{}_{it}$ variables are always 0. As IPOs in our sample are spread over time, the specification also incorporates calendar-year dummies. Since the specification is estimated with firm fixed

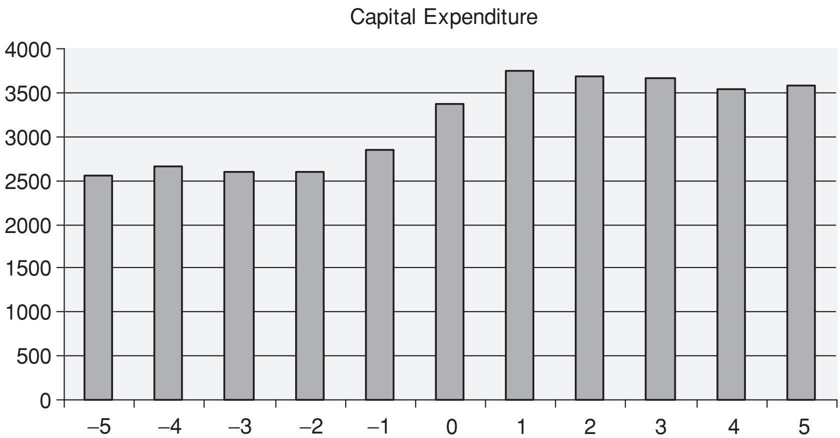

Figure 3
Dynamic pattern of capital expenditures around the IPO

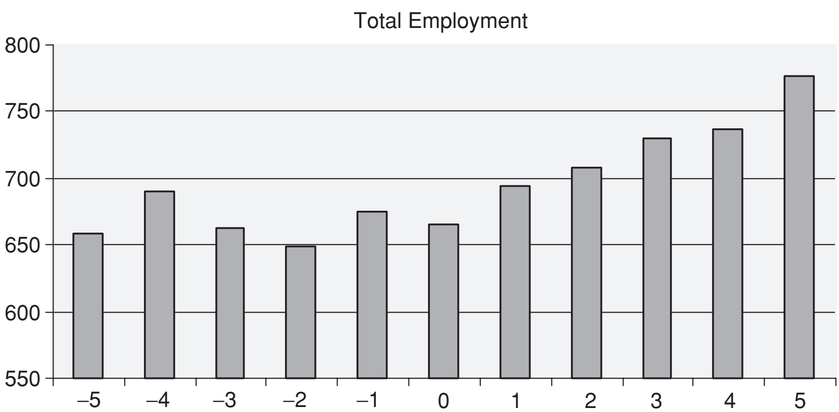

Figure 4
Dynamic pattern of total employment around the IPO

effects, we cluster the standard errors at the firm level as suggested by Petersen (2009). The dynamic pattern of the effect of an IPO on the variables of interest is captured by the coefficients δ_s and λ_s.

The above specification corresponds to a differences-in-differences estimation strategy and has been used previously by Bertrand and Mullianathan (2003) and Schoar (2002), among others, to study firm performance around different events. In this specification, since the sample of IPOs are dispersed over time, the year fixed effects control for calendar-time fixed effects, which accounts for variations over time associated with market movements that may influence IPO issues, such as the clustering of IPOs. The *Before* and *After* year dummies in

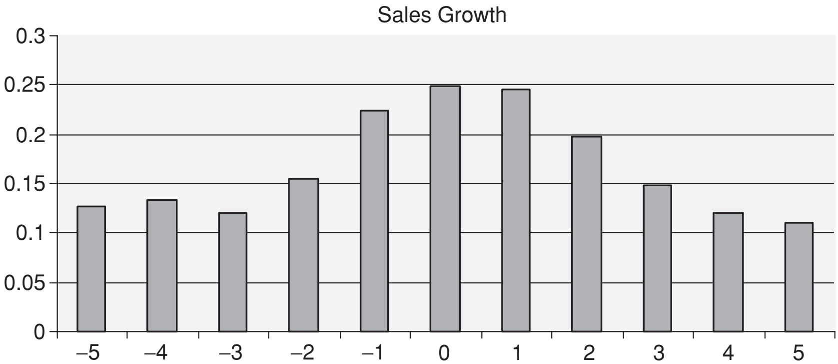

Figure 5
Dynamic pattern of sales growth around the IPO

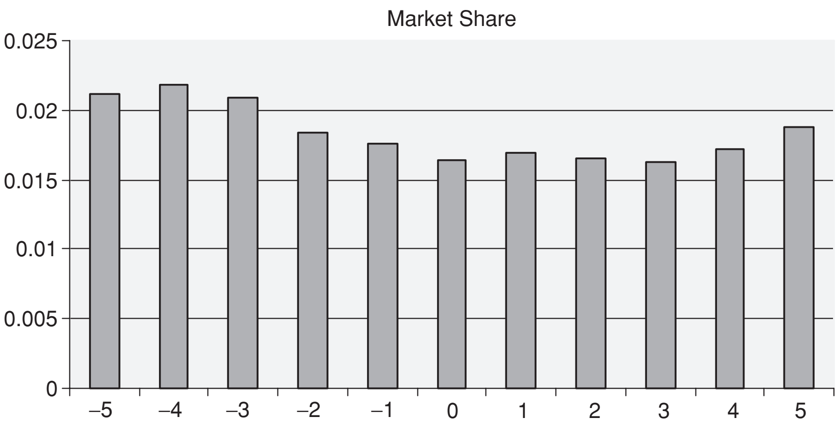

Figure 6
Dynamic pattern of market share around the IPO

the specification, in contrast, are event-time dummies around the year of going public that capture residual changes in the dependent variables around the IPO after accounting for the calendar-time and firm fixed effects. In all the specifications, our base year is the year of the IPO (year 0). Thus, the coefficients δ_s and λ_s reflect the deviations of the variables of interest with respect to the year of going public.[52]

We first examine the dynamic patterns of TFP, sales, and capital expenditures over the five years before and the five years after the IPO. Table 9 presents the regression results. Consistent with Clementi (2002), the TFP of firms going public exhibit an inverted U shape, which increases before the IPO, reaches

[52] In results not reported, we also specify the year prior to the IPO year (i.e., year −1) as our base year. The results obtained remain qualitatively similar to those reported here.

Table 9
Dynamic characteristics of TFP, sales, and capital expenditure around the IPO

	TFP	Sales	Capital expenditure
$Before^5$	−0.062***	−55,401.577***	−1601.378***
	[0.014]	[13,109.283]	[491.206]
$Before^4$	−0.030*	−26,818.511***	−1034.309***
	[0.017]	[7715.876]	[349.653]
$Before^3$	−0.034**	−26,361.378***	−1166.384***
	[0.014]	[6788.267]	[314.299]
$Before^2$	−0.022*	−21,038.925***	−1364.398***
	[0.013]	[5034.832]	[247.683]
$Before^1$	−0.012	−9343.458***	−724.504***
	[0.011]	[3122.467]	[190.721]
$After^1$	−0.008	13,948.441***	838.002***
	[0.010]	[3899.842]	[224.133]
$After^2$	−0.014	22,298.150***	1144.740***
	[0.012]	[4677.845]	[261.523]
$After^3$	−0.024*	28,110.585***	953.912***
	[0.013]	[6787.258]	[312.186]
$After^4$	−0.033**	33,229.682***	1181.384***
	[0.014]	[8378.680]	[385.333]
$After^5$	−0.023	62,613.088***	1534.649***
	[0.014]	[9995.167]	[409.366]
Size	−0.007***	6018.237***	202.907***
	[0.000]	[205.587]	[7.223]
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	883,319	932,831	932,831
Adjusted R-square	0.36	0.855	0.705

This table presents the dynamic pattern of TFP, sales, and capital expenditure before and after going public. The dynamic pattern is estimated based on the following panel regression specifications: $Y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \sum_{s=1}^{5} \delta_s Before_{it}^s + \sum_{s=1}^{5} \lambda_s After_{it}^s + \varepsilon_{it}$, where Y_{it} is firm TFP, sales, and capital expenditure, respectively. The sample includes all firm year observations in the LRD of firms that either went public or remained private between 1972 and 2000; the dynamic pattern of these variables in firms going public is benchmarked against those of firms that remain private. *TFP* is the lagged value weighted average of plant-level total factor productivity at the four-digit SIC level, in which one regresses the value of output (total value of shipments adjusted for changes in inventories) on labor (production worker-equivalent man-hours), capital stock, and material inputs (intermediate inputs, fuels, and energy consumed). *Sales* is the total value of shipments in thousands of dollars. *Capital Expenditure* is the dollar value of capital expenditure by the firms, in thousands of dollars. The control variable *Size* is the natural logarithm of firm capital stock, where capital stock is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets in thousands of dollars. All the *Before* and *After* variables with superscripts are dummy variables. $Before^5$ equals 1 for year 5 before the firm goes public, and 0 otherwise. $Before^4$, $Before^3$, $Before^2$, $Before^1$ equals 1 for 4, 3, 2, 1 year(s) before the firm goes public, respectively, and 0 otherwise. Similarly, $After^1$, $After^2$, $After^3$, $After^4$ equals 1 for 1, 2, 3, 4 year(s) after the firm goes public, respectively, and 0 otherwise. $After^5$ equals 1 for year 5 after the firm goes public and 0 otherwise. All dollar values are in real terms. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

its peak at the year of the IPO, and subsequently declines. These results are also consistent with the analysis of Spiegel and Tookes (2007), who predict that firms will first finance projects with the greatest revenue generating ability privately, and will then go to the public markets only when more modest innovations remain, implying that firm productivity will peak around the IPO. Compared with the IPO year, in panel A, the coefficients on all the *Before* and

After dummies are negative, with the coefficients on $Before^5$, $Before^4$, $Before^3$, and $Before^2$ being significant, and the coefficients on $After^3$ and $After^4$ being significant. The changes in TFP in the years prior to going public are also economically significant. The increase in TFP from year −2 to year −1 of 1% translates to a roughly 6% increase in profits. Similarly, the increase in TFP over the four years prior to going public (i.e., from year −5 to −1) of 5% translates to an increase in profits of roughly 30%.[53] Similarly, the decrease in TFP after going public (from the year of the IPO to three years after) of 2.4% corresponds to a decrease of 14.4% in profits. Figure 1 presents the univariate results (median TFP) of firms going public, depicting the dynamic pattern of firm TFP from five years before the IPO to five years after the IPO.

The coefficients on sales keep increasing throughout the years around the IPO. All the coefficients on the *Before* dummies are negative and significant at the 1% level, while all the coefficients on the *After* dummies are positive and significant at the 1% level. This implies that the sales of IPO firms are growing over the years around the IPO compared with their private peers. The analysis of capital expenditures shows a similar increasing pattern, with all the coefficients on the *Before* dummies being negative and significant at the 1% level, while all the coefficients on the *After* dummies are positive and significant at the 1% level. Figures 2 and 3 present the univariate results (median sales and capital expenditures, respectively) of firms going public, depicting the dynamic pattern of firm sales and capital expenditure from five years before the IPO to five years after the IPO.

We examine the dynamic pattern of total employment, labor costs, and other costs around the IPO in Table 10. The analysis shows that total employment, total wages, material costs, and rental and administrative expenses all increase over the years around the IPO, with all the coefficients on the *Before* dummies being negative and significant, and all the coefficients on the *After* dummies being positive and significant. These results again show that the increase of these costs in IPO firms is greater compared with those for firms remaining private throughout. These results are consistent with Clementi's (2002) theoretical argument that the firm's scale of operations increases from before the IPO to after, which therefore leads to the continued increase in employment, wages, materials costs, and other administrative expenses. Figure 4 presents the univariate results for firms going public (median employment of firms going public), depicting the dynamic pattern of firm total employment from five years before the IPO to five years after the IPO.

Finally, in Table 11, we examine two sales-related variables, sales growth and market share. In Table 9, we have already shown that sales of IPO firms grow throughout the years around the IPO. The result on sales growth in Table

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[53] For a detailed explanation of the relation between TFP and profits, see Schoar (2002). The calculations presented above assume a revenue margin of 20% over costs.

Table 10
Dynamic characteristics of firm employment, labor, and other costs around the IPO

	Total employment	Total wage	Materials cost	Rental and administrative expenses
Before^5	−210.535***	−6879.724***	−43,763.266***	−1663.407***
	[77.544]	[2294.544]	[8518.342]	[512.782]
Before^4	−98.914**	−3033.130**	−22,205.835***	−538.021*
	[44.735]	[1288.800]	[5294.214]	[299.291]
Before^3	−86.080**	−3014.675***	−18,288.265***	−568.337**
	[34.337]	[1039.801]	[4404.328]	[256.604]
Before^2	−92.877***	−2856.003***	−13,283.631***	−623.220***
	[25.265]	[755.954]	[3383.643]	[187.830]
Before^1	−28.201*	−914.498**	−6820.265***	−14.55
	[16.532]	[451.620]	[2302.195]	[133.618]
After^1	43.986**	1497.810**	8728.325***	315.007*
	[20.042]	[622.586]	[2625.924]	[170.850]
After^2	93.240***	2732.651***	13,693.674***	598.048***
	[23.238]	[740.551]	[3133.602]	[180.122]
After^3	111.785***	3617.166***	12,969.480***	630.771**
	[34.926]	[1137.768]	[4103.531]	[254.956]
After^4	129.893***	4127.858***	15,465.973***	1051.019***
	[44.200]	[1374.316]	[4744.735]	[322.079]
After^5	193.574***	6649.724***	29,831.602***	1551.954***
	[56.978]	[1669.798]	[5857.263]	[374.709]
Size	32.252***	943.994***	3890.464***	196.964***
	[1.097]	[32.929]	[122.480]	[7.180]
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	932,831	932,831	929,366	932,831
Adjusted R-square	0.869	0.875	0.823	0.846

This table presents the dynamic pattern of employment, total wage, materials cost, and rental and administrative expenses before and after going public. The dynamic pattern is estimated based on the following panel regression specifications: $Y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \sum_{s=1}^{5} \delta_s Before_{it}^s + \sum_{s=1}^{5} \lambda_s After_{it}^s + \varepsilon_{it}$, where Y_{it} is firm employment, total wage, materials cost, and rental and administrative expenses, respectively. The sample includes all firm year observations in the LRD of firms that either went public or remained private between 1972 and 2000; the dynamic pattern of these variables in firms going public is benchmarked against those of firms that remain private. *Total Employment* is the total number of employees in the firm. *Total Wage* is the total payroll of the firm in thousands of dollars. *Materials Cost* is the expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased, in thousands of dollars. *Rental and Administrative Expenses* is the rental payments or equivalent charges made during the year for the use of buildings, structures, and various pieces of office equipment, in thousands of dollars. The control variable *Size* is the natural logarithm of firm capital stock, where capital stock is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets in thousands of dollars. All the *Before* and *After* variables with superscripts are dummy variables. *Before*^{5} equals 1 for five years before the firm goes public, and 0 otherwise. *Before*^{4}, *Before*^{3}, *Before*^{2}, *Before*^{1} equals 1 for 4, 3, 2, 1 year(s) before the firm goes public, respectively, and 0 otherwise. Similarly, *After*^{1}, *After*^{2}, *After*^{3}, *After*^{4} equals 1 for 1, 2, 3, 4 year(s) after the firm goes public, respectively, and 0 otherwise. *After*^{5} equals 1 for five years after the firm goes public, and 0 otherwise. All dollar values are in real terms. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

11 shows that all the *Before* and *After* coefficients are negative, implying that sales growth (like TFP) also reaches a peak in the year of the IPO. Other than the one year immediately before and after the IPO, the coefficients on all the other years are significant. Thus, we find that the sales growth of IPO firms exhibit an inverted U shape. As discussed in Section 2.2, we were essentially agnostic about the dynamic pattern of market share around the going-public

Table 11
Dynamic characteristics of firm sales growth and market share around the IPO

	Sales growth	Market share
Before^5	−0.087***	−0.536*
	[0.021]	[0.278]
Before^4	−0.068***	−0.209
	[0.025]	[0.163]
Before^3	−0.078***	−0.031
	[0.023]	[0.274]
Before^2	−0.059***	−0.057
	[0.019]	[0.214]
Before^1	−0.012	−0.039
	[0.015]	[0.067]
After^1	−0.007	0.027
	[0.015]	[0.115]
After^2	−0.037**	0.018
	[0.018]	[0.124]
After^3	−0.077***	0.06
	[0.021]	[0.117]
After^4	−0.104***	0.123
	[0.022]	[0.137]
After^5	−0.111***	0.044
	[0.021]	[0.182]
Size	0.007***	0.049***
	[0.001]	[0.004]
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Observations	649,933	929,311
Adjusted R-square	0.552	0.704

This table presents the dynamic pattern of sales growth and market share of the firm before and after going public. The dynamic pattern is estimated based on the following panel regression specifications: $Y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \sum_{s=1}^{5} \delta_s Before_{it}^s + \sum_{s=1}^{5} \lambda_s After_{it}^s + \varepsilon_{it}$, where Y_{it} is firm sales growth and market share, respectively. The sample includes all firm year observations in the LRD of firms that either went public or remained private between 1972 and 2000; the dynamic pattern of these variables in firms going public is benchmarked against those of firms that remain private. *Sales* growth is the average growth in sales in the past three years. *Market share* is the firm's market share in terms of total value of shipment in its three-digit SIC industry. The control variable *Size* is the natural logarithm of firm capital stock, where capital stock is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets in thousands of dollars. All the *Before* and *After* variables with superscripts are dummy variables. *Before*^{5} equals 1 for five years before the firm goes public, and 0 otherwise. *Before*^{4}, *Before*^{3}, *Before*^{2}, *Before*^{1} equals 1 for 4, 3, 2, 1 year(s) before the firm goes public, respectively, and 0 otherwise. Similarly, *After*^{1}, *After*^{2}, *After*^{3}, *After*^{4} equals 1 for 1, 2, 3, 4 year(s) after the firm goes public, respectively, and 0 otherwise. *After*^{5} equals 1 for five years after the firm goes public, and 0 otherwise. All dollar values are in real terms. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity-corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

decision. The result in Table 11 shows that market share essentially remains flat over the eleven-year horizon around the IPO. For market share, the coefficients on the *Before* and *After* dummies are statistically insignificant in almost all cases, with the coefficients in the years after the IPO being positive. Figures 5 and 6 present the univariate results (median sales growth and market share, respectively) of firms going public, depicting the dynamic pattern of firm sales growth and market share from five years before the IPO to five years after the IPO.

Thus, our results on the dynamic pattern of firm characteristics are mostly consistent with the predictions of various theories, discussed in Section 2.2. TFP and sales growth both depict an inverted U shape, implying that they reach their peak in the year of going public, consistent with the predictions of Spiegel and Tookes (2007) and Clementi (2002); sales, capital expenditures, and various costs associated with the product and labor markets show gradually increasing patterns from five years prior to the IPO to five years subsequent to the IPO, benchmarked against firms remaining private throughout.[54]

6. Conclusion

In this article, we used a large and representative sample of U.S. manufacturing firms to study two related questions regarding the going-public decisions of private firms. In the first part of the article, we studied the relationship between firms' ex ante product market characteristics and their decision to go public, both after directly controlling for access to private funding (venture capital financing or bank loan financing or both) and after controlling for the selection effects of firms having access to private financing using a two-stage instrumental variables framework. In the second part of the article, we studied the dynamics of a firm's product market performance for a number of years before and after it went public, using the contemporaneous performance of firms that remained private throughout as a benchmark. Our findings were as follows. First, firms with larger size, sales growth, total factor productivity (TFP), market share, capital intensity, access to private financing, and high-tech industry membership are more likely to go public. Second, firms operating in less-competitive and more capital-intensive industries, and those in industries characterized by riskier cash flows, are more likely to go public. Third, firms with projects that are cheaper for outsiders to evaluate, operating in industries characterized by less information asymmetry, and having greater average liquidity of already listed equity, are more likely to go public. We also show that, as more firms in an industry go public, the concentration of that industry increases in subsequent years. All the above results are robust to controlling for the interactions between various product market and firm-specific variables.

Our dynamic analysis of firm performance around the IPO contemporaneously compared the performance of firms that went public with those of firms that remained private throughout. The results of this dynamic analysis indicated that although TFP and sales growth exhibit an inverted U-shaped pattern (with peak productivity and sales growth occurring in the year of IPO), sales, capital expenditures, employment, total labor costs, materials costs, and selling and

[54] In unreported results, we also analyzed the dynamic pattern of the interactions between various firm-specific and product market variables around the IPO year. The results of this analysis indicate that the dynamic pattern of these interaction variables does not deviate significantly from that of the original firm-specific variables documented above.

administrative expenses exhibit a consistently increasing pattern in the years before and after the IPO. The dynamic pattern in various firm performance variables before and after the IPO (and especially the inverted U-shaped pattern of productivity changes) that we document around the IPO is inconsistent with the notion that the operating post-IPO underperformance of firms is generated solely by earnings management by firms immediately prior to the IPO. In particular, the consistent growth in firm productivity that we document for *five years* before the IPO is unlikely to be generated purely by the manipulation of accounting numbers, since the performance effects of such manipulation are likely to be confined to the years immediately prior to the IPO, and they would not persist over so many years (especially given the fact that measures of economic performance such as TFP, being derived from a variety of other performance measures, are much harder to manipulate compared with accounting numbers). Instead, the above dynamic pattern of various variables (and especially the inverted U-shaped pattern of productivity changes and sales growth) is broadly consistent with the implications of the dynamic models of Spiegel and Tookes (2007) and Clementi (2002).

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