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THE GOING PUBLIC DECISION AND THE PRODUCT MARKET

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Abstract

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 paper, 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 (market share, competition, capital intensity, cash flow riskiness) significantly affect its likelihood of going public. Second, private firms facing less information asymmetry and those with projects that are cheaper for outsiders to evaluate are more likely to go public (consistent with Chemmanur and Fulghieri (1999)). Third, IPOs of firms occur at the peak of their productivity cycle (consistent with Clementi (2002)): the dynamics of total factor productivity (TFP) and sales growth exhibit an inverted U-shaped pattern. 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 widely documented post-IPO operating underperformance of firms being due to the real investment effects of a firm going public, and inconsistent with underperformance being solely due to earnings management immediately prior to the IPO.

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The Going Public Decision and the Product Market

1. Introduction

“Going public” is one of the most important events in the life of a firm. Since an 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, while the going public decision has generated considerable theoretical research in recent years (see, e.g., Boot, Gopalan, and Thakor (2006), Chemmanur and Fulghieri (1999), and Clementi (2002)), there has been very little empirical research on this topic: two prominent exceptions are Lerner (1994), who studies the timing 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 paper is to bridge the above 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 the second part of our analysis, we will study the dynamics of a firm’s product market performance in the years leading up to its IPO, and in the years after it has

gone public. We conduct this latter analysis using two different samples. We first conduct this analysis of the dynamics of firm performance only using firms that eventually went public, comparing the performance of these firms in the years before and after the IPO to their performance in the IPO year. We then perform this analysis using both firms that went public during our study period and those that remained private throughout, thus allowing us to compare the changes in the performance of firms going public to these 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. In their setting the decision to go public emerges from the trade-off between raising capital from a number of well-diversified investors in the public equity market (thus avoiding the risk-premium charged by private financiers who provide a significant fraction of the capital required for any given firm), and the duplication of outsiders' evaluation (information production) costs that arises from raising capital from a larger number of investors. This theory 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 (2000) argue that the decision to go public emerges from the trade-off between the costs of increased product market competition arising from the firm having to release confidential information (helpful to competitors) at the time of IPO, and 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. Finally, Clementi (2002) argues that firms go public as a result of a positive and persistent productivity shock: while a borrowing constraint kept the firm

operating at a suboptimal scale before the shock, the deviation between actual and efficient scale becomes wider after the shock, making it optimal for the firm to go public (and expand scale) despite the fixed costs of going public. 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.

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 is 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; we discuss their findings in more detail later. In more recent research, Fischer (2000) investigates a sample of privately held German firms, some of which went public on the *Neuer Market*. While providing important insights into the going public decision, it is difficult to generalize the results of the above papers to draw broader conclusions about the going public decision of the majority of U.S. firms. For example, only 69 of the more than 2000 firms eligible to go public in the PPZ sample went public in over 10 years; of these, more than 40 percent were equity carve-outs. Further, the typical newly listed company in Italy is several times larger and older than its counterpart in the U.S. Finally, the tax and regulatory environment in the U.S. and the stage of development of the U.S. capital markets are dramatically different from those in Italy. Several concerns apply to generalizing German evidence to the U.S. as well.¹ A recent paper which

¹ Apart from the dramatic differences in the tax and regulatory environment in the U.S. and in Germany, there are also significant differences in the stage of development of the capital markets in Germany and in the

provides some evidence regarding the going public decisions of U.S. firms is Helwege and Packer (2003), who make use of a sample of 178 non-financial firms mainly consisting of firms which had to file financial reports with the S.E.C. since they issued publicly traded bonds *prior* to their IPO.² 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 U.S., given that private firms which issue public bonds before their IPO tend to be large and highly leveraged (in contrast to the average firm going public in the U.S. 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. Our paper complements the above empirical research by developing the first large sample study of the going public decisions of U.S. firms, using the Longitudinal Research Database (LRD) of the U.S. Bureau of Census (which covers the entire universe of private and public manufacturing firms in the U.S.).

It is also important to note that, while some earlier papers have documented the operating underperformance subsequent to IPO of firms going public relative to seasoned firms (e.g., Jain and Kini (1994) and 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 TFP, market share, capital expenditures, employment, total labor costs, materials costs, and sales and administrative expenses) are novel to the literature as well. A secondary objective of this paper is to shed new light on the operating underperformance of firms subsequent to IPOs. The reasons underlying this operating underperformance 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

U.S. Thus, while the number of IPOs on the Neuer Markt 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 U.S.

² 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.

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 before). Second, in contrast to earlier studies (which focus on accounting numbers), we focus on performance measures such as the total factor productivity (TFP) which are derived from a variety of different measures of firm performance, and are thus less subject to manipulation compared to 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.³ First, we find that firms which are larger in size and have higher sales growth are more likely to go public. Second, firms which have greater productivity (TFP) than their industry peers, greater market share, and those with projects which 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. While the first set of findings above is consistent with those documented by Pagano, Panetta, and Zingales (1998) for Italian firms, and Helwege and Packer (2003) for bond-issuing U.S. firms, we are the first in the literature to document the second, third, and fourth set of results above. The above findings are consistent with the implications of three of the theories of going public mentioned above, namely, the

³ We conduct this analysis using a probit model as well as the Cox proportional hazard model and find similar results in both cases.

information production theory of Chemmanur and Fulghieri (1999); the confidential information release theory of Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2000); 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 both in the years 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) and Mikkelsen, 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 to 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), which we discuss in detail in section 2.2.

Our paper is related to several other strands in the theoretical and empirical literature. In addition to the theoretical models of the going public decision discussed above, 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 paper. This paper 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).

The rest of the paper is organized as follows. Section 2 reviews various theories of the going public decision and develops hypotheses, both for our empirical analysis of the relationship between *ex ante* product market characteristics of a firm and its likelihood of going public (section 2.1) and for our analysis of the dynamic pattern of firm performance before and after the IPO (section 2.2). 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 before and after the IPO. Section 6 concludes.

2. Theory and Hypotheses

In section 2.1, we will review the theoretical literature relating the *ex ante* product market characteristics of a firm and the likelihood of its going public and develop hypotheses for the empirical tests we present in section 4. Similarly, in section 2.2, we will review the implications of various theories for the dynamics of firm characteristics around the IPO and develop hypotheses which will serve as the basis for the empirical tests we present in section 5.

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 need to produce information about firm value (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 born 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 provider of private financing will charge 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 is in a "complex" industry where the firm's project is hard to evaluate (so that outsiders' evaluation cost is 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 is otherwise easier to evaluate for outsiders (so that each investor's evaluation cost for the firm is low), the effect of the above duplication in information production is outweighed by the premium demanded by the 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 in a riskier industry), such a firm 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 of the firm.

In summary, the above theory leads to the following testable predictions:

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 where 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 which is an industry leader to raise external capital (at a cheaper rate than private financing), thus allowing it to implement its project at its optimal scale. However, going public has the disadvantage of releasing confidential information to competing firms which can then compete more effectively with the firm going public.⁴ Their arguments imply that, 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 such firms are 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

⁴ Campbell (1979) was the first to point out the danger of a firm releasing confidential information to product market competitors at the time of accessing the capital market. Similar arguments have also been made by Yosha (1995).

industries where the value of confidentiality is greater (e.g., firms in high tech industries) are less likely to go public.

In summary, the above theory leads to the following testable predictions:

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 where the value of confidentiality is greater (e.g., high tech firms) are less likely to go public.

Clementi (2002) builds a dynamic stochastic model of firm behavior explicitly incorporating the going public (IPO) decision. In his model, the firm operates in an industry characterized by decreasing returns to scale. Further, going public is costly, and prior to going public, a borrowing constraint keeps the firm's scale of production at a suboptimal level. In such a setting, the decision to go public is triggered by a sudden and persistent increase in the firm's total factor productivity (resulting in a new set of positive NPV projects becoming viable to the firm). Such a productivity shock has the effect of widening the gap between the efficient and the actual capital level of the firm, so that the marginal benefit of expanding operations (i.e., undertaking the additional positive NPV projects available to the firm) by going public outweighs the marginal cost of going public. The above theory implies that firms that have greater levels of total factor productivity (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).

The above theory, therefore, has the following testable predictions:

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.

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) discussed above has implications for firm productivity, sales, and capital expenditures before and after the IPO. In its early stages, when the firm is a start-up, the borrowing constraint precludes the entrepreneur from reaching its efficient size. While an infusion of capital would allow the firm to bridge the gap at least partially between actual and efficient capital, 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).

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).⁵

The predictions of the above theory for the dynamics of firm characteristics differ markedly from those of other theories. One such theory (see, e.g. Teoh, Welch and Wong (1998)) is the earnings management or “creative accounting” explanation. 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, they 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 to accounting numbers, since they are derived from a variety of different measures of firm performance. Second, we study various measures of firm performance for a number of years (five) before the IPO as well as after the IPO. It is unlikely that, even if firms attempt to manipulate their reporting of performance numbers prior to their IPO, they will be able to show consistently superior performance for many years pre-IPO purely by manipulating these numbers.

A third possible reason that has been advanced 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 managers 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 (1977)). However, unlike the previous two theories, this “incentive” theory does not predict an increase in

⁵ 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.

firm performance prior to the IPO, since managerial ownership does not increase (and often decreases) in the years prior to IPO.

While the above theories have predictions regarding the dynamics of various firm characteristics around its IPO, the arguments made by Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001) (discussed in the previous section) have interesting predictions for the dynamics of an IPO firm relative to its product market competitors around its IPO. In particular, it has implications for its market share. 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 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 is the Longitudinal Research Database (LRD), maintained by the Center of Economic Studies at the U.S. Bureau of Census.⁶ The LRD is a large micro database which provides plant level information for firms in the manufacturing sector (SIC codes 2,000 to 3,999). 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 non-census 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

⁶ See McGuckin and Pascoe (1988) who provide a detailed description of the Longitudinal Research Database (LRD) and the method of data collection.

LRD database on a yearly basis from 1972 to 2000, and smaller plants with fewer than 250 employees are included in the LRD database every census year and are also randomly included in the non-census years, continuously for five years, as a rotating five year panel.⁷ 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.

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.⁸ Moreover, the panel format of the LRD (1972-2000) provides data on both the private and the IPO firms 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 the 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), and thus these measures provide more precise estimates as they are not 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.

⁷ Given that a random sample of smaller plants is continuously present in our sample, our data is not substantially skewed towards 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 non-census years in order to minimize such a bias in the data.

⁸ Unfortunately, due to the data limitations, we are unable to look at the ownership composition and capital structure of the firm before going public.

Our sample of IPOs is drawn from Security Data Corporation's (SDC) Platinum New Issues Database. As in most empirical studies on IPOs, we removed from our sample all IPOs related to equity carve-outs, ADRs, ADSs, global deposit recs, 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 2000 to 3999) and that the firm is present on the Compustat annual industrial database 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.⁹ Out of the 2578 firms, we matched 1315 firms to the LRD.¹⁰ 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 same approach. In our analysis of the going public decision we eliminate these public firms from our sample. Thus, our final sample in the regression analysis contains all firms remaining private throughout the years 1972 to 2000 and the firms which went public between 1972 and 2000. Since the LRD provides plant level information, we aggregated all the plant level measures to the firm level by the firm identifier provided in the LRD.¹¹

Table 1 presents the industry distribution at the 2 digit SIC level of the firms that went public in our sample.¹² 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.

⁹ 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 forwards and backwards in time.

¹⁰ The discrepancy in the number of IPOs between the LRD and SDC is mostly due to the incorrect industry classification of the firm in the SDC. Often times a manufacturing firm in the SDC was not defined as manufacturing by the Bureau of Census classifications.

¹¹ For TFP we aggregated the plant level measures using a value weighted approach, where 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 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).

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. TFP captures a firm's productivity relative to that of its industry peers. We obtain measures of TFP at the plant level by estimating a log-linear Cobb-Douglas production function for each industry and year. Industry is defined at the level of four-digit SIC codes.¹³ Individual plants are indexed i ; industries j ; for each year t , in the sample:

$$\ln(Y_{ijt}) = \alpha_{jt} + \beta_{jt} \ln(K_{ijt}) + \gamma_{jt} \ln(L_{ijt}) + \delta_{jt} \ln(M_{ijt}) + \varepsilon_{ijt}, \quad (1)$$

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 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

¹³ As a robustness check, we re-estimate the production function using two and three digit SIC industry classifications. We also estimate TFP with value added production function specifications and separate white and blue collar labor inputs including non-production workers. In all cases we find qualitatively similar results.

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.¹⁴ Deflators for capital stock are available from the Bureau of Economic Analysis.¹⁵

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. These production function estimates are pooled across the entire universe of manufacturing plants. 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 to 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 only contains the idiosyncratic part of plant productivity.¹⁶ Plant level TFP measures are then aggregated to the firm level by a value weighted approach, where the weights on the plants 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 percentile.

¹⁴ See Bartelsman and Gray (1996) for details.

¹⁵ For a detailed description of the construction of TFP measures from LRD variables see Lichtenberg (1992).

¹⁶ As a robustness check for our regression results we use an alternative measure of productivity; 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 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 the different firm specific product market variables as well as the proxies in our regression analysis. The LRD data 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, equipments 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, which has been discussed earlier in section 3.1. We measure age as the number of years since the firm first appeared in the LRD.¹⁷ Sales is defined as the total value of shipment in thousands of dollars. Capital expenditure is the dollar value the firm spends on the purchase and maintenance of plant, machinery, and equipment, etc. Material 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 office equipments. Total wage is the total payroll of the firms. Average wage is the total wage over total employment. All the dollar values in the LRD are in thousands of dollars and all the firm level measures are winsorized at the 1 percentile and 99 percentile.¹⁸

To test *H1*, and also to control for firm size in other specifications, we define firm size (*SIZE*) as the natural logarithm of capital stock of the firm.¹⁹ We define age as the natural logarithm

¹⁷ 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 is available from the Census Bureau. For plants which 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.

¹⁸ All dollar values are in 1998 real terms.

¹⁹ For robustness, we also rerun our regressions using log (employment) and log (sales) as proxies of firm size. The results remain qualitatively unchanged.

of age (*AGE*) in our regression analysis. 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 the total factor productivity (*TFP*) measure for each firm within each industry²⁰. This measure of TFP captures a firm's productivity level relative to its industry peers. A firm that enjoys 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 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 3 digit SIC level. We expect *INDRSK* to have a positive relationship with 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 in the past three years.²¹ 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 3 digit SIC level. We use the market share of the firm to proxy for 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.

²⁰ For detailed explanation of the TFP calculation, see section 3.1.

²¹ As robustness check, we also use alternative measures of sales growth. We defined sales growth as the growth in firm sales over a one year period. We also defined sales growth as a dummy variable which equals one if the firm had a high growth rate. We define high growth rate if the average sales growth over the last 3 years was above 25%, with each year's growth being at least 10%. The results remain qualitatively unchanged.

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 3 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 by the 3 digit SIC code in 357, 366, 367, 372, 381, 382, and 384.²² 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 the public firms in the same 3 digit SIC industry to proxy for the expected liquidity in that industry and expect it to have a positive effect on the probability of going public.²³ We use the number of firms already listed in CRSP in the same 3 digit SIC industry to proxy the ease of evaluation in an industry. The more firms already listed in the industry; in general, the easier it is for the investors to evaluate a firm in that particular industry. Therefore, this measure is expected to have a positive relationship with the probability of firm going public from that industry.

To test *H2* regarding the extent of information asymmetry faced by a firm and the likelihood of going public, we also construct information asymmetry measures using analysts' forecasts from I/B/E/S. Following Christie (1987) and Krishnaswamy and Subramaniam (1999), we use three different measures to proxy for information asymmetry. We use the industry average

²² This definition is similar to that in Loughran and Ritter (2002).

²³ Stock market liquidity is a proxy for the cost of raising public capital. The higher the stock market liquidity in an industry, the lower is the cost of raising capital through the public equity market, and the more likely are 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 higher.

standard deviation in analysts' forecast (*STDEV*), the industry average analysts' forecast error (*FORERR*), and the industry average number of analysts following (*NUMA*) at the 3 digit SIC level. Higher standard deviation in analysts' forecast, higher analysts' forecast error, and fewer analysts following in an industry, proxy for higher information asymmetry in that industry. We expect higher information asymmetry to have a negative relationship with the probability of going public.

Table 2 presents the summary statistics of firm characteristics for the private firms which eventually go public during the sample period and also for the firms which remain private throughout the sample period in the LRD. All reported statistics are firm-year observations. We see that the firms that eventually go public in our sample period are on average larger firms (about 6 times), and firms that are on average older. Moreover, firms that have an IPO, on average invest more (about 17%) than private firms. Also the average sales growth for IPO firms is 13.3% which is about 250% higher than the sales growth of firms remaining private. Finally, the *TFP* of IPO firms is on average 0.036, while that of private firms is -0.014. Thus, while the *TFP* of the firms going public is positive, implying that they perform better than their industry average, the *TFP* of the firms remaining private is negative and hence their performance is below that of their industry average.²⁴

²⁴ We also look at the summary statistics of the IPO sample only in the years prior to going public. The same trend is observed for nearly all the firm characteristics. These firms on average are larger, older and more productive than those which remain private. For example, the average sales growth for this sample is 12.9%; the average *TFP* is 0.042. Detailed results are available from the authors upon request.

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

4.1. Analysis using the Probit Model

In this section, we analyze the going public decision of firms. Using a large sample of private firms from the U.S. Census Bureau's LRD database, we look at the determinants of going public, with emphasis on the product market characteristics of the firm.

On the basis of the hypotheses developed in section 2.1, we estimate the following maximum likelihood probit model of the probability of going public.²⁵ Individual firms are indexed i ; industries j ; for each year t , in the sample:

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

where IPO is a dummy variable which equals 1 if the firm goes public in year t , and 0 if the firm remains private.²⁶ $F(\bullet)$ is the cumulative distribution function of a standard normal variable and $SP500$ is the annual return on Standard & Poor's 500 Index.²⁷ All other variables are as described in the previous section. At any time t , the sample includes all firms which are private at that point in time, and the firms which go public (had an IPO) in that year. After a firm goes public, that firm is dropped from the sample.

²⁵ The main reason as to why we present results based on the probit model is to provide comparability of our results with that of Pagano, Panetta, and Zingales (1998), who also estimate the probability of going public using a probit model. Since it may also be appropriate to use a hazard model to estimate the probability of going public, we present results from the hazard analysis in the next subsection. Our results remain qualitatively unchanged irrespective of the model used.

²⁶ Note that for firms which remain private throughout, this dummy variable is always equal to zero.

²⁷ 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 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 the year dummies perfectly capture the annual market performance component. Therefore, when we use year dummies as control, we do not use the S&P500 annual return.

Table 3 presents the maximum likelihood estimates of the probit model. In panel A, the explanatory variables are limited to firm specific product market variables. In panel B, the firm specific product market variables are supplemented by industry specific variables. Finally, panel C includes information asymmetry proxies as well as the firm specific and industry specific variables of panels A and B. We can think of panel C as incorporating the entire regression model of the firm's decision to go public, as hypothesized in section 2.1. The methodology adopted in our regression framework throughout this paper is consistent with that suggested by Petersen (2005), where he advocates using fixed effects and adjusting the standard errors for correlations within clusters.

From panel A, we can see that all the firm specific product market variables are significant determinants of the firm's decision to go public. Consistent with *H1*, *SIZE* has a positive effect on the probability of going public. In all specifications, the coefficients of *SIZE* are positive and significant at the 1% level. Consistent with *H8*, *TFP* has a positive effect on the probability of going public. In all specifications, the coefficients of *TFP* are also positive and significant at the 1% level. Consistent with *H9*, *CAPR* and *SGTH* both have positive effects on the probability of going public, and the coefficients on *CAPR* and *SGTH* across all specifications are significant at the 1% level respectively. Consistent with *H5*, *MSHR* is positively related to the going public decision, and its coefficients are all positive and significant at the 1% level. In regressions 1 to 5 in panel A, we use the *SP500* variable to control for market fluctuations instead of year dummies. As expected, the coefficient on *SP500* is positive, implying that firms are more likely to go public after a positive market performance. The coefficient on *SP500* is significant at the 1% level. However, we find that the *HTEK* dummy is positively related to the probability of going public (with the coefficient being significant at the 1% level in all specifications), which is inconsistent with *H7*. Thus, it appears from our empirical results that high tech firms have a higher probability of going

public.²⁸ In summary, with the exception of high tech firms, the results in panel A strongly support our hypotheses that larger, more productive firms and firms with higher sales growth, higher capital expenditures, and bigger market shares have a higher probability of going public.²⁹

Panel B regressions includes industry specific characteristics such as industry risk, industry concentration, and the average share liquidity in the industry in addition to the firm specific product market variables in panel A. Comparing the regression 1 in panel B with regression 1 in panel A, we see that the coefficients on the firm specific product market variables have similar magnitudes, direction and significance, in both regressions. Moreover in panel B, all the three industry level explanatory variables (*INDRSK*, *HI*, *TOV*) are positive and statistically significant at the 1%, 5%, and 1% levels respectively, and their directions are as predicted by the hypotheses (*H4*, *H6*, *H2*). Regression 3 in panel B also includes the high tech dummy variable. The coefficient on the high tech dummy coefficient is positive, and significant at the 1% level and thus still inconsistent with our hypothesis *H7*, which predicts that firms in high tech industries are less likely to go public. Since the high tech dummy also captures some of the common characteristics across industries, the magnitude of the coefficients on the industry related measures (*INDRSK*, *HI*, *TOV*) are affected, even though they remain qualitatively similar (only the significance for *HI* is reduced).

Regressions 5 to 8 in panel B shows the effect of *CAPINT* and *AGE*. Due to a multicollinearity problem between *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 at the 1% level, implying that more the capital intensive the firm the more likely it is to go public. Consistent

²⁸ One caveat of this result is that our high tech industries are all within the manufacturing sector. Thus, service oriented high tech industries, such as internet firms are not included in our sample.

²⁹ The coefficients in a probit regression are difficult to interpret directly. For example, the coefficient on *TFP* in regression 1, of 0.284 means that each one unit increase in *TFP*, increases the standard deviation of the probit index by 0.284. Similarly, for *SIZE* in regression 2, a one unit increase in *SIZE*, increases the standard deviation of the probit index by 0.215.

with *H1*, the coefficient on *AGE* has the correct sign, and is statistically significant at the 1% level in two of the specifications.

The regressions in Table 3 panel C include information asymmetry proxies along with the firm specific and industry specific variables from panels A and B. Regression 1 in panel C includes *LIST* as a proxy for the ease of evaluation in addition to all the variables in panel B regression 2. The coefficient on *LIST* is positive and significant at the 1% level. This is consistent with *H3* that firms operating in industries that are easier for public investors to evaluate are more likely to go public. Regression 2 in panel C also includes the three proxies for information asymmetry.³⁰ Consistent with *H2*, the coefficient on *STDEV* in regression 2 is negative and statistically significant at the 5% level, which implies that higher the information asymmetry, less likely the firm to go public. The coefficient on the number of analysts is negative and significant at the 10% level, which seems inconsistent with our information asymmetry hypothesis, however, this is due to a correlation problem between firm size and the number of analysts. Once we remove size and rerun the specification, as in regression 6, *NUMA* turns out to be positive and significant at the 5% level, consistent with *H2* that firms with lower information asymmetry are more likely to go public. In regression 6, *STDEV* continues to be negative and significant at the 5% level as before.

In regression 3, we use *SP500* as a control for the market fluctuations instead of the year dummies. Consistent with our hypothesis, the coefficient on *SP500* is positive and significant at the 1% level, similar to that in panels A and panel B. Consistent with our hypothesis (*H2*) the results in regression 3 show that firms in industries with higher asymmetric information have a lower probability of going public. While the coefficient on *STDEV* is negative and significant, the coefficient on *FORERR* is negative but not significant.

Regressions 5 through 8 examine the effects of *CAPINT* and *AGE* along with the other explanatory variables as well as the information asymmetry proxies. The results are mostly

³⁰ The information asymmetry proxies constructed from I/B/E/S only starts from 1976. Therefore, regressions in panel C that use the information asymmetry measure(s) are based on the sample in the period from 1976 to 2000 instead of the full sample.

consistent with our hypothesis as well as the results from the earlier specifications. Consistent with *H4*, the coefficients on *CAPINT* across the specifications are positive and significant at the 1% level. Consistent with *H1*, the coefficients on *AGE* are positive and significant at the 1% level in regression 7; while in regressions 5, 6, and 8, they are positive but insignificant. Coefficients of the other variables follow a similar pattern as before.

In summary, the regression results in Table3 are generally consistent with our hypotheses. We find that larger, older, more capital intensive firms, firms with higher total factor productivity, higher growth in output (sales), firms with high capital expenditure ratio, and firms with higher market share are more likely to go public. In addition, inconsistent with our hypothesis *H7* we also find that high tech firms are more likely to go public. Firms operating in more concentrated industries, firms in more risky industries, and firms in industries with higher liquidity and less information asymmetry are more likely to go public.

While some of our results agree with those in Pagano, Panetta, and Zingales (1998) and Helwege and Packer (2003), to the best of our knowledge our findings on total factor productivity, market share of the firm, industry risk and concentration, and industry liquidity and asymmetric information are completely new. This is the first paper in the literature which documents that TFP and market share of the firm are important determinants of the going public decision. A one unit increase in TFP leads to roughly a 7% increase in the sample average probability of an IPO. Similarly a one standard deviation increase in market share leads to an increase in the probability of going public, by one-fourth of a percentage point which corresponds to a 42% increase in the sample average probability of going public.

Similar to Pagano, Panetta, and Zingales (1998) and Helwege and Packer (2003), we show that size and capital expenditure are important determinants also. A unit increase in size leads to an increase in the sample average probability of an IPO by 4.25%; while a similar increase for capital expenditure increases the probability by 26.5%. Additionally we also show that sales growth is positively related to the going public decision. A unit increase in sales growth leads to roughly a

13% increase in the sample average probability of an IPO. Contrary to the results in Helwege and Packer (2003), but consistent with those of Boehmer and Ljungqvist (2004) (who study a sample of German IPO's), we document that more mature (older) firms have a higher probability of going public. A one unit increase leads to roughly a 7% increase in the sample average probability of an IPO.³¹

As mentioned before, this is the first paper to show that industry risk and concentration, as well as industry liquidity and the level of asymmetric information in the industry have a significant impact on the probability of a firm going public. Firms in industries associated with higher risk, higher concentration, higher liquidity and less asymmetric information tend to go public earlier. These results are highly consistent with predictions of prior theoretical studies on IPO's, as outlined in section 2.1.

4.2. Analysis using the Cox Proportional Hazard Model

In addition to the analysis of the going public decision presented earlier using the probit model, we are also interested in using the information about the actual timing of the going public decision and thus, in order to incorporate this information, a duration analysis is more appropriate. Hazard models resolve the problems of static models by explicitly accounting for time (see, e.g., Kiefer (1988), LeClere (2000), Shumway (2001)). In a hazard model, a private firm's probability of going public changes through time and is a function of its latest financial and product market characteristics and the extent to which those variables impact the timing of its decision to go public.³² On the other hand, the probability of going public that a static model (such as a probit

³¹ Unlike Helwege and Packer (2003), our sample of private firms is the universe of all private manufacturing firms in the U.S., while the sample of private firms in Helwege and Packer (2003) are typically much older and larger private firms which have previously issued corporate debt. Thus, compared to their sample, our sample of private firms is much more representative of the U.S. economy.

³² We consider the period from the birth of the firm, i.e., when the firm first appears in our sample, or 1970, whichever is earlier. The hazard rate, $h(t)$, is the likelihood that a firm goes public at time t , given that it is still private.

model) assigns to a private firm does not vary with time.³³ We therefore repeat our analysis of the going public decision using a semi-parametric analysis and estimating the Cox proportional hazard model, which has the following specification:

$$h(t, X(t)) = h(t,0) \exp(\beta'X(t)) \quad (3)$$

where $h(t, X(t))$ is the hazard rate of going public at time t for a firm with covariate $X(t)$, and $h(t,0)$ is the baseline hazard. The advantage of using the Cox proportional hazard model is that it does not impose any structure on the baseline hazard rate, $h(t,0)$, which is free to take any functional form. The Cox regression estimates the coefficient vector β . Cox's partial likelihood estimator provides a way of estimating β without estimating $h(t,0)$.³⁴ A positive coefficient on variable x in the hazard regressions imply that a higher x is linked to a higher hazard rate and thus a lower expected duration, which corresponds to a higher probability of going public earlier. The hazard ratio which is simply $\exp(\beta)$ tells us how much the instantaneous risk of going public increases for a unit change in the independent variable.

Similar to the probit estimation reported in section 4.1., we estimate the Cox proportional hazard model to examine the effect of firm specific product market characteristics, firm specific and industry specific product market characteristics, and the extent of information asymmetry facing the firm (measured at the industry level), on the probability of a firm going public. To control for the macroeconomic environment that might affect a firm's going public decision, we use the Standard & Poor's 500 Index (*SP500*) as a market-wide control variable. In some specifications, we also include two decade dummies (80s dummy and 90s dummy) to account for

³³ An advantage of using the duration analysis in this study is that the hazard model explicitly accounts for time and handles censored observations and time-varying covariates. Since our sample period ends in 2000, at that point there are firms in our sample that continue to remain private, even though there is a positive probability that they may go public. Thus, clearly some of our observations are right censored. In addition, due to the annual survey technique employed in non-census years in our data, there are also firms that leave (or drop out from) the sample (e.g., due to mergers and acquisitions or other smaller firms with very little employment which do not get surveyed) for reasons other than going public. Hazard models are flexible enough to handle these complexities and use estimation techniques that incorporate information from both censored and uncensored observations to provide consistent parameter estimates.

³⁴ A detailed description of the Cox proportional hazard models is provided in Cox (1972).

the increased IPO market activities in the later periods, specifically during the 90s decade, which also includes the last year in our sample, namely, the year 2000.

Table 4 reports the coefficients, β 's, and their standard errors from the Cox regressions. Regression 1 in Table 4 only includes the firm specific characteristics as the covariates, $X(t)$. Regression (2) and (3) include both the firm specific characteristics and industry specific variables, corresponding to Panel B of Table 3 of the probit regressions. Regression (4) through regression (9) also includes the information asymmetry proxies in addition to the other variables, corresponding to the probit regressions reported in Panel C of Table 3.³⁵ Overall, the coefficients from the hazard regressions are consistent with our results reported in Table 3 and support the various hypotheses discussed earlier: firms with larger size, higher sales growth and capital expenditure ratio, higher market share, higher total factor productivity, and more capital intensity are more likely to go public. Further, firms operating in industries with riskier cash flows, higher average liquidity of already listed firms, and firms in more concentrated industries are more likely to go public. Finally, the coefficients on the ease of evaluation proxy (number of firms already listed in CRSP in the same 3-digit SIC industry) and the information asymmetry proxies continue to support our hypotheses, implying that firms which are easier for outsiders to evaluate and firms in industries with lower levels of information asymmetry are more likely to go public. However, as in the probit analysis results presented in Table 3, we find that high tech firms are more likely to go public than non high-tech firms, contradicting hypothesis *H7*.

The results are also economically significant, for example, the average hazard ratio for TFP is about 2.2, which implies that a unit increase in TFP more than doubles the instantaneous risk of going public. Figure 1 illustrates the estimated hazard function of going public as firm age increases, holding all covariates at their sample means. Specifically, the hazard function is estimated using regression 5 of Table 4. Figures 2 and 3 illustrate the economic significance of

³⁵ Since the hazard analysis estimation techniques provide consistent parameter estimates, the results reported in Table 4 can also be viewed as a robustness check of our probit regressions reported in Table 3.

several firm specific product market characteristics and industry characteristics on the going public decision. Specifically, in Figure 2 we illustrate the difference in the hazard of going public of firms at the tenth and ninetieth percentile of the following variables: total factor productivity (TFP), sales growth, capital expenditure ratio, capital intensity, firm size, and high tech status.³⁶ Similarly, Figure 3 illustrates the economic significance for the Herfindahl index, the industry turnover, and the last decade (1990 – 2000) in our sample period. The differences in the hazard of going public of firms with high versus low firm size, high versus low TFP, high versus low sales growth, *high tech* firms versus *non high tech* firms, and between firms going public in other decades versus the 1990 to 2000 decade, are the most dramatic, indicating the importance of these variables in determining the decision to go public.

In summary, the analysis using the hazard model strongly supports the various hypotheses discussed earlier, and confirms the importance of several firm specific and industry characteristics found to significantly impact the probability of going public in our earlier probit analysis. Thus, our hazard model analysis lends additional support to the role of the above factors in determining a private firm's going public 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) and Mikkelsen, Parch, and Shah (1997)) which look at the operating performance of IPO firms subsequent to the 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 database of

³⁶ Since the high tech variable is a dummy variable, we evaluate the hazard function separately for high tech and non high tech firms. In all these specifications, all other covariates are held at their sample means except the one being evaluated.

the U.S. Census Bureau, this paper, analyzes for the first time in the literature, the dynamic pattern of firm productivity and other product market firm characteristics from 5 years prior to the IPO to 5 years after the IPO.³⁷

Operating performance of firms after an IPO has been extensively studied in the existing empirical literature. However, mostly due to data limitations, firm performance prior to the IPO has been understudied. As discussed in section 2.2, there are various theories which provide interesting implications of firm dynamics 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:

$$y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \sum_{s=1}^5 \delta_s \text{Before}_{it}^s + \sum_{s=1}^5 \lambda_s \text{After}_{it}^s + \varepsilon_{it}, \quad (3)$$

where Y_{it} is the variables of interest (e.g., TFP, sales, capital expenditures, etc.), X_{it} is a control for firm size which is time varying, Before_{it}^s is a dummy variable equal to 1 if the firm goes public and the observation is s years prior to the IPO, where $s = 1, 2, 3, 4,$ and 5 years and above, After_{it}^s is a dummy variables equal to 1 if the firm goes public and the observation is s years after the IPO, where $s = 1, 2, 3, 4,$ and 5 years and above, i indexes firms, t indexes years, and β_i are firm-specific fixed effects. The specification also incorporates year dummies. The dynamic patterns of the effect of an IPO on the variables of interest are captured by the coefficients δ_s and λ_s .³⁸

We first examine the dynamic patterns of TFP, sales and capital expenditures over five years before and after the IPO. Table 5 presents the regression results. While the results reported in panel A include firms going public along with firms which remain private throughout our sample,

³⁷ The results are robust to the choice of this 5-year window on each side of the IPO. We obtain similar results when considering 7-year and 3-year windows also.

³⁸ In all the specifications, our base year is the year of the IPO (year 0). Thus the coefficients δ_s and λ_s reflects the deviations of the variable of interest with respect to the year of going public. In results not reported we also specify the year prior to the IPO year (year -1) as our base year. The results obtained are consistent with those reported here.

panel B reports the results only for the subsample of the firms going public.³⁹ Consistent with Clementi (2002), the TFP of firms going public exhibit an inverted U shape, which increases before the IPO, reaches its peak at the year of the IPO, and subsequently declines. Compared to the IPO year, in panel A, the coefficients on the all the *Before* and *After* dummies are negative, with the coefficients on *Before*⁵⁺, *Before*⁴, *Before*³, and *Before*² being significant at the 1% level, and the coefficients on *After*³ and *After*⁴ significant at the 5% and the 10% level respectively. The changes in TFP in the years prior to going public are also very significant economically. The increase in TFP from year -2 to year -1 of 2.2%, translates to an increase in profits of approximately 13%. Similarly, the increase in TFP over the four years prior to going public, (i.e., from year -4 to 0) of 4.6% translates to an increase in profits of 28%.⁴⁰ In panel B, this pattern is even stronger. The increase in TFP from year -2 to -1, corresponds to an increase of 13% in profits; from year -4 to 0, an increase of 23% in profits; from year 0 to 2, a decrease of 10% in profits; and from year 0 to 4, a decrease of 16% in profits.

The coefficients on sales keep increasing throughout the years. In panel A, 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, with the *After*¹ coefficient significant at the 5% level and the *After*² through *After*⁵ coefficients being significant at the 1% level. The result implies that the IPO firms are growing over the years around the IPO compared to their private peers. The result on capital expenditures in panel A shows similar increasing patterns as sales, with all the coefficients on the *Before* dummies negative and significant at the 1% level, while all the coefficients on the *After* dummies are positive, with the *After*⁴ coefficient significant at the 10% level and other *After* dummy coefficients significant at the 1% level. When the regression is restricted to the sample of the going public firms (panel B), the increasing pattern of sales and

³⁹ In results not reported, we also look at the dynamic pattern of firm characteristics of the firms going public along with those which have already gone public previously. The results obtained are consistent with those presented here.

⁴⁰ 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.

capital expenditures after IPO is weak, after controlling for the growth in size of IPO firms. This means that for a unit increase in size, the sales and capital expenditures of IPO firms grow faster than those of the private firms.

We examine the dynamic pattern of total employment, labor costs and other costs in Table6. Panel A in Table6 shows that total employment, total wages, material costs, and rental and administrative expenses all increase over the years around IPO, with all the coefficients on the *Before* dummies being negative, and all the coefficients on the *After* dummies being positive. Other than the years immediately before and after the IPO, the coefficients on other years are significant at the 1% level. These results again show that the rates of growth of these costs in IPO firms are faster compared to the firms remaining private. In panel B of Table6, when we restrict the sample to only the IPO firms, the results seem to suggest that the increase in total employment, total wages, material cost, and rental and administrative expenses around the years before and after the IPO are mostly proportional to the firms' growth in size. However, in years -3 and -2, there seems to be an additional surge in employment and administrative expenses, which could be due to the sudden increase in the firm's scale of operations, as suggested by the theoretical literature.

Finally, in Table7 we examine two sales related variables, sales growth and market share. In Table5 we have already shown that sales of IPO firms grow throughout the years around the IPO. The result on sales growth in Table7, shows that all the *Before* and *After* coefficients are negative, implying that sales growth reaches its peak at 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 at the 1% level. Thus consistent with our hypothesis, we find that sales growth of IPO firms exhibit an inverted U shape. This pattern holds in both panel A and panel B of Table7. As discussed in section 2.2, we were agnostic about the dynamic pattern of market share. The results both in panels A and B of Table7 shows market share remains flat after adjusting for firm size over the 9-year horizon around the IPO. The coefficients on the *Before* and *After* dummies are statistically insignificant most times.

Thus the results on the dynamic pattern of firm characteristics are mostly consistent with our predictions from section 2.2. While, TFP and sales growth both depict an inverted U shape, implying that they reach their peak in the year of going public; sales, capital expenditures and various costs associated with the product and labor markets show gradually increasing patterns from 5 years prior to the IPO to 5 years subsequent to the IPO when compared to their private peers.

6. Conclusion

We use 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 paper, we study the relationship between a firm's *ex ante* product market characteristics and its decision to go public. In the second part of the paper, we study the dynamics of a firm's product market performance for a number of years before and after it goes public. Our findings are as follows. First, firms with larger size, sales growth, total factor productivity (TFP), market share, capital intensity, and high tech firms 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, and operating in industries characterized by less information asymmetry and greater average liquidity of already listed equity are more likely to go public. Our results are robust - we present our analysis using both a probit model and a Cox proportional hazard model and arrive at the same conclusions.

Our analysis of the dynamic pattern of firm performance around the IPO indicates that while 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 administrative expenses exhibit a consistently increasing pattern in the years before and after the IPO. 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 to 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), and subsequently facing decreasing returns to scale which leads to the fall in the productivity.

References:

- Allen, F., and Faulhaber, G. (1989) "Signaling by underpricing in the IPO market" *Journal of Financial Economics* Vol. 23, 303 – 323.
- Bartelsman E., and Gray, W. (1996) "The NBER Manufacturing Productivity Database." *Technical Working Paper*. National Bureau of Economic Research.
- Bhattacharya, S., and Ritter, Jay (1983) "Innovation and Communication: Signalling with Partial Disclosure," *Review of Economic Studies*, Vol. 50, pp. 331-346.
- Boehmer, E., and Ljungvist, A. (2004) "On the Decision to Go Public: Evidence from Privately Held Firms," SSRN working paper.
- Boot, A.W., Gopalan, R., and Thakor, A.V. (2006) "The Entrepreneur's Choice between Private and Public Ownership." *Journal of Finance* 61, 803-836.
- Campbell, Tim (1979) "Optimal investment financing decisions and the value of confidentiality," *Journal of Financial and Quantitative Analysis*, Vol. 14, 913-924.
- Chemmanur, Thomas J. (1993) "The pricing of initial public offerings: a dynamic model with information production", *Journal of Finance* Vol. 48, 285 – 304.
- Chemmanur, Thomas J., and Fulghieri, Paolo (1999) "A Theory of the going-public decision," *The Review of Financial Studies*, Vol. 12, pp. 249-279.
- Christie, A. (1987) "On Cross-sectional Analysis in Accounting Research," *Journal of Accounting and Economics*, Vol. 9, pp. 231-258.
- Clementi, Gian Luca (2002) "IPOs and the growth of firms," Working paper, New York University.
- Cox, D.R., (1972) "Regression Models and Life Tables", *Journal of the Royal Statistical Society*, B34, 187-220.
- Fischer, Christoph (2000) "Why do companies go public? Empirical evidence from Germany's Neuer Market," Working paper, University of Munich.
- Helwege, Jean, and Packer, Frank (2003) "The decision to go public: evidence from mandatory SEC filings of private firms," Working paper, Ohio State University.
- Jain, Bharat A., and Kini, Omesh (1994) "The post-issue operating performance of IPO firms," *Journal of Finance*, Vol. 49, pp. 1699-1726.
- Jensen, M., and Meckling, W. (1976) "Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure," *Journal of Financial Economics*, Vol. 3, pp. 305-360.
- Kiefer, N. M. (1988) Economic duration data and hazard functions, *Journal of Economic Literature* Vol. 26, pp. 646-679.
- Krishnaswami, S., and Subramaniam, V. (1999) "Information asymmetry, valuation, and the corporate spin-off decision," *Journal of Financial Economics*, Vol. 53, pp. 73-112.

- Lerner, J. (1994) "Venture Capitalists and the Decision to Go Public," *Journal of Financial Economics*, 35, 293-316.
- Lichtenberg, F. and Siegel, D. (1992) *Corporate Takeovers and Productivity*, Cambridge, Mass: MIT Press.
- LeClere, M.J., (2000) "The Occurrence and Timing of Events: Survival Analysis Applied to a Study of Financial Distress," *Journal of Accounting Literature* 19, 158-189.
- Loughran, Tim and Ritter, Jay R. (2004) "Why has IPO underpricing Changed Over Time?," *Financial Management*, Vol. 33, pp 5-37.
- Maksimovic, Vojislav, and Pichler, Pegaret (2001) "Technological innovation and initial public offerings," *The Review of Financial studies*, Vol. 14, pp. 459-494.
- McGuckin, R., and Nguyen, S. (1995) "On productivity and plant ownership change: New evidence from the Longitudinal Research Database," *Rand Journal of Economics*, Vol. 26, pp. 257-276.
- McGuckin, R. H., and Pascoe, G. (1988) "The Longitudinal Research Database: Stats and research possibilities," *Survey of Current Business*, Vol. 68, pp. 30-37.
- Mikkelson, Wayne H., Partch, M. Megan and Shah, Kshitij (1997) "Ownership and operating performance of companies that go public," *Journal of Financial Economics* Vol. 44, pp. 281-307.
- Pagano, Marco, Panetta, Fabio and Zingales, Luigi (1998) "Why do companies go public," *Journal of Finance* Vol. 53, pp. 27-64.
- Pagano, Marco and Roell, Ailsa, (1998) "The Choice of Stock Ownership Structure: Agency Costs, Monitoring and the Decision to go Public," *Quarterly Journal of Economics*, Vol. 113, pp. 187-225.
- Petersen, Mitchell, (2005) "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," Working paper, Kellogg School of Management, Northwestern University and NBER.
- Ritter, Jay R., and Welch, Ivo, (2002) "A review of IPO activity, pricing, and allocations," *Journal of Finance* Vol. 57, pp. 1795 – 1828.
- Schoar, Antoinette (2002) "Effects of Corporate Diversification on Productivity," *Journal of Finance* Vol. 57, pp. 2379-2403.
- Shumway, T. (2001) "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *Journal of Business* 74, pp.101-124.
- Teoh, Siew Hong, Welch, Ivo and Wong, T.J. (1998) "Earnings Management and the Long-Run Market Performance of Initial Public Offerings," *Journal of Finance* Vol. 53, pp. 1935-1974.
- Welch, Ivo, (1989) "Seasoned offerings, imitation costs, and the underpricing of initial public offerings," *Journal of Finance* Vol. 44, 421 – 449.

Yosha, Oved (1995) "Information disclosure costs and the choice of financing source," *Journal of Financial Intermediation* Vol. 4, pp. 3-24.

Zingales, Luigi (1995) "Insider Ownership and the Decision to Go Public," *Review of Economic Studies* Vol. 62, pp. 425-448.

Table 1: Industry Distribution of the Going Public Sample: This table presents the 2 digit level SIC industry distribution of the sample of manufacturing firms in the LRD which eventually went public during the period of 1972 to 2000. ND stands for Not Disclosed to comply with the U.S. Census Bureau's disclosure criteria.

<u>2 Digit SIC</u>	<u>Industry Name</u>	<u>Number of IPO Firms</u>
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

Table 2: Summary Statistics: This table presents summary statistics for firms eventually going public and private firms in the LRD between 1972 and 2000. The firms eventually going public are those firms in the manufacturing sector (SIC 2000-3999) that went public between 1972 and 2000 as recorded from SDC. The firms remaining private are all the firms in the LRD which did not have an IPO between 1972 and 2000, and which were not public prior to 1972. Size is the natural logarithm of firm capital stock (in thousands of dollars). Capital Stock is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets. 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 3 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 firm first appeared in the LRD sample. 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 Hitech is the percentage of firms in the sample that are high tech companies (i.e., belonging to 3 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. Material 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 office equipments, in thousands of dollars. All the dollar values are in real terms. All the observations are firm year observations. The last two columns report the T stat and the Z-stat for the test of difference in means and median between the firms eventually going public group and the firms remaining private group, respectively. ***, **, and * indicate significance at the 1, 5, and 10 percent level respectively.

Sample:	<u>Firms Eventually Going Public</u>			<u>Firms Remaining Private</u>			<u>Test of Difference</u>	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	T-test (T stat)	Mann-Whitney Test (Z-stat)
Capital Stock	30637	41161	13,296	4168	13977	916,031	74.089***	122.983***
Total Employment	777	805	13,270	132	292	916,106	92.213***	142.263***
Sales	108141	124449	13,214	14828	41322	907,109	86.123***	142.503***
Market Share	0.022	0.061	14,383	0.002	0.014	914,928	38.023***	123.907***
Capital Expenditure	3484	4401	13,222	457	1498	915,900	79.018***	137.016***
CAPEX Ratio	0.143	0.146	12,877	0.122	0.179	677,601	16.371***	46.622***
Age	9.473	7.300	14,386	5.178	5.652	918,445	70.247***	83.967***
Capital Intensity	38.812	36.890	13,966	22.017	28.292	875,493	53.553***	70.499***
TFP	0.036	0.219	13,792	-0.014	0.207	851,555	26.434***	30.212***
Sales Growth	0.133	0.325	12,646	0.038	0.356	637,287	32.558***	39.472***
Percentage of Hi-tech	0.282	0.450	14,386	0.049	0.215	918,445	62.075***	124.723***
Total Wage	22120	23377	13,196	3366	8125	916,188	92.075***	146.619***
Average Wage	29.798	9.689	13,867	24.232	9.727	864,986	67.111***	65.560***
Material Cost	103962	163221	14,386	10512	42367	918,445	68.635***	146.106***
Rental and Admin. Exp.	4449	4959	13,241	650	1706	916,213	88.078***	145.103***

Table 3: Determinants of the Going Public Decision: This table presents the effects of firm specific product market variables, industry specific characteristics and asymmetric information on firm's decision to go public. The effect of the variables on the probability of going public is estimated by the following probit model. $Pr(IPO_{ijt} = 1) = F(\beta_1 SIZE_{i,t-1} + \beta_2 SGTH_{i,t-1} + \beta_3 MSHR_{i,t-1} + \beta_4 TFP_{i,t-1} + \beta_5 CAPINT_{i,t-1} + \beta_6 AGE_{i,t-1} + \beta_7 CAPR_{i,t-1} + \beta_8 INDRSK_{j,t-1} + \beta_9 HI_{j,t-1} + \beta_{10} TOV_{j,t-1} + \beta_{11} HTEK_{i,t-1} + \beta_{12} LIST_{j,t-1} + \beta_{13} STDEV_{j,t-1} + \beta_{14} FORERR_{j,t-1} + \beta_{15} NUMA_{j,t-1} + \beta_{16} SP500_{t-1})$ 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 on the year of the IPO. Note that the sample does not contain any existing public firms. *SIZE* is the lagged value of logarithm of capital stock. *SGTH* is the average growth in sales in the past 3 years. *MSHR* is the lagged value of a firm's market share in terms of total value of shipment in its 3 digit SIC industry. *TFP* is the lagged value of weighted average of plant level Total Factor Productivity at the four digit SIC level, where 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). *CAPINT* is the lagged value of capital stock per worker. *AGE* is the natural logarithm of firm age. *CAPR* is the lagged value of capital expenditures over capital stock (CAPEX Ratio). *HTEK* dummy is 1 if the firm is in the 3 digit SIC code of 357, 366, 367, 372, 381, 382, 384, and 0 otherwise. *INDRSK* is the median of the 5 year standard deviation in sales at the SIC 3 digit industry level of all the firms covered in the LRD that year. It is also lagged by one year. *HI* is the lagged value of Herfindal Index in the 3 digit SIC industry level. The higher the Herfindal Index, the more concentrated the industry is. *LIST* is the total number of firms in the same 3 digit SIC industry that are listed in the CRSP in the last year. *TOV* is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the 3 digit SIC level in the last year. *NUMA* is the 3 digit SIC industry level mean of the number of analysts covering firms in an industry. *FORERR* is the 3 digit SIC level mean of average analysts forecast errors across firms in the industry. *STDEV* is the 3 digit SIC level mean of the standard deviation in Analysts Forecast of EPS. *NUMA*, *FORERR*, and *STDEV* are all measured from I/B/E/S and the observations are lagged by a year. *SP500* is the last year's annual return of the Standard & Poor's 500 index. All dollar values are in real terms. All observations are firm year observations. Panel A presents results on the effects of firm specific product market variables on the firm's decision to go public. Panel B presents the effect of firm specific variables along with industry specific characteristics on the firm's decision to go public. Panel C presents the effect of firm specific variables along with industry specific characteristics and asymmetric information variables on firm's decision to go public. Calendar year dummies and Industry dummies are included in some specifications. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level respectively.

Panel A: Effect of Firm Specific Product Market Variables								
	<u>Reg. 1</u>	<u>Reg. 2</u>	<u>Reg. 3</u>	<u>Reg. 4</u>	<u>Reg. 5</u>	<u>Reg. 6</u>	<u>Reg. 7</u>	<u>Reg. 8</u>
Size	0.207*** [0.009]	0.215*** [0.009]				0.223*** [0.009]	0.232*** [0.010]	
Sales Growth	0.387*** [0.036]	0.386*** [0.037]	0.333*** [0.028]	0.374*** [0.030]	0.383*** [0.030]	0.398*** [0.039]	0.396*** [0.039]	0.373*** [0.032]
Market Share	1.249*** [0.301]	1.146*** [0.340]	2.887*** [0.251]	2.827*** [0.243]	2.689*** [0.248]	1.499*** [0.305]	1.380*** [0.354]	3.231*** [0.318]
TFP	0.284*** [0.067]	0.272*** [0.066]	0.262*** [0.052]	0.262*** [0.053]	0.256*** [0.054]	0.297*** [0.067]	0.285*** [0.066]	0.265*** [0.055]
Capital Intensity			0.003*** [0.000]		0.003*** [0.000]			0.002*** [0.000]
Ln(Age)				0.148*** [0.018]	0.132*** [0.018]			0.03 [0.022]
CAPEX Ratio	0.359*** [0.089]	0.350*** [0.090]	0.145** [0.067]	0.157** [0.069]	0.191*** [0.070]	0.503*** [0.093]	0.500*** [0.095]	0.264*** [0.074]
Hitech Dummy	0.639*** [0.035]	0.409*** [0.058]	0.673*** [0.033]	0.656*** [0.032]	0.681*** [0.033]	0.630*** [0.037]	0.390*** [0.061]	0.448*** [0.058]
SP500	0.631*** [0.081]	0.632*** [0.082]	0.672*** [0.083]	0.629*** [0.088]	0.618*** [0.089]			
Year Dummies	No	No	No	No	No	Yes	Yes	Yes
Industry Dummies	No	Yes	No	No	No	No	Yes	Yes
Number of obs	486322	481870	480613	491107	480613	457511	453292	452188
Pseudo R ²	0.15	0.16	0.08	0.08	0.09	0.2	0.21	0.14

Panel B: Combined Effect of Firm Specific Product Market Variables and Industry Characteristics								
	<u>Reg. 1</u>	<u>Reg. 2</u>	<u>Reg. 3</u>	<u>Reg. 4</u>	<u>Reg. 5</u>	<u>Reg. 6</u>	<u>Reg. 7</u>	<u>Reg. 8</u>
Size	0.209*** [0.009]	0.229*** [0.009]	0.205*** [0.009]	0.222*** [0.009]				
Sales Growth	0.403*** [0.035]	0.403*** [0.037]	0.375*** [0.038]	0.382*** [0.039]	0.373*** [0.031]	0.366*** [0.032]	0.380*** [0.029]	0.371*** [0.030]
Market Share	0.841** [0.350]	0.987*** [0.356]	1.319*** [0.327]	1.457*** [0.344]	2.999*** [0.242]	3.225*** [0.302]	2.791*** [0.236]	3.024*** [0.292]
TFP	0.295*** [0.069]	0.297*** [0.069]	0.281*** [0.067]	0.290*** [0.068]	0.251*** [0.054]	0.264*** [0.055]	0.257*** [0.054]	0.266*** [0.055]
Capital Intensity					0.003*** [0.000]	0.003*** [0.000]	0.002*** [0.000]	0.002*** [0.000]
Ln(Age)					0.116*** [0.019]	0.03 [0.022]	0.099*** [0.019]	0.017 [0.021]
CAPEX Ratio	0.443*** [0.084]	0.594*** [0.088]	0.360*** [0.090]	0.511*** [0.094]	0.196*** [0.071]	0.263*** [0.074]	0.247*** [0.065]	0.308*** [0.068]
Industry Risk	1.375*** [0.164]	1.715*** [0.227]	0.575*** [0.209]	0.637** [0.282]	0.174 [0.211]	-0.352 [0.283]	0.949*** [0.178]	0.650*** [0.237]
Herfindahl Index	0.263** [0.133]	0.390*** [0.144]	0.236 [0.162]	0.449*** [0.169]	0.205 [0.141]	0.522*** [0.151]	0.251** [0.108]	0.500*** [0.120]
Turnover	0.126*** [0.006]	0.124*** [0.014]	0.103*** [0.008]	0.074*** [0.017]	0.097*** [0.007]	0.064*** [0.013]	0.118*** [0.006]	0.105*** [0.011]
Hitech Dummy			0.563*** [0.039]	0.569*** [0.040]	0.630*** [0.034]	0.637*** [0.036]		
SP500	0.599*** [0.087]		0.583*** [0.086]		0.597*** [0.092]		0.644*** [0.093]	
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	465921	438286	465921	438286	460398	433136	460398	433136
Pseudo R-square	0.14	0.18	0.16	0.2	0.09	0.13	0.06	0.1

Panel C: Combined Effect of Firm Specific Product Market Variables, Industry Characteristics, and Information Asymmetry Variables (the Complete Model)

	<u>Reg. 1</u>	<u>Reg. 2</u>	<u>Reg. 3</u>	<u>Reg. 4</u>	<u>Reg. 5</u>	<u>Reg. 6</u>	<u>Reg. 7</u>	<u>Reg. 8</u>
Size	0.215*** [0.009]	0.229*** [0.010]	0.202*** [0.010]	0.223*** [0.010]				
Sales Growth	0.378*** [0.039]	0.399*** [0.038]	0.382*** [0.040]	0.377*** [0.041]	0.360*** [0.033]	0.371*** [0.031]	0.369*** [0.033]	0.364*** [0.033]
Market Share	1.566*** [0.342]	0.567 [0.496]	1.344*** [0.497]	1.200** [0.503]	3.514*** [0.393]	3.317*** [0.405]	3.429*** [0.365]	3.610*** [0.416]
TFP	0.290*** [0.067]	0.288*** [0.071]	0.275*** [0.069]	0.279*** [0.070]	0.253*** [0.056]	0.255*** [0.058]	0.244*** [0.056]	0.251*** [0.057]
Capital Intensity					0.002*** [0.000]	0.002*** [0.000]	0.002*** [0.000]	0.002*** [0.000]
Ln(Age)					0.03 [0.022]	0.013 [0.022]	0.077*** [0.020]	0.029 [0.022]
CAPEX Ratio	0.537*** [0.092]	0.590*** [0.092]	0.354*** [0.096]	0.505*** [0.099]	0.295*** [0.075]	0.311*** [0.071]	0.196*** [0.075]	0.267*** [0.078]
Industry Risk	0.575* [0.305]	1.942*** [0.228]	0.252 [0.261]	0.721** [0.320]	-0.468 [0.329]	1.026*** [0.237]	-0.228 [0.266]	-0.485 [0.335]
Herfindahl Index	0.517*** [0.161]	0.685*** [0.201]	0.514** [0.219]	0.786*** [0.222]	1.015*** [0.186]	0.822*** [0.180]	0.571*** [0.205]	0.888*** [0.206]
Turnover	0.069*** [0.018]	0.126*** [0.016]	0.077*** [0.010]	0.065*** [0.020]	0.052*** [0.017]	0.116*** [0.014]	0.072*** [0.009]	0.049*** [0.018]
Hitech Dummy			0.466*** [0.061]	0.508*** [0.070]			0.357*** [0.061]	0.405*** [0.067]
Number of Firms Listed in CRSP	0.003*** [0.000]		0.001** [0.000]	0 [0.000]	0.004*** [0.000]		0.002*** [0.000]	0.002*** [0.000]
Std. Dev. of Analysts Forecasts		-0.056** [0.028]	-0.036* [0.022]	-0.045 [0.030]	-0.042* [0.024]	-0.038** [0.019]	-0.039* [0.020]	-0.032 [0.021]
Analysts Forecast Error		-0.003 [0.010]	-0.02 [0.013]	-0.005 [0.014]		0 [0.001]	-0.014 [0.011]	-0.001 [0.001]
Number of Analysts		-0.009* [0.005]	-0.005 [0.005]	-0.015** [0.006]		0.010** [0.005]	0.007 [0.005]	0.003 [0.006]
SP500			0.375*** [0.110]				0.471*** [0.111]	
Year Dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Observations	437658	363437	366717	363437	371714	359745	362984	359745
Pseudo R-square	0.19	0.17	0.15	0.19	0.12	0.09	0.09	0.13

Table 4: Determinants of the Timing and Probability of Going Public: Cox Proportional Hazard Model This table presents the Cox Hazard Model estimation on the probability of going public. The time-to-failure is the age of firms at IPO. The tables report the coefficients and in bracket, the standard errors. 80s Dummy equals 1 for the years 1980 to 1989, and 0 otherwise; 90s Dummy equals 1 for the years 1990 to 2000, and 0 otherwise. All other variables are as defined in table 3. ***, **, and * indicate significance at the 1, 5, and 10 percent level respectively.

	Panel A	Panel B		Panel C					
	<u>Reg. 1</u>	<u>Reg. 2</u>	<u>Reg. 3</u>	<u>Reg. 4</u>	<u>Reg. 5</u>	<u>Reg. 6</u>	<u>Reg. 7</u>	<u>Reg. 8</u>	<u>Reg. 9</u>
Size	0.604*** [0.029]	0.634*** [0.028]	0.596*** [0.029]	0.630*** [0.030]	0.588*** [0.031]	0.572*** [0.030]			
Sales Growth	0.854*** [0.115]	0.893*** [0.109]	0.826*** [0.115]	0.856*** [0.113]	0.793*** [0.120]	0.852*** [0.117]	1.168*** [0.099]	1.191*** [0.100]	1.081*** [0.106]
Market Share	3.765*** [0.633]	1.963** [0.837]	3.419*** [0.712]	0.833 [1.135]	2.910*** [0.977]	2.931*** [1.047]	5.738*** [0.720]	5.565*** [0.652]	7.136*** [0.700]
TFP	0.741*** [0.196]	0.863*** [0.207]	0.745*** [0.197]	0.841*** [0.211]	0.730*** [0.202]	0.703*** [0.207]	0.781*** [0.186]	0.769*** [0.188]	0.688*** [0.178]
Capital Intensity							0.004*** [0.001]	0.005*** [0.001]	0.003*** [0.001]
CAPEX Ratio	1.282*** [0.276]	1.469*** [0.260]	1.303*** [0.278]	1.481*** [0.270]	1.303*** [0.289]	1.189*** [0.286]	1.105*** [0.236]	0.992*** [0.234]	1.040*** [0.245]
Industry Risk		2.343*** [0.525]	-0.029 [0.719]	2.789*** [0.507]		0.532 [0.772]	1.913*** [0.611]	2.741*** [0.533]	-0.857 [0.792]
Herfindahl Index		0.866* [0.461]	1.062** [0.506]	1.315** [0.567]	1.659*** [0.602]	1.431** [0.607]	1.813*** [0.560]	1.218** [0.574]	1.940*** [0.625]
Turnover		0.240*** [0.028]	0.117** [0.053]	0.241*** [0.029]	0.102* [0.060]	0.225*** [0.030]	0.293*** [0.023]	0.331*** [0.018]	0.118** [0.052]
Hitech Dummy	1.439*** [0.110]		1.384*** [0.122]		1.369*** [0.116]				
Number of Firms Listed in CRSP						0.007*** [0.001]			0.009*** [0.001]
Std. Dev. of Analysts Forecasts				-0.124** [0.063]	-0.08 [0.051]	-0.142* [0.081]	-0.086** [0.040]	-0.134** [0.059]	-0.083* [0.046]
Analysts Forecast Error				-0.007 [0.019]	-0.01 [0.034]	-0.05 [0.035]	-0.003 [0.006]	-0.029 [0.025]	-0.004 [0.008]
Number of Analysts				-0.011 [0.016]	-0.023 [0.018]	-0.003 [0.017]	0.034** [0.014]	0.047*** [0.014]	0.027 [0.017]
SP500	0.799*** [0.309]	0.775** [0.319]			0.463 [0.326]	0.827** [0.356]		1.430*** [0.382]	0.661** [0.332]
80s Dummy	2.209*** [0.265]	2.161*** [0.266]	2.228*** [0.261]	2.126*** [0.355]	2.013*** [0.355]		1.733*** [0.336]		1.618*** [0.341]
90s Dummy	2.845*** [0.262]	2.767*** [0.262]	2.831*** [0.258]	2.705*** [0.350]	2.627*** [0.353]		2.495*** [0.333]		2.341*** [0.340]
Observations	384533	369193	369193	300626	300626	300626	298570	298570	298570
Wald Chi-square	1626.64	1406.14	1617.81	1204.57	1450.07	1425.06	685.78	806.01	1024.91

Table 5: Dynamic Characteristics of TFP, Sales, and Capital Expenditure around the IPO: This table presents the dynamic pattern of TFP, Sales, and Capital Expenditure before and after the going public event. TFP is the weighted average of plant level Total Factor Productivity at the four digit SIC level, where 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 five years and more 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 and more after the firm goes public, and 0 otherwise. All dollar values are in real terms. All observations are firm year observations. Panel A regressions are based on all the firm year observations in the LRD for the firms eventually going public along with the firms remaining private. Panel B regressions are restricted to all the firm year observations in the LRD for the firms eventually going public. The following panel regression is estimated in all the specifications:

$$Y_{it} = \alpha_i + \beta_i + \gamma X_{it} + \sum_{s=1}^5 \delta_s Before_{it}^s + \sum_{s=1}^5 \lambda_s After_{it}^s + \varepsilon_{it}$$
All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity corrected robust standard errors are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level respectively.

Panel A: Firms Eventually Going Public with Firms Remaining Private			
	TFP	Sales	Capital Expenditure
Before ⁵⁺	-0.07669*** (0.009)	-35784.1*** (2914.961)	-1204.38*** (132.711)
Before ⁴	-0.04607*** (0.013)	-24502.6*** (3615.822)	-980.286*** (161.560)
Before ³	-0.04349*** (0.011)	-24925.5*** (3509.558)	-1079.68*** (157.041)
Before ²	-0.03386*** (0.011)	-20169.9*** (3205.442)	-1072.70*** (153.438)
Before ¹	-0.01075 (0.010)	-9540.61*** (2988.118)	-632.979*** (145.581)
After ¹	-0.00532 (0.010)	5983.689** (2933.623)	527.2257*** (150.842)
After ²	-0.01214 (0.010)	9710.441*** (3121.548)	489.9394*** (152.572)
After ³	-0.02467** (0.011)	12386.40*** (3384.595)	473.7660*** (161.014)
After ⁴	-0.02084* (0.012)	15025.85*** (3679.922)	307.5759* (166.957)
After ⁵⁺	-0.01314 (0.009)	34068.86*** (2832.707)	417.7095*** (132.305)
Size	-0.01922*** (0.001)	15047.51*** (153.400)	698.4720*** (6.387)
Year Dummies	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Number of obs	652522	671479	679187
Adj R-square	0.4237	0.8499	0.6472

Panel B: Firms Eventually Going Public Only			
	TFP	Sales	Capital Expenditure
Before ⁵⁺	-0.05918*** (0.010)	-2046.42 (3178.816)	-644.958*** (143.032)
Before ⁴	-0.03790*** (0.012)	-7599.41** (3379.836)	-671.880*** (153.436)
Before ³	-0.03784*** (0.011)	-11001.2*** (3188.024)	-828.452*** (145.459)
Before ²	-0.03001*** (0.010)	-8418.18*** (2891.402)	-844.571*** (140.320)
Before ¹	-0.00771 (0.010)	-3771.76 (2631.379)	-501.126*** (132.419)
After ¹	-0.00989 (0.010)	-57.1106 (2571.309)	326.4364** (136.011)
After ²	-0.01630* (0.010)	-767.918 (2758.495)	199.5122 (137.251)
After ³	-0.02965*** (0.010)	-3073.04 (3008.317)	70.31916 (145.465)
After ⁴	-0.02741** (0.011)	-4519.83 (3294.916)	-145.975 (152.652)
After ⁵⁺	-0.02721*** (0.010)	-828.062 (2975.410)	-296.154** (141.317)
Size	-0.01171*** (0.003)	46491.36*** (1233.075)	1904.036*** (50.517)
Year Dummies	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Number of obs	11641	11645	11655
Adj R-square	0.3848	0.8162	0.6786

Table 6: Dynamic Characteristics of Firm Employment, Labor and Other Costs around the IPO: This table presents the dynamic pattern of Employment, Total Wage, Materials cost, and Rental and Administrative Expenses before and after the going public event. Total employment is the total number of employees in the firm. Total wage is the total payroll of the firm in thousands dollar unit. Material 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 office equipments, 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 and more 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 and more after the firm goes public, and 0 otherwise. All dollar values are in real terms. All observations are firm year observations. Panel A regressions are based on all the firm year observations in the LRD for the firms eventually going public along with the firms remaining private. Panel B regressions are restricted to all the firm year observations in the LRD for the firms eventually going public. The following panel regression is estimated in all the specifications: $Y_{it} = \alpha_i + \beta_i + \gamma X_{it} + \sum_{s=1}^5 \delta_s Before_{it}^s + \sum_{s=1}^5 \lambda_s After_{it}^s + \varepsilon_{it}$. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity corrected robust standard errors are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level respectively.

Panel A: Firms Eventually Going Pubic with Firms Remaining Private				
	Total Employment	Total Wage	Material Cost	Rental and Admin. Exp.
Before ⁵⁺	-121.043*** (18.532)	-3906.716*** (518.851)	-40299.33*** (3372.928)	-851.085*** (117.488)
Before ⁴	-83.672*** (23.384)	-2713.484*** (659.404)	-23417.29*** (4072.890)	-458.793*** (147.240)
Before ³	-97.113*** (21.847)	-3229.870*** (622.501)	-20627.82*** (3880.541)	-608.476*** (142.950)
Before ²	-81.663*** (19.637)	-2783.815*** (563.547)	-14383.02*** (3554.104)	-474.265*** (130.722)
Before ¹	-22.724 (19.028)	-946.702* (546.262)	-7960.128** (3411.038)	-24.908 (128.548)
After ¹	20.933 (17.866)	774.131 (506.782)	8800.081*** (3416.539)	196.067* (118.361)
After ²	60.041*** (19.534)	1724.727*** (548.049)	13515.890*** (3578.004)	320.099*** (124.234)
After ³	86.922*** (20.893)	2788.974*** (603.837)	14069.310*** (3900.736)	462.715*** (134.171)
After ⁴	86.871*** (21.174)	3048.244*** (615.607)	16867.200*** (4155.568)	676.281*** (147.305)
After ⁵	107.712*** (17.843)	4507.771*** (519.824)	34733.780*** (3190.289)	1013.526*** (116.822)
Size	120.167*** (1.011)	3273.781*** (29.354)	11021.770*** (156.999)	648.084*** (6.314)
Year Dummies	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Number of obs	679032	679207	680646	679229
Adj R-square	0.8650	0.8714	0.7911	0.8336

Panel B: Firms Eventually Going Public Only				
	Total Employment	Total Wage	Material Cost	Rental and Admin. Exp.
Before ⁵⁺	-25.557 (19.390)	-644.690 (556.856)	8559.916** (3614.585)	50.416 (126.611)
Before ⁴	-36.875* (20.860)	-1102.374* (585.703)	-556.249 (3816.329)	-36.077 (134.824)
Before ³	-53.040*** (19.375)	-1790.368*** (549.176)	-2930.734 (3593.000)	-254.184** (128.695)
Before ²	-36.788** (17.363)	-1338.798*** (492.981)	-1164.833 (3247.449)	-156.200 (116.600)
Before ¹	-1.873 (16.360)	-240.648 (464.334)	-945.270 (3058.638)	105.069 (112.073)
After ¹	-4.797 (15.248)	-38.889 (430.022)	2565.610 (3028.898)	28.993 (102.294)
After ²	16.784 (16.843)	349.975 (469.551)	3002.394 (3209.293)	88.467 (109.742)
After ³	23.155 (18.321)	734.506 (518.796)	373.703 (3557.679)	88.802 (118.974)
After ⁴	8.425 (18.993)	506.169 (547.497)	-900.103 (3780.201)	118.115 (130.724)
After ⁵	-9.056 (18.937)	638.763 (537.861)	-6791.753** (3436.794)	83.940 (122.465)
Size	346.089*** (7.831)	10030.520*** (226.896)	34811.750*** (1266.895)	2014.691*** (48.790)
Year Dummies	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Number of obs	11587	11602	11989	11627
Adj R-square	0.8270	0.8397	0.7652	0.8105

Table 7: Dynamic Characteristics of Firm Sales Growth and Market Share around the IPO: This table presents the dynamic pattern of Sales growth and Market share of the firm before and after the going public event. Sales growth is the average growth in sales in the past three years. Market share is the firm's market share in terms of sales in the same 3 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 and more 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 and more after the firm goes public, and 0 otherwise. All dollar values are in real terms. All observations are firm year observations. Panel A regressions are based on all the firm year observations in the LRD for the firms eventually going public along with the firms remaining private. Panel B regressions are restricted to all the firm year observations in the LRD for the firms eventually going public. The following panel regression is estimated in all the specifications: $Y_{it} = \alpha_i + \beta_i + \gamma X_{it} + \sum_{s=1}^5 \delta_s Before_{it}^s + \sum_{s=1}^5 \lambda_s After_{it}^s + \varepsilon_{it}$. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity corrected robust standard errors are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level respectively.

Panel A: Firms Eventually Going Pubic with Firms Remaining Private		
	Sales Growth	Market Share
Before ⁵⁺	-0.110*** (0.015)	-0.008*** (0.001)
Before ⁴	-0.089*** (0.021)	-0.003* (0.002)
Before ³	-0.082*** (0.019)	-0.001 (0.002)
Before ²	-0.050*** (0.019)	-0.001 (0.002)
Before ¹	-0.010 (0.018)	-0.000 (0.001)
After ¹	-0.018 (0.017)	-0.000 (0.001)
After ²	-0.045*** (0.017)	-0.001 (0.001)
After ³	-0.080*** (0.017)	0.000 (0.001)
After ⁴	-0.103*** (0.017)	-0.000 (0.001)
After ⁵	-0.116*** (0.015)	0.000 (0.001)
Size	0.036*** (0.001)	0.002*** (0.000)
Year Dummies	Yes	Yes
Firm Fixed Effect	Yes	Yes
Number of obs	514897	680646
Adj R-square	0.5454	0.6921

Panel B: Firms Eventually Going Public Only

	Sales Growth	Market Share
Before ⁵⁺	-0.079*** (0.016)	-0.003* (0.002)
Before ⁴	-0.073*** (0.020)	-0.001 (0.002)
Before ³	-0.071*** (0.018)	0.001 (0.002)
Before ²	-0.041** (0.017)	0.001 (0.002)
Before ¹	-0.007 (0.016)	0.000 (0.001)
After ¹	-0.019 (0.015)	-0.001 (0.001)
After ²	-0.049*** (0.015)	-0.002* (0.001)
After ³	-0.086*** (0.016)	-0.001 (0.001)
After ⁴	-0.112*** (0.016)	-0.002 (0.001)
After ⁵	-0.143*** (0.015)	-0.004*** (0.001)
Size	0.040*** (0.005)	0.006*** (0.001)
Year Dummies	Yes	Yes
Firm Fixed Effect	Yes	Yes
Number of obs	10729	11989
Adj R-square	0.3436	0.6297

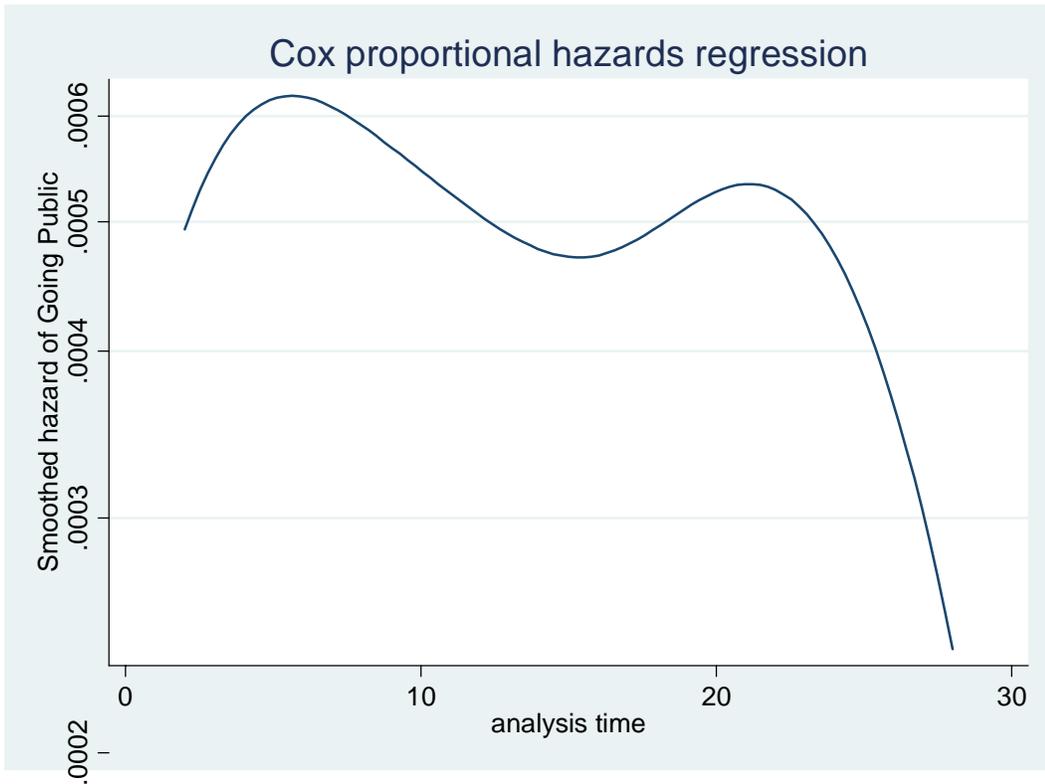


Figure 1: Estimated Hazard Function.

This figure displays the smoothed hazard of Going Public using the Cox proportional hazard model. Specifically the hazard function is generated from regression 5 in Table 4. The time-to-failure is the age of firms at IPO. The hazard is evaluated at the sample mean of all the explanatory variables in that regression.

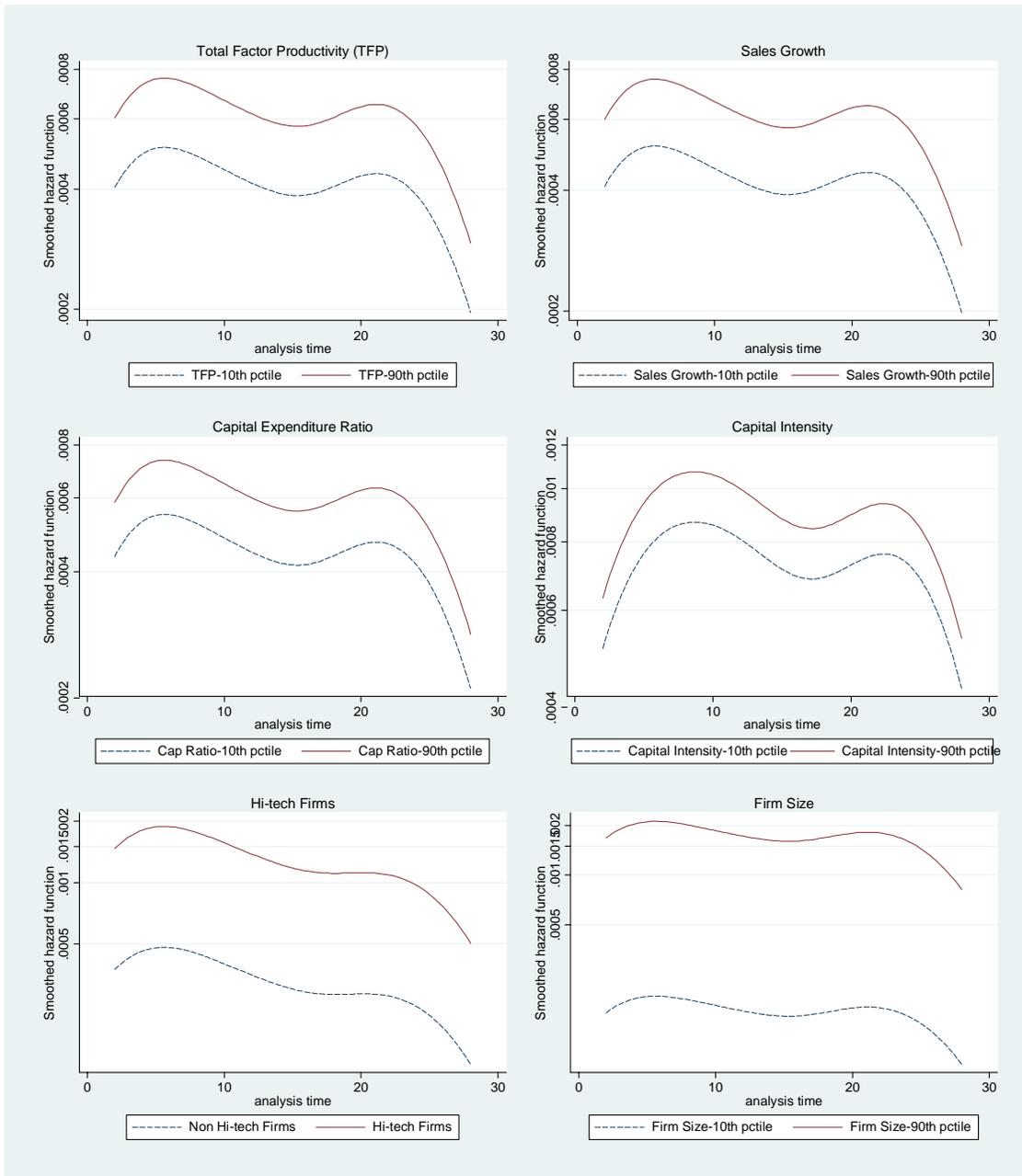


Figure 2: Economic significance of firm specific characteristics

This figure displays the effect of six firm specific characteristics on the hazard of going public. The time-to-failure is the age of firms at IPO. The hazard is evaluated at the 10th and 90th percentile for each specified variable (other than Hi-tech, which is evaluated at Hitech=1 and Hitech=0) as indicated above in the graph, with the other explanatory variables being held at their sample means.

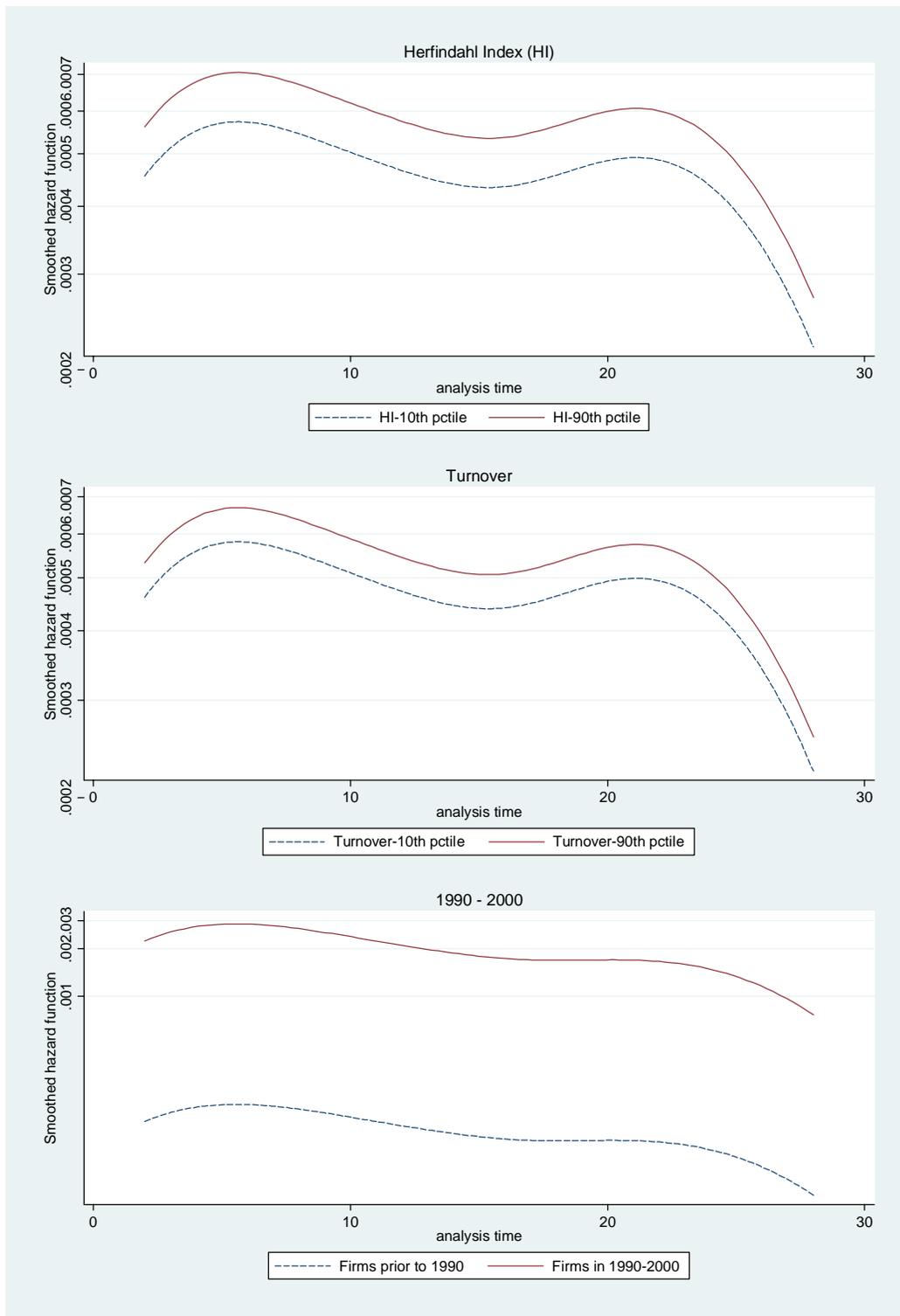


Figure 3: Economic significance of industry concentration, liquidity, and post-90 period

This figure displays the effect of industry concentration, liquidity of already listed equity in the industry, and the post-90s period on the hazard of going public. The time-to-failure is the age of firms at IPO. The hazard is evaluated at the 10th and 90th percentile for the Herfindahl index, turnover rate of already listed equity in the same 3-digit SIC industry, and at 0 and 1 for the post-90s period dummy for the three graphs respectively, with all other explanatory variables being held at their sample means.

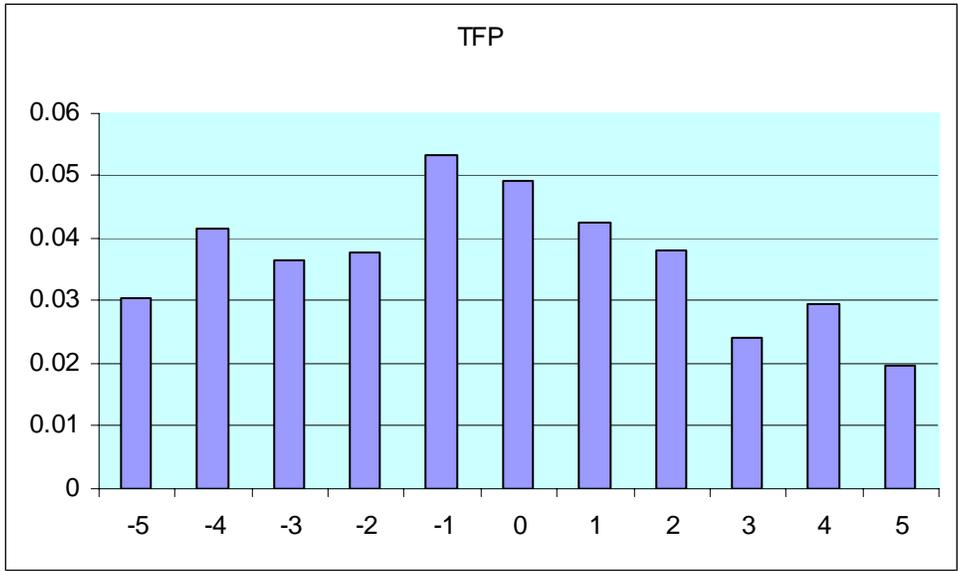


Figure 4: The dynamic pattern of TFP around the IPO.

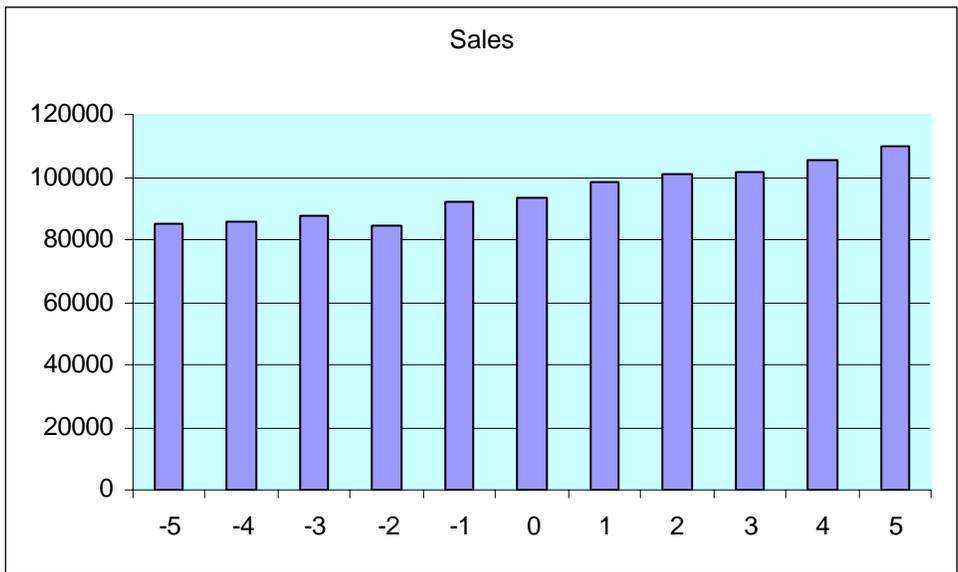


Figure 5: The dynamic pattern of Sales around the IPO.

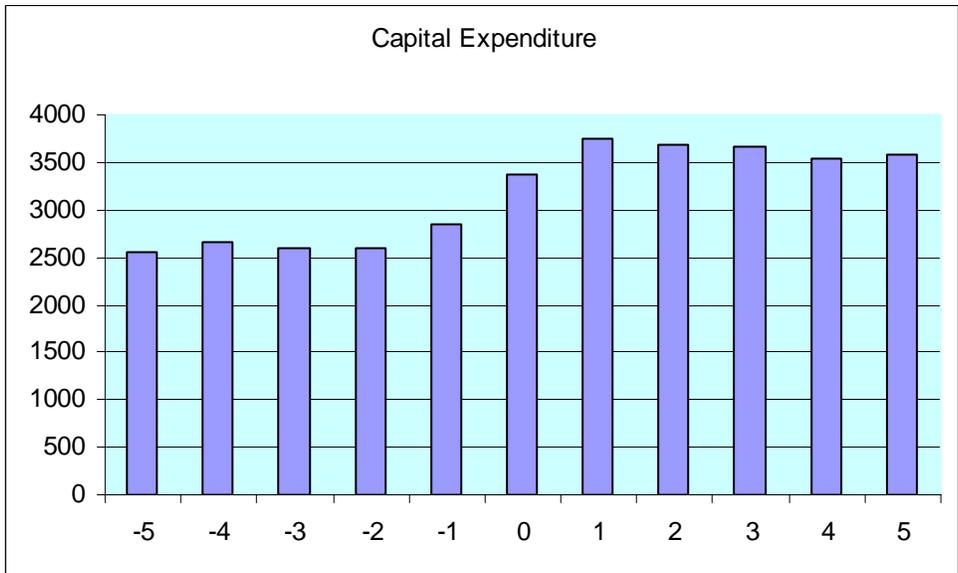


Figure 6: The dynamic pattern of Capital Expenditures around the IPO.

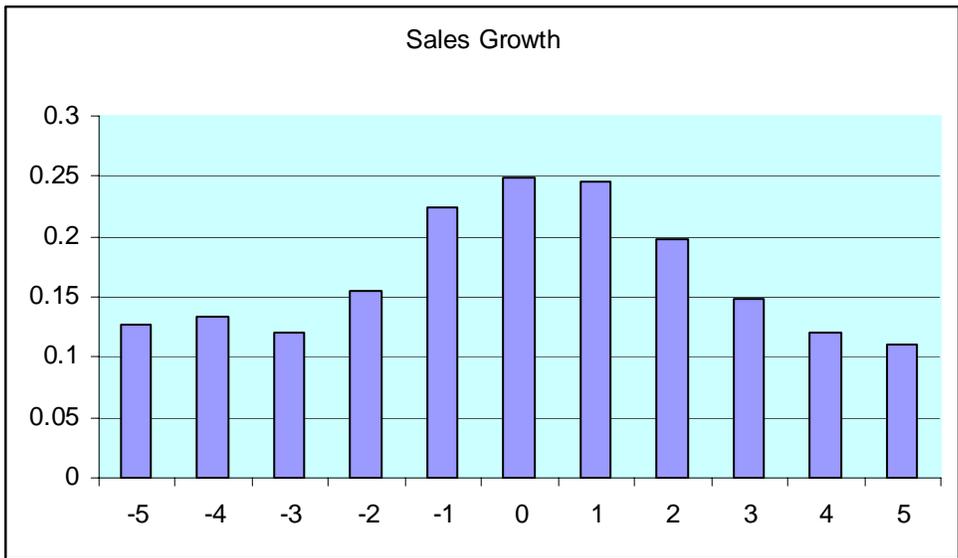


Figure 7: The dynamic pattern of Sales Growth around the IPO.

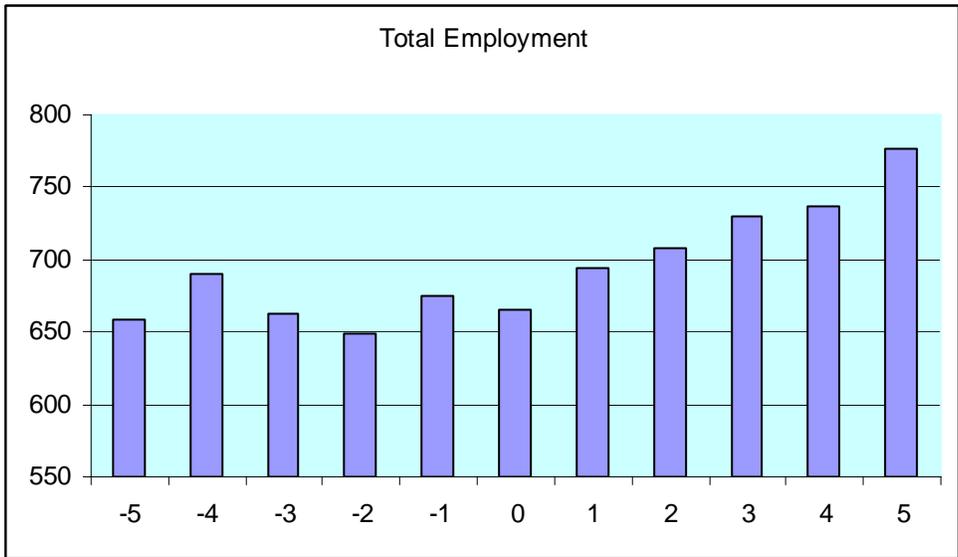


Figure 8: The dynamic pattern of Total Employment around the IPO.

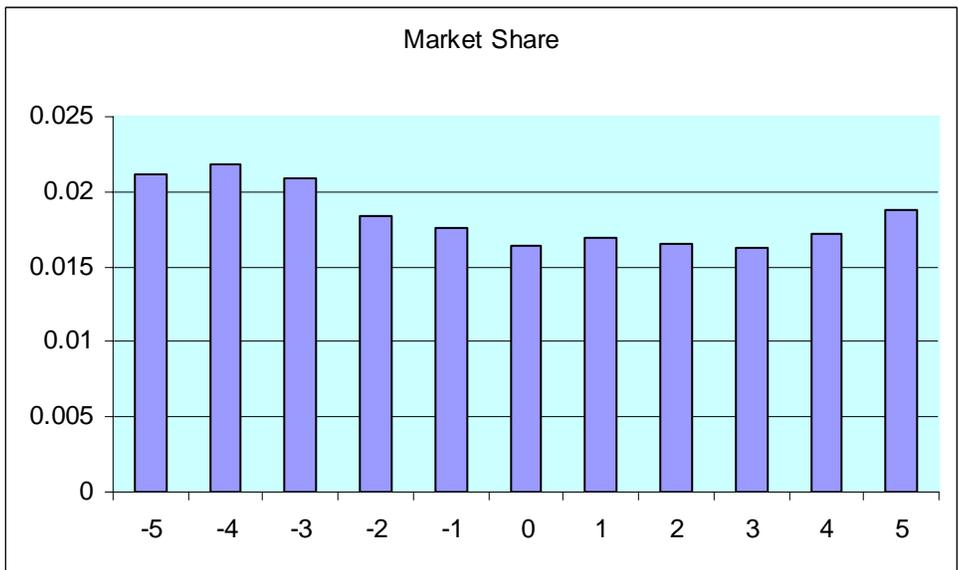


Figure 9: The dynamic pattern of Market Share around the IPO.

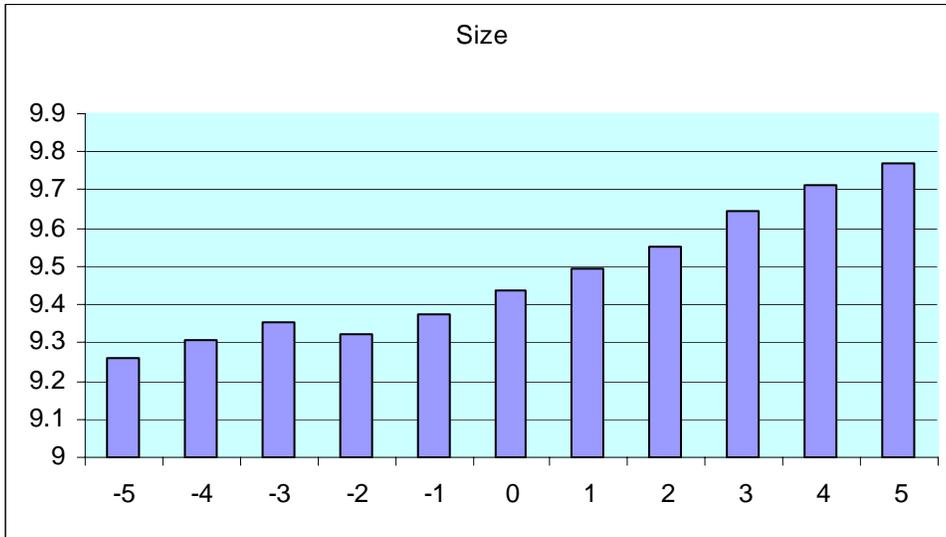


Figure 10: The dynamic pattern of Firm Size around the IPO.