Product Market Characteristics and the Choice between IPOs and Acquisitions

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Abstract

Using unique U.S. Census datasets, we analyze how entrepreneurial firms' product market characteristics affect their choice between going public, being acquired, or remaining private. Total factor productivity (*TFP*), size, sales growth, market share, capital expenditure, human capital intensiveness, and access to private funding significantly increase a private firm's likelihood of an IPO relative to an acquisition. Firms in industries with less information asymmetry and higher stock liquidity are more likely to choose an IPO instead of an acquisition. While *TFP* peaks around either form of exit, the rate of increase in *TFP* prior to acquisitions and the subsequent decrease is smaller than that around IPOs.

1. Introduction

Traditionally, going public has been considered the "best" exit choice for private firms, where the most successful firms choose to have an initial public offering, while less successful firms are acquired by another firm. However, more recently, a private firm was much more likely to be acquired than to go public: see, e.g., Gao, Ritter, and Zhu (2013), who provide evidence on the dramatic reduction in IPOs in the U.S. over the last decade.[1] Studies of the IPO versus acquisition decisions, with some notable exceptions, have been few in the literature, possibly because of data limitations. The objective of this paper is to fill the gap in the literature by conducting the first large sample study of the exit decision (i.e., the decision of whether to go public, to be acquired, or to remain private) of U.S. firms and the consequences of such exit on subsequent firm performance, using the Longitudinal Research Database (LRD) of the U.S. Census Bureau, which covers the entire universe of private and public U.S. manufacturing firms, and the Ownership Change Database (OCD) of the U.S. Census Bureau, which covers a very large sample of private and public firm acquisitions.[2]

We focus on the relationship between the product market characteristics of a firm and its exit choice between IPOs and acquisitions. Starting with Bhattacharya and Ritter (1983), several theoretical papers have argued that the exit choice of a firm may be affected by the nature of the firm's industry and its product market characteristics. While most of these theoretical papers have focused on the going public (IPO) decision, we extend these theories to the IPO versus acquisition (versus remaining private) choice, and develop testable hypotheses. Thus, we are able to make use of the comprehensive databases mentioned above to analyze how the predictions of various theories of entrepreneurial firm exit choice hold up in the data. We analyze two important issues in the first part of the paper. First, we study the relationship between the *ex ante* product market characteristics of a firm and its choice between going public, being acquired, or remaining private. Second, we study how the fact of a firm having obtained

[1] According to the National Venture Capital Association (NVCA), there were more exits by venture capitalists through acquisitions than by IPOs in each of the last ten years. The NVCA reports that acquisitions constituted 89% of the value of exits of venture backed firms in 2009: while acquisitions of venture backed firms accounted for $13.53 billion in value, IPOs of venture backed firms accounted for only $1.64 billion.

[2] As we discuss later, using the OCD dramatically increases the size of our sample of acquisitions relative to a sample obtained from the Securities Data Co. (now Thomson Reuters)'s database, which is commonly used in the existing literature on IPOs versus acquisitions.

private financing (in the form of venture capital or loan financing) affects its propensity to have an IPO versus an acquisition (versus remaining private). In the second part of our paper, we analyze the dynamics of a firm's product market performance around its point of exit, i.e., the behavior of various performance variables in the years leading up to its exit and in the years after exit. We perform this analysis using firms that remained private throughout as the benchmark: this allows us to contemporaneously compare the changes in the performance of firms going public or being acquired to the changes in the performance of firms remaining private throughout.

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 exit decision, but also for the dynamics of these characteristics before and after a firm's exit. Surprisingly, however, existing empirical research on the choice between going public, being acquired, or remaining private is scant. There are only three pieces of U.S. based evidence dealing partially with the above choice. Using a sample of firms exiting between 1995 and 2004, Poulsen and Stegemoller (2008) study the choice between sell-outs to publicly held acquirers and IPOs for firms moving from private to public ownership. Given that they have data on private firms only immediately prior to exit, they are able to address only a firm's choice between IPOs and acquisitions but not the choice to remain private. Further, they are not able to address the dynamics of various firm performance variables before and after exit perhaps also due to data limitations (note that private firms that are acquired become part of the acquiring firms). Bayar and Chemmanur (2012) also study the IPO versus acquisition decision, but their focus is on the "valuation premium puzzle", namely, the fact that many private firms choose to be acquired than go public at a higher valuation. Like Poulsen and Stegemoller (2008), they have access to private firm data only immediately prior to exit, so they address only a firm's choice between IPOs and acquisitions but not the choice to remain private. Neither are they able to study the dynamics of firm performance before and after exit. Brau, Francis, and Kohers (2003) examine how various industry, stock market, and deal characteristics affect a private firm's choice between an IPO and an acquisition by a public acquirer. While some of their results on industry characteristics (e.g., firms in more concentrated and high-tech industries choosing IPO over acquisitions) are broadly consistent with ours, they do not address any of the main questions we study here, given their lack of firm-level data and their primary focus on industry characteristics and macroeconomic conditions. Unlike our paper, none of the above studies include in their sample acquisitions made by *private* acquirers, which constitute a significant part of entrepreneurial exits.[3] Further, our use of the two census bureau databases mentioned above enables us to overcome the data limitations (of various kinds) suffered by all existing studies of private firms' choice between IPOs and acquisitions, allowing us to present the first comprehensive analysis of the three-way choice of private firms between IPOs, acquisitions, and remaining private in the literature. [4]

In contrast to the above three studies, which limit themselves to the sample of acquisitions reported by the Securities Data Co.'s (SDC's) Mergers and Acquisitions Database, our paper makes use of the Manufacturing Plant Ownership Change Database (OCD) maintained by the U.S. Census Bureau to supplement the sample of acquisitions obtained from SDC. SDC tends to record only very large transactions so that any studies that purely rely on SDC data will not be able to examine targets that are small and young, which is typically true for private entrepreneurial firms. Unlike the SDC database, the OCD contains acquisitions of manufacturing firms of *all* sizes, which helps to alleviate the sample selection bias arising from studying the acquisitions of only large firms. In fact, the OCD database increases our sample of acquisitions of manufacturing firms by almost 200%, and therefore makes our paper by far the most comprehensive study of private firms' exit choice.[5]

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[3] Aslan and Kumar (2009) develop a theoretical model analyzing how estimation risk affects a private firm's choice between IPOs and takeovers, and make use of U.K. data to test the implications of their theory. While some of their results are consistent with ours as well as the other two firm-level studies using U.S. data, namely, Poulsen and Stegemoller (2008) and Bayar and Chemmanur (2009), many of their results contradict those based on U.S. studies: for example, they find that firms with higher future sales growth, younger firms, and those from more concentrated industries are more likely to be acquired than go public.

[4] There is a literature on the exit decisions of a subset of entrepreneurial firms, namely, venture backed firms: see, e.g., Cumming (2008) and Ball, Chiu, and Smith (2011). To the best of our knowledge, this literature also suffers from the data limitations of the broader literature on entrepreneurial firm exits that we discuss here. Further, by focusing only on venture backed firms, these papers are unable to provide a complete picture of the exit choices of entrepreneurial firms.

[5] As discussed in the data section below, while our final sample (based on LRD) is somewhat tilted towards large firms with more than 250 employees, our matched IPO and acquired firms are very much representative of U.S. IPOs and acquisitions in the manufacturing sector, with some concentration in electronics and precision instruments industries for IPOs, and some concentration in industrial machinery and food industries for acquired firms. Moreover, approximately 62% of high-tech industries, in which we expect to see a high rate of exits (through either IPOs or acquisitions), fall within the scope of the LRD, as these industries are part of manufacturing.

Our findings on the relationship between the *ex ante* product market characteristics of a firm and its likelihood of going public versus getting acquired can be summarized as follows.[6] First, we find that firms that are larger in size, have greater total factor productivity (*TFP*) than their industry peers, higher sales growth, higher capital expenditure ratio, higher human capital intensiveness (white-collar salary proportion), greater market share, and have access to private financing (in the form of either venture capital or bank loans) are more likely to go public than to get acquired. Second, high tech firms and those with projects which are easier for outsiders to evaluate are more likely to go public rather than be acquired. Third, 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 public firms in that industry, i.e., the number of already listed firms, the number of analysts following, standard deviation of analyst forecasts, and analyst forecast error) and with greater average liquidity of already listed stocks are more likely to go public than to get acquired. All the above results are robust to controlling for access to private financing and market conditions.

The above findings are broadly consistent with the implications of five of the theories of private firm exits that we discuss below, namely, the information production theory of Chemmanur and Fulghieri (1999); the productivity shock theory of Clementi (2002); the product market competition theory of Bayar and Chemmanur (2011); the competition for market share theory of Spiegel and Tookes (2007); and the stock-based incentive contracting theory of Aron (1991), Bayar, Chemmanur, and Liu (2011), and He and Li (2014).[7] While some of our empirical results are consistent with those of Poulsen and Stegemoller (2008) and Bayar and Chemmanur (2012), our findings on total factor productivity, human capital intensiveness, market share of the firm, capital intensity, industry risk, industry liquidity, and industry asymmetric information are completely new to the literature.

[6] We conducted our analysis using both a dynamic multinomial logit model and a dynamic logit model involving only the two exit choices. While, due to space limitations, we report results only from the dynamic multinomial model, our results from the dynamic logit model are essentially the same.

[7] More broadly, our study also throws light on the implications of theory models of product and financial market interactions: see, e.g., Dasgupta and Titman (1998), Lyandres (2006), Fulghieri and Sevilir (2009) and Chod and Lyandres (2011).

Our results on the exit choice between IPOs and acquisitions continue to hold after we conduct two robustness tests, namely, a propensity score matching analysis and an endogenous switching regression analysis. Since we use the universe of private manufacturing firms in our baseline analysis, we may have included many small and poorly-run family businesses, which have no intention (or ability) to have a successful exit, and compared them with higher-quality firms aiming for a successful exit. To alleviate this concern, we use a propensity score matching algorithm to match the three groups of firms (i.e., IPO firms, acquired firms, and firms remaining private throughout) along all important observable dimensions and follow them over time to see how changes in their product market characteristics relate to their exit outcomes. We find similar results from our empirical analysis using this subset of private firms with comparable observable quality several years prior to the exit event.

Another concern is the possibility that our observed access to private funding may be caused by unobservable firm quality that also directly affects the exit decision. For instance, higher quality firms are more likely to obtain funding from venture capitalists or banks, while at the same time more likely to go public (i.e., taking the more "successful" exit route) than to get acquired. To address this concern, we explicitly account for the endogenous nature of private financiers' selection process using a Heckman style two-stage endogenous switching model. We find that the various firm specific, industry specific, and information asymmetry variables affect the exit decision in a similar manner to that of our findings from our baseline empirical analysis even after controlling for such selection effects.

Our analysis of the dynamic pattern of firm performance before and after IPOs and acquisitions indicates that total factor productivity (*TFP*) shows an inverted-U shape for both IPO firms and acquired firms, implying that it reaches its peak near the exit year, consistent with the predictions of our extensions of the models of Clementi (2002) and Spiegel and Tookes (2007). Most interestingly, the rate of change in *TFP* before and after the exit year is smaller for firms that are acquired than for those going public. Second, sales growth exhibits a similar (inverted-U) pattern for IPO firms and (weakly) for firms that are acquired. Third, while sales, capital expenditures, and total employment exhibit a consistently increasing pattern both in the years before and after the exit for IPO firms, these variables show inverted-U patterns for acquired firms (benchmarked against firms remaining private throughout). For firms going public, our results indicating a decline in *TFP* and an increase in sales and capital expenditures after the IPO are broadly consistent with the performance implications of a firm increasing its scale of operations around the IPO, as characterized by the theoretical analysis of Clementi (2002). On the other hand, for firms that are acquired, the inverted-U shaped pattern of sales, capital expenditures, and total employment is consistent with the notion that the products of an acquired firm compete with those of the acquirer (and some of these may be discontinued due to consolidation with the acquirer) and that most synergies from the acquisition actually accrue to the plants of the acquirer. Our comparison of post-exit capital expenditures of IPO firms versus acquired firms also indicates that the latter do not obtain as efficient access to the capital markets as the former through the exit.[8]

In summary, the contribution of this paper is twofold. First, this is the first large sample study in the literature to analyze a private firm's choice among going public, being acquired, or remaining private. Second, while Chemmanur, He, and Nandy (2010) have studied the dynamics of a firm's product market characteristics around a private firm's exit through an IPO, this paper examines the dynamic pattern of the performance of a private firm around its exit through an acquisition. Thus, the fact that we are able to use the entire universe of U.S. manufacturing firms and a very large sample of both IPOs and acquisitions allows us to develop a comprehensive empirical analysis of the determinants of a private firm's exit choice and the consequences of the choice, and thereby better evaluate the implications of various theoretical arguments regarding this exit choice.

The rest of the paper is organized as follows. Section 2 reviews theories of the exit decision and develops testable hypotheses. Section 3 describes data and sample selection. Section 4 analyzes the *ex ante* product market characteristics of a firm and its likelihood of going public versus getting acquired. Section 5 uses the propensity-score matching method and the endogenous switching model as robustness tests. Section 6 studies firm dynamics around IPOs and acquisitions. Section 7 concludes.

2. Theory and Hypotheses

[8] To the extent that they also study the relationship between exit choices and post-exit outcomes, our dynamic analysis is related to Hsu and Aggarwal (2013), who study the relationship between the exit choices and innovation outcomes of venture-backed biotechnology firms, as measured by patent counts and patent citations.

2.1 Relationship between product market characteristics, the decision to exit, and the choice between IPOs and acquisitions

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. We can extend their analysis to a firm's choice between IPOs and acquisitions. In this context, the choice of a private firm between going public and being acquired depends on the following trade-off: On the one hand, in the case of an acquisition, the transaction is less affected by the information asymmetry facing the firm, since the relevant outsiders evaluating the firm are the top officers of the acquiring firm, who can be expected to have significant industry expertise in evaluating such firms (see Bayar and Chemmanur (2011) for a formal theoretical analysis incorporating this notion). This implies that smaller firms and firms in industries characterized by more information asymmetry and by harder-to-evaluate projects are more likely to choose to be acquired over an IPO. On the other hand, a negative feature of being acquired is that, even if the acquirer is a public firm (and therefore has less costly access to the capital market itself), the private firm being acquired will have to compete with other divisions of the acquiring firm for capital (see, e.g., Stein (1997) for a theoretical analysis). This implies that private firms requiring a larger amount of capital are likely to prefer to go public over being acquired. Further, if the firm requires a larger amount of capital or has riskier cash flows (see Chemmanur and Fulghieri (1999)), private financiers (and potential acquirers) will demand a larger rate of return from the firm either due to risk aversion or their greater bargaining power, making the firm more likely to go public. In summary, the above theory leads to the following predictions:

H1: The largest firms and those operating in industries characterized by the least information asymmetry (and the greatest stock market liquidity) are most likely to go public, smaller firms in industries with greater information asymmetry (and less stock market liquidity) are likely to be acquired, and the smallest firms in industries with the greatest extent of information asymmetry (and the least stock market liquidity) are likely to remain private.

H2: The most capital intensive firms and those operating in industries with the greatest riskiness of cash flows are most likely to go public, less capital intensive firms and those in less risky industries are likely to be acquired, and the least capital intensive firms and those in the least risky industries are likely to remain private.

Clementi (2002) argues that firms go public as a result of a positive and persistent productivity shock: while a borrowing constraint keeps 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 existence of fixed costs associated with going public. Clementi and Hopenhayn (2006) show that a borrowing constraint along the lines postulated by Clementi (2002) may arise endogenously in a multi-period setting with asymmetric information. We can extend the Clementi (2002) model to the IPO versus acquisition decision. In this case, the choice between IPOs, acquisitions, and remaining private will depend on the following trade-off. On the one hand, being acquired by a larger firm is much cheaper than going public, since the latter involves significantly larger transactions costs (not only direct costs such as underwriting fees, but also indirect costs such as IPO "underpricing"). On the other hand, going public allows the private firm cheap and repeated access to the public capital market, while the private firm obtains only imperfect access to the capital markets in the case of an acquisition (even if the acquirer is a public firm), since they have to compete with other divisions of the acquiring firm for capital (Stein (1997)). This implies that the TFP threshold at which a firm chooses to exit through an acquisition will be lower compared to that for an IPO. The above extended theory predicts that firms characterized by greater productivity, output growth, and capital expenditures are more likely to go public rather than to be acquired.

H3: Firms with the highest total factor productivity (TFP), the highest levels of sales growth, and the highest levels of capital expenditures are most likely to go public; those with intermediate levels of TFP, sales growth, and capital expenditures are likely to be acquired; and those with the lowest levels of TFP, sales growth, and capital expenditures are likely to remain private.[9]

Bayar and Chemmanur (2011) develop a model explicitly analyzing a firm's choice between IPOs and acquisitions to raise external financing for its projects in a setting where insiders have private information about firm value. The advantage to a private firm of an acquisition rather than an IPO is that

[9] Note that a higher level of TFP translates into a higher optimal scale, so that the ordering of TFP between IPOs, acquisitions, and remaining private translates into a corresponding ordering for capital expenditures as well.

the insiders of the acquiring firm, given their industry expertise, are able to value it more or less correctly while IPO market investors suffer from information asymmetry in valuing it. Further, the acquiring firm may be able to help the acquired firm in product market competition, whereas it has to fend for itself in the case of an IPO. The disadvantage of an acquisition is that the entrepreneur is likely to lose his control benefits, while in an IPO he remains in control of the firm.[10] Bayar and Chemmanur (2011) also argue that the entrepreneur and the venture capitalist may disagree about whether the firm should go public or be acquired, since the venture capitalist typically has a much shorter investment horizon in the firm than the entrepreneur and the latter receives benefits of control unavailable to the venture capitalist. This theory implies that firms characterized by greater information asymmetry will choose an acquisition over an IPO (see hypothesis *H1*). It also implies that the most productive firms are likely to choose an IPO over an acquisition (see hypothesis *H3*). Further, it implies that firms that are most viable in product market competition are most likely to go public. Finally, it implies that venture backed firms are more likely to go public rather than to be acquired compared to non-venture backed firms. The last two implications yield the following testable hypotheses:

H4: Firms with the greatest existing market share in the product market are most likely to go public, those with an intermediate market share are likely to be acquired, and those with the least market share are likely to remain private.

H5: Firms that are venture backed are more likely to exit through an IPO rather than an acquisition compared to non-venture backed firms. Further, such firms are more likely to have an IPO or acquisition rather than remain private compared to non-venture backed firms.[11]

Bhattacharya and Ritter (1983) and Maksimovic and Pichler (2001) 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.[12] We can extend these

[10] It can be argued that the set of potential acquirers, which varies across industries, can also affect the choice between IPOs, acquisitions, and remaining private. Our inclusion of industry dummies in various regression specifications can control for this variation to a significant extent.

[11] The second part of this hypothesis also requires the assumption that venture capitalists contribute to the success of the firms in addition to providing financial capital: see, e.g., Chemmanur, Krishnan, and Nandy (2011) for empirical support for this assumption.

[12] The competition for market share model of Spiegel and Tookes (2007) also makes a somewhat similar assumption. However, their unique testable predictions for the exit decision are primarily for the dynamics of a

models by assuming that while the loss of confidentiality is significantly less in an acquisition compared to an IPO, an acquisition gives the private firm significantly less efficient access to additional external financing compared to an IPO. These extended theories imply that firms with the greatest value for confidentiality are likely to choose an acquisition over an IPO, *ceteris paribus*. On the other hand, those operating in industries where the cost of revealing private information to competitors is less (e.g., those operating in more concentrated industries) are likely to choose an IPO over an acquisition. These theories generate the following testable predictions.

H6: Firms operating in industries where the value of confidentiality is the least are most likely to go public; those in industries where the value of confidentiality is greater are likely to be acquired; and those in industries where the value of confidentiality is the greatest are likely to remain private.

H7: Firms operating in the most concentrated industries are most likely to go public; those operating in less concentrated industries are likely to be acquired; and those operating in the least concentrated industries are likely to remain private.

The ability to provide incentives to employees may also have an effect on a private firm's exit choice. For human capital intensive firms, a significant portion of firm value comes from workers' contribution to each division's long-run growth: since most employees are more likely to contribute to value creation in one division of a firm (and not to all divisions), ideally one would like to be able to write contracts to compensate an employee based on the stock price of the particular division he or she is employed in. This is clearly most easily done when the firm is a stand-alone firm; it is harder to do when the entrepreneurial firm is taken over and is part of a conglomerate; and is the hardest when the firm remains private (and has no traded stock price). This is because the share price of a stand-alone public firm has a higher signal-to-noise ratio than the share price of the combined firm as a whole, and the share price of a private firm is the least informative about its employees' efforts: see, e.g., Aron (1991), Bayar, Chemmanur, and Liu (2011), and He and Li (2014). The above argument leads to the following hypothesis:

H8: Firms that are most human capital intensive are most likely to go public; less human capital intensive firms are likely to be acquired; and the least human capital intensive firms are likely to remain private.

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firm's characteristics around IPOs and acquisitions. We describe these predictions in detail and develop testable hypotheses in Section 2.2.

2.2 The dynamics of firm characteristics before and after IPOs and acquisitions

Several theories have implications for the dynamics of firm characteristics around the IPO. In particular, the model of Clementi (2002) has implications for firm productivity, sales, and capital expenditures before and after the IPO. In his model, while an infusion of capital would allow the firm to bridge the gap at least partially between actual and efficient scale, going public too early in its life is not optimal, since it involves incurring the fixed costs of doing so. The optimal policy of the entrepreneur is, therefore, to wait for a large enough positive productivity shock so that the benefits of going public exceed the costs of doing so: at this point, the firm goes public and increases 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 pattern of firm productivity around the IPO (with the peak occurring roughly in the year of the IPO).[13]

We can extend the model of Clementi (2002) to develop implications for the dynamics of firm characteristics around acquisitions as well. On the one hand, being acquired by a larger firm is cheaper than going public, which involves significantly larger transactions costs. On the other hand, going public allows the private firm cheaper and more efficient access to the public capital market than getting acquired (for reasons discussed in Section 2.1). This implies that, while we can expect an inverted-U shape pattern of firm productivity around an acquisition as well, the properties of the two legs of the inverted-U will be different in an acquisition compared to an IPO. First, given that the threshold level of TFP in the Clementi (2002) setting required for an entrepreneur to exit through an acquisition is lower than in an IPO (since the exit costs are lower in the case of an acquisition), the run-up in TFP prior to the exit will be less steep in an acquisition compared to that in an IPO.[14] Second, given that the increase in scale in an acquisition is likely to be less than that in an IPO (given the imperfect access to the public

[13] The prediction that sales growth peaks around the year of IPO is also consistent with a signal-jamming equilibrium in Stein (1989).

[14] Recall that in the setting of Clementi (2002), a firm exits when the cost of remaining private (arising from maintaining a smaller scale than is optimal, due to capital constraints) exceeds the cost of exit. Further, the higher the current level of TFP of a firm, the greater its optimal scale. Then, given the lower cost of exit through an acquisition than an IPO, the threshold level of TFP at which the entrepreneur will choose to exit through an acquisition will be lower than the corresponding value for an IPO.

capital markets), the rate of fall in TFP subsequent to the acquisition is also likely to be less compared to that after an IPO.

The model of Spiegel and Tookes (2007) also has implications for the dynamic pattern of firm productivity around IPOs and acquisitions. Their model predicts that firms would implement their most productive innovations with the greatest revenue-generating ability when they are private firms due to a concern for confidentiality during the IPO process (i.e., the fear of leaking details of their innovations to competitors due to disclosure requirements when they go public), and will go to the public markets only when more modest innovations remain. This implies that firm productivity will peak around the IPO. Since, as we discussed in Section 2.1, the loss of confidentiality arising from an acquisition will be lower than that arising from an IPO, their model also implies that, while, as in the case of an IPO, there will be a drop in the firm's productivity from before to after an exit even in the case of an acquisition, this drop would be smaller for an acquisition compared to that for an IPO.

Clementi (2002) also has implications for the dynamic pattern of sales (output), capital expenditures, and employment of the firm around the IPO. As the firm experiences a series of positive productivity shocks prior to the IPO and increases its scale of operations, capital expenditures, total employment, and output increase in the years leading up to the IPO. Further, assuming that it takes time to put physical capital in place to be productive, the above model also predicts that the firm's scale of operations (capital expenditures, total employment, and output) would continue to increase for a few years after the IPO. In summary, Clementi (2002) predicts that sales and capital expenditures would increase monotonically before and after the IPO. Further, the above theory also predicts that while 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), sales growth will be much smaller subsequent to the IPO since the firm would have come closer to its optimal scale after the IPO.[15]

The Clementi (2002) model can also be extended to generate predictions for the dynamic pattern of capital expenditures, sales (outputs), and employment of the firm around an acquisition. As in an IPO,

[15] 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.

as the firm experiences positive productivity shocks prior to an acquisition and increases its scale of operations, capital expenditures, total employment, and output will increase in the years prior to the firm being acquired, though at a lower rate than in the case of an IPO (for reasons discussed earlier in the context of TFP growth around an acquisition). However, since the acquired firm is likely to have less efficient access to the capital market compared to an IPO (as it has to compete with other plants of the acquiring firm for new capital, unlike in an IPO), the increase in capital expenditures and total employment subsequent to an acquisition is likely to be less significant compared to that after an IPO. Further, since in many cases, the products of the firm being acquired may compete with those of the acquirer and any synergies from the acquisition may accrue to plants of the acquiring firm, the target firm output (sales) may either increase or decrease after an acquisition (i.e., the theory does not have clear predictions on the behavior of sales post-acquisition).

3. Data, Sample Selection, and Variable Construction

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.[16] 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 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.[17] Most of the data items reported in the LRD (e.g., the number of employees,

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

[17] 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

employee compensation, capital expenditures, and total value of shipments) are also reported to the IRS, thus increasing the accuracy of the data.

Most previous studies on firms' choice of IPO versus acquisition (see, e.g., Poulsen and Stegemoller (2008)) have two major data limitations. First, they can only obtain a small sample of private firms. For example, those studies usually collect data for private target firms acquired only by public firms (from the S-4 statements filed by the latter) and for target firms that are large enough (usually with deal value exceeding 10% or 20% of acquirers' assets). Likewise, those studies mainly rely on Compustat or individual prospectuses to gather pre-IPO information, which is quite limited (in terms of both the number of IPO firms and the number of years before their going public action). Second, previous studies do not observe private firms that could have chosen IPO or acquisitions but did not, which might cause sample selection problems.

The crucial advantage of using the LRD data relative to Compustat data in this paper is that the LRD covers both public and private firms in the manufacturing industries. The comprehensive coverage of private firms and public firms at their private stage of life enables us to examine the product market determinants of young firms' exit choice between IPOs and acquisitions.[18] Moreover, the panel format of the LRD (1972-2000) allows us to compare the dynamics of the IPO firms' and the acquired firms' performance both pre- and post- their exit years, benchmarked against their peers that choose to remain private throughout. Another advantage of using the LRD for this study is that it enables us to construct precise measures of firms' product market performance such as total factor productivity and market share, which are relative measures based on the entire sample of private and public firms available in the LRD. These measures therefore provide more precise estimates compared to those constructed relative to only the public firms that are available in Compustat. Since the LRD provides plant level information, we aggregate all plant level measures to the firm level using a sales-weighted approach.[19]

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sampled by the Census Bureau each year in the non-census years in order to minimize such a bias in the data. Since smaller establishments do not show up in our data for all years, we also repeated our analysis by confining only to firms with more than 250 employees and found similar results.

[18] Unfortunately, due to data limitations, we are unable to look at the ownership composition and capital structure of the firms while they are private.

[19] 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.

Our sample of IPOs is drawn from the Security Data Corporation's (SDC's) New Issues Database. As in most empirical studies on IPOs, we removed from our sample all IPOs related to equity carve-outs, ADRs, ADSs, global deposit receipts, global deposit shares, units, trust receipts, and trust units. We also require that the primary industry of the firm going public is within the manufacturing sector (SIC codes 2000 to 3999) and that the firm is present on Compustat for the fiscal year of the IPO. Thus, our sample of IPOs from SDC comprises 2578 firms during the years 1972 to 2000. We then 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.[20] Out of the 2578 firms, we matched 1315 firms to the LRD. This match rate is comparable to previous studies adopting the name and address matching methodology.

Our sample of U.S. private firms that are acquired comes from two sources. First, we use the Securities Data Co.'s (SDC's) Mergers and Acquisitions Database. Consistent with previous studies, we removed from our sample all deals that are reverse takeovers, spin-offs, recapitalizations, self-tenders, exchange offers, repurchases, minority stake purchases, acquisitions of remaining interest, privatizations, leveraged buyouts, reverse leveraged buyouts, and those deals whose status is identified as "incomplete" by SDC.[21] We then match this sample of private target firms to the Standard Statistical Establishment List (SSEL), which is a list of business establishments in the U.S. maintained by the U.S. Census Bureau and updated on an annual basis.[22] We employ standard matching procedures using the names and addresses of firms that are commonly used by U.S. Census Bureau researchers and those working with these databases, and focus on firms within the manufacturing sector (SIC codes 2000 to 3999).[23] This yields a positive

[20] 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.

[21] We followed previous literature such as Bayar and Chemmanur (2012) to drop LBO deals from our study. Since there are only 22 LBOs in our final estimation sample, however, adding them back does not change our results qualitatively.

[22] The SSEL is the Business Register or the "master" data set of the U.S. Census Bureau from which the LRD is constructed. The SSEL contains data from the U.S. government administrative records, such as tax returns, and is augmented with data from various Census surveys. The SSEL data is at the establishment level - an establishment is a single physical location where business is conducted. The SSEL provides names and addresses of establishments and also numerical identifiers at both the establishment level as well as the firm level, through which one can link the SSEL to the LRD. A good description of the SSEL can be found in Jarmin and Miranda (2002).

[23] See Puri and Zarutskie (2012) for more details on such name and address matching procedures.

match of 5,836 firms. We then merge this data to the LRD and keep only those firms for which we have detailed information to calculate key variables in our study such as TFP, capital stock, and sales growth at the 4-digit SIC and annual level. Last, in case a firm is a target for multiple acquisitions within a five-year period, we only consider its first acquisition. The last few steps leave us with a sample of 2,437 private firms that are acquired.

Second, we make use of the Manufacturing Plant Ownership Change Database (OCD), constructed (by the Center for Economic Studies, U. S. Bureau of the Census) by using plant-level data taken from the LRD. The OCD contains data on all manufacturing establishments that have experienced ownership change at least once during the period 1972-2000. For multi-plant firms, we make sure that all of their plants changed ownership to a same firm before including such transactions into our sample. This avoids including partial asset sales during which a multi-plant firm sells some of its plants to (possibly multiple) outside buyers. Unlike SDC, which only keeps records of relatively larger transactions, the OCD contains acquisitions for firms with all sizes, including those small entrepreneurial enterprises. The OCD yields 7240 acquisitions of manufacturing private firms in addition to what we collect from SDC. Our final sample of private firm acquisitions contains a total of 9677 transactions, which makes our paper by far the most comprehensive study of private firm exits. [24] [25]

Table 1 presents the industry distribution at the 2 digit SIC level of the firms that either went public or got acquired in our sample.[26] As can be seen from this table, our matched IPO and acquired firm samples are very much representative of U.S. IPOs and acquisitions in the manufacturing sector, with some concentration in electronics and precision instruments industries for IPOs, and some concentration in industrial machinery and food industries for acquired firms. The sectors that are excluded from our

[24] We use both SDC and OCD to identify acquisitions of private firms because each has its relative advantage. On the one hand, SDC includes only relatively larger M&A deals with detailed information such as the effective dates of the deals, whether the deals are partial asset sales, and the identity and type of the acquirers. On the other hand, OCD does not have detailed information about the acquisitions but has a comprehensive coverage of smaller deals.

[25] 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 private firms' exit choice between IPOs and acquisitions, we eliminate these public firms from our sample. Thus, the final sample in our regression analysis contains all firms remaining private throughout the years 1972 to 2000, all firms going public between 1972 and 2000, and all firms getting acquired during this time period.

[26] 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).

sample are: non-packaged software, e-commerce and Internet, and other service-oriented industries such as financials. It should be noted that a majority of high-tech industries, in which we expect to see a high rate of exits (via either IPOs or acquisitions), fall within the scope of the LRD, which uses a slightly different definition for manufacturing industries from the SIC codes. For example, most computer software and hardware companies are considered to be part of the manufacturing sector by the LRD.

Finally, to control for access to private financing before exits, we obtain data on venture capital and bank loans and merge it to the LRD. Our sample of VC financing is drawn from *VentureXpert*, maintained by Thomson Reuters, which contains round by round information for both the firms in which VCs invest as well as the VC firms themselves. Our data on bank loans is drawn from Reuters Loan Pricing Corporation's (LPC's) *DealScan* database, which is the primary source of bank loan data used by the banking literature. Since the data from *DealScan* is at the loan facility level, we first aggregate the loans for each borrower to the annual level and then merge the aggregated data to the LRD.[27]

3.1 Construction of firm specific, industry specific, information asymmetry, and control variables

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 as in Chemmanur, He, and Nandy (2010), and Chemmanur, Krishnan, and Nandy (2011). In particular, we obtain measures of *TFP* at the plant level by estimating a log-linear Cobb-Douglas production function for each industry and year where the dependent variable is plant output and independent variables include capital stock, labor input, and material input. Plant level *TFP* is then computed as the residuals of the above regression, estimated separately for each year and each four-digit SIC industry. Thus, TFP can be understood as the relative productivity rank of a plant within its industry in any given year. Finally, the *TFP* of the firm is then calculated as a weighted sum of plant *TFP* at the annual level. See Internet Appendix A for a detailed description of how we construct *TFP*.

Capital Stock is constructed via the perpetual inventory method, also discussed in detail in Appendix A. We measure firm age (*AGE*) as the natural logarithm of the number of years since the birth

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

of the firm as recorded in the Census data.[28] Sales are 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 firms. *Average Wage* is the total wage over total employment. All dollar values in the LRD are in thousands of dollars (1998 real terms) and all firm level measures are winsorized at the 1st and 99th percentile.

We define firm size (*SIZE*) as the natural logarithm of the capital stock of the firm. Capital intensity (*CAPINT*) is defined as a firm's capital stock over total employment. 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 (arithmetic mean of) annual growth in sales (in real dollars) over the past three years. 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 capture the firm's industry leader position. We define high tech (*HTEK*) companies as those with the 3 digit SIC codes 357, 366, 367, 372, 381, 382, and 384.[29] *VC* is a dummy to indicate whether for a certain year the firm is backed by venture capital, and *LOAN* is a dummy to indicate whether for a particular year the firm has bank loans as identified by *DealScan*. Private financing indicator (*FINDUM*) is a dummy to indicate if the firm is either backed by venture capitalists or financed by bank loans. White-collar salary proportion (*WHITE*) is the average proportion of total wages that is for white-collar workers in the past three years. This measure captures the human capital intensiveness of a firm.[30]

Industry risk (*INDRSK*) is the industry median of the five-year coefficient of variation of firm sales at the 3 digit SIC level. Herfindahl Index (*HI*) is calculated by summing up the square of each LRD

[28] 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 exit, is captured very well by this measure.
[29] This definition is similar to that in Loughran and Ritter (2004).
[30] Alternatively, we use the percentage of employees that are white-collar workers to proxy for the human capital intensiveness of a firm and the results are qualitatively similar.

firm's market share (in sales) at the 3 digit SIC level. The share turnover measure (*TOV*) and the number of public firms listed in CRSP (*LIST*) are industry level measures constructed from CRSP. We use the mean of the share turnover across public firms in the same 3 digit SIC industry to proxy for expected liquidity in that industry.[31] We use the number of public firms already listed in CRSP in the same 3 digit SIC industry to proxy for outsiders' ease of evaluation of firms in that industry. The more firms already listed in an industry, in general, the easier it is for outside investors to evaluate a firm in that industry. We also construct three more industry-level measures to proxy for information asymmetry, using analysts' forecasts from I/B/E/S. We use the industry average standard deviation in analysts' forecast (*STDEV*), the industry average analysts' forecast error (*FORER*), and the industry average number of analysts following (*NUMA*) at the 3 digit SIC level. The higher the standard deviation in analysts' forecasts, the higher the analysts' forecast error, and the fewer the analysts following in an industry, the greater the information asymmetry facing firms in that industry.

3.2 Summary statistics

Table 2 presents the summary statistics and univariate comparisons of firm characteristics (Panel A) and industry characteristics (Panel B) for the firms that either go public or get acquired or remain private throughout our sample period. All reported statistics are firm-year observations and for the sample of IPO or acquired firms, only the years prior to the firm's exit (IPO or acquisition) are included. Consistent with most of our hypotheses discussed in Section 2.1, these basic comparisons show a clear ordering across the three groups of firms. Panel A reveals that firms going public during our sample period are on average (more than four times) larger than firms that get acquired, which in turn are (more than three times) larger than firms that remain private, consistent with *H1*. Moreover, other firm scale variables, such as total value of shipments (*Sales*), *Total Employment*, *Total Wage*, total *Material Cost*, and total *Rental and Administrative Expenditure* all exhibit the same ordering across the three groups of firms, providing strong evidence to support *H1*.

[31] 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 or get acquired by a public acquirer. Microstructure models such as Kyle (1985) also suggest that the stock market liquidity is lower when the information asymmetry regarding the valuation of a firm's equity is greater.

The average sales growth for firms that have an IPO is 14%, which is significantly higher than the sales growth of acquired firms (8%). Firms remaining private have an average sales growth of 4%, which is the lowest among all three groups of firms. This is consistent with *H3*. Also consistent with *H3*, firms that have an IPO on average invest (nearly four times) more than firms that get acquired, which in turn has significantly higher total capital expenditures than those private firms. However, the capital expenditure ratio (*CAPR*) is highest for IPO firms, followed by firms remaining private, and then followed by firms that get acquired, thus providing only mild support to *H3*. Consistent with *H3*, the TFP of firms going public is on average 0.08, significantly higher than that of acquired firms, 0.04, which is in turn higher than the TFP of private firms, -0.01. Consistent with *H2*, firms going public have the highest capital intensity, followed by acquired firms, and then followed by private firms. Consistent with *H4*, the market share of firms going public is on average 2.48%, significantly higher than that of acquired firms, 0.56%, which is in turn higher than the market share of private firms, 0.22%. However, high tech firms are most likely to go public, then to get acquired, and then to remain private, which is surprising and inconsistent with *H6*. Hence, our results do not support the implications of confidential information theories such as Maksimovic and Pichler (2001). Consistent with *H5*, our univariate comparisons indicate that firms with private financing (venture backed firms or firms with private bank loans) are more likely to exit relative to remaining private, and to choose IPO over acquisition as a means of exit. Lastly, firms with a higher white-collar salary proportion are more likely to exit through IPOs over acquisitions, supporting *H8*. Overall, the evidence from panel A suggests that firms going public are on average more productive and efficient and perform better than their industry peers exiting through acquisitions.

Since reporting age on a firm-year basis does not reveal useful information, we compare the age of IPO firms and acquired firms in the year of their exit. Our un-tabulated results show that the age of IPO firms is on average 6.66 years at the time of their going public, slightly lower than that of acquired firms at the time of acquisition, 7.12 years, with a p-value of 0.09 in a two-sample t-test.

Panel B of Table 2 summarizes and compares the industry characteristics for firms that go public, get acquired, or remain private in our sample. Partly consistent with *H1*, we find that the industries of IPO firms are most likely to be characterized by the least information asymmetry (the greatest number of already public firms, the greatest number of analyst following, the smallest analyst forecast error, the smallest standard deviation in analyst's forecast) and the largest average stock liquidity (for a value of 0.58). The industries of acquired firms are characterized by intermediate levels of information asymmetry (in terms of the number of already listed firms and the number of analysts following). The industries of firms remaining private are characterized by the greatest extent of information asymmetry (in terms of the number of already listed firms and the number of analysts following). However, the industries of acquired firms have smaller average stock liquidity than those of firms remaining private. Consistent with *H7,* we find that the industries of IPO firms are the most concentrated (having the largest Herfindahl Index), the industries of acquired firms are less concentrated, and the industries of firms remaining private are the least concentrated. Finally, partially inconsistent with *H2*, the industries of firms remaining private have the greatest cash flow risk, the industries of IPO firms have the intermediate cash flow risk, and the industries of firms getting acquired have the smallest cash flow risk. Overall, the univariate comparisons in panel B support most (but not all) of our theoretical arguments and hypotheses.

4. Product Market Characteristics and the Decision to Exit through IPOs vs. Acquisitions

In this section, we use LRD to analyze how product market characteristics affect private firms' exit decision. Following the hypotheses developed in Section 2.1, we estimate the following dynamic multinomial logit model.[32]

$$EXIT_{i,j,t} = F\,(\beta_1 SIZE_{i,t-1} + \beta_2 TFP_{i,t-1} + \beta_3 SGTH_{i,t-1} + \beta_4 CAPR_{i,t-1} + \beta_5 WHITE_{i,t-1} + \beta_6 MSHR_{i,t-1} + \beta_7 AGE_{i,t-1} + \beta_8 HTEK_{i,t-1} + \beta_9 CAPINT_{i,t-1} + \beta_{10} TOV_{j,t-1} + \beta_{11} INDRSK_{j,t-1} + \beta_{12} HI_{j,t-1} + \beta_{13} LIST_{j,t-1} + \beta_{14} NUMA_{j,t-1} + \beta_{15} FORER_{j,t-1} + \beta_{16} STDEV_{j,t-1} + \beta_{17} FINDUM_{i,t-1} + \beta_{18} SP500_{t-1}\,) + \varepsilon_{i,j,t} \quad (1)$$

, where *i* indexes firm, *j* indexes industry, and *t* indexes time. *EXIT* is a categorical variable with three values: it equals 0 if the firm is private (the base category); it equals 1 if the firm goes public in year *t*;

[32] We believe a multinomial logit model is the most appropriate to analyze firms' choice of going public, getting acquired, or remaining private. A nested logit/probit model that treats firms' decision to be non-private as the first layer of choice and the specific exit decision (via IPO or acquisition) as the second layer is not feasible because we do not have exit-choice-specific information such as how much it will cost a given firm to go public versus getting acquired. An ordered logit/probit model is too restrictive because it imposes the *proportional odds assumption*, which requires that the relationship between any two pairs of exit choices be statistically the same. But this assumption seems too strong and does not obviously hold. A simple logit/probit model that only considers the IPO vs. acquisition choice also makes a strong assumption that the choice to remain private does not affect the relative probabilities that either IPO or acquisition is chosen, which does not seem true. That's why we choose to adopt the multinomial logit model. However, to make our results comparable to those of previous literature, we also conduct a simple logit analysis where the independent variable is 1 if the firm goes public and 0 if the firm is acquired (by using only the data for IPO and acquired firms one year prior to the exit), and find similar (even stronger) results.

and it equals 2 if the firm gets acquired in year *t*.[33] It is a well-known fact that both the IPO and the M&A markets exhibit cyclical patterns over time. To control for this time varying effect of market conditions, we use calendar year dummies. Many theoretical and empirical papers argue that this cyclical pattern is partly due to overall market performance. Hence, in alternate specifications, we use *SP500*, the annual return on Standard & Poor's 500 Index, as a control. Since our calendar year dummies already capture the annual stock market performance component, we do not use *SP500* when using year dummies.[34] 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, the firms which go public (have an IPO) in that year, and the firms which get acquired in that year. After a firm goes public or gets acquired, it is dropped from the sample.[35]

Figure 1 summarizes the theoretical hypotheses developed in Section 2.1 and gives predictions for the signs and relative magnitudes of the related variables (for the IPO vs. acquisition columns) in the multinomial logit model.

Figure 1: Summary of Hypotheses and Predictions

Hypotheses [Related Theories]	Variables	Predicted Signs for the Coef.		
		IPO	*ACQ*	*IPO - ACQ*
H1 [Chemmanur and Fulghieri (1999); Bayar and Chemmanur (2011)]	*SIZE*	(+)	(+)	(+)
	TOV	(+)	(+)	(+)
	LIST	(+)	(+)	(+)
	NUMA	(+)	(+)	(+)
	FORER	(-)	(-)	(-)
	STDEV	(-)	(-)	(-)
H2 [Chemmanur and Fulghieri (1999)]	*CAPINT*	(+)	(+)	(+)
	INDRSK	(+)	(+)	(+)
H3 [Clementi (2002); Stein (1997)]	*TFP*	(+)	(+)	(+)
	SGTH	(+)	(+)	(+)
	CAPR	(+)	(+)	(+)
H4 [Bayar and Chemmanur (2011)]	*MSHR*	(+)	(+)	(+)

[33] Note that for firms which remain private throughout our sample, this variable is always equal to zero. Moreover, although we present results by using the effective year of the acquisition to define *EXIT*, we also defined the acquisition by using the announcement year. The results are qualitatively similar.
[34] In un-tabulated analysis, we also use industry-level public market (IPO) and private market (takeover) multiples (such as P/E ratios) as proxies for market conditions, and find that controlling for these multiples does not change the coefficients on other variables qualitatively.
[35] For firms that both have IPO and are acquired firms, we only analyze their first exits.

H5 [Bayar and Chemmanur (2011)]	*FINDUM*	(+)	(+)	(+)
H6 [Bhattacharya and Ritter (1983); Maksimovic and Pichler (2001)]	*HTEK*	(-)	(-)	(-)
H7 [Bhattacharya and Ritter (1983); Maksimovic and Pichler (2001)]	*HI*	(+)	(+)	(+)
H8 [Aron (1991); He and Li (2014) Bayar, Chemmanur, Liu (2011)]	*WHITE*	(+)	(+)	(+)

From Table 3, we can see that all the firm specific product market variables are significant determinants of a firm's choice of exit between IPOs and acquisitions. Consistent with *H1*, firm size (*SIZE*) has a positive effect on the probability of choosing IPOs or acquisitions over remaining private, and has a positive effect on the probability of choosing IPOs over acquisitions: the coefficient on *SIZE* is positive and significant at the 1% level for both the IPO and acquisition regressions in all specifications; moreover, the coefficient on *SIZE* in the IPO regression is much higher than that in the acquisition regression, and a Wald test of the equality of the two coefficients also shows significance at 1% level in all specifications.

Consistent with *H3*, total factor productivity (*TFP)* has a positive effect on the probability of choosing IPOs over acquisitions over remaining private: the coefficient on *TFP* is positive and significant at the 1% level for both the IPO and acquisition regressions in all specifications. Further, the coefficient on *TFP* in the IPO regression is significantly higher than that in the acquisition regression in all specifications. Also consistent with *H3*, sales growth (*SGTH)* has significantly positive effects on the probability of choosing IPOs over acquisitions over remaining private. Capital expenditure ratio (*CAPR)* has a significantly positive effect on the probability of choosing IPO over the other two exit alternatives, but the coefficient on *CAPR* is not significantly different for the choice of being acquired and the choice of remaining private.

Consistent with *H8*, white-collar salary proportion (*WHITE)* has a significantly positive effect on the probability of choosing IPOs over acquisitions over remaining private. Partly consistent with *H4*, market share (*MSHR)* is significantly positively related to the decision to choose IPOs over acquisitions or remaining private. However, the coefficient on *MSHR* for the choice of acquisitions is only insignificantly positive when capital intensity (*CAPINT*) (rather than firm size) is used as a control. Once we control for firm size, the coefficient on *MSHR* for the choice of acquisitions becomes significantly negative.[36] We also find that firm age (*AGE*) reduces a firm's probability of exit through an IPO but increases its probability of an acquisition.

Whether a firm belongs to the high tech industry in a given year (*HTEK*) is significantly positively related to the probability of IPOs or acquisitions relative to remaining private, and the coefficient on *HTEK* for IPOs is significantly higher than that for acquisitions at 1% level all the time, contradicting *H6*. This result suggests that high-tech firms have a higher probability of going public than getting acquired than remaining private, which is inconsistent with the implications of confidential information theories such as Maksimovic and Pichler (2001).[37]

Regression 3 and 4 show the effect of capital intensity (*CAPINT)*. Due to a multi-collinearity problem between *SIZE* and *CAPINT*, we do not include *SIZE* as a control in these regressions. Partially consistent with *H2*, the estimate on *CAPINT* is positive and significant for both the IPO regression and the acquisition regression. However, the difference between IPO and acquisition is statistically insignificant, and the coefficient on *CAPINT* is larger for the acquisition than for the IPO regression.

Partially consistent with *H5*, our indicators for private funding (*FINDUM)* are positive and significant in all specifications for the IPO regression and the coefficients are significantly higher than for the acquisition regression at 1% level, implying that firms that receive private funding (either venture capital or bank loans) are more likely to go public relative to getting acquired or remaining private.[38] The coefficients on *FINDUM* for the acquisition regression are insignificantly positive or even significantly negative, indicating that firms that receive private funding have a similar (or lower) probability to get acquired than to remain private, which is partially inconsistent with *H5*. In sum, the evidence suggests that access to private funding enables firms to build up more capital stock and thus allow them to grow faster, thereby increasing their probability of exiting via an IPO. However, even though access to private

[36] To evaluate the potential collinearity effect that market share (*MSHR*) has on the coefficients of other explanatory variables, we dropped *MSHR* in all our specifications and found that our results are similar.
[37] One caveat to this result is that our high-tech industries are all within the manufacturing sector. Recall that, service oriented high tech industries, such as internet firms, are not included in our sample.
[38] We also use a VC-backing dummy or a bank loan dummy to replace *FINDUM* and find similar results.

funding is an important determinant of the exit choice, it is crucial to note that, even after directly controlling for it, the various firm specific, industry specific, and information asymmetry variables arising from our theoretical hypotheses continue to be significant determinants of firms' exiting decisions (we discuss our results on the effects of industry and information asymmetry variables on the exit decision below). Dropping this potential endogenous variable (as in the first two specifications) also does not change our results qualitatively. Moreover, in the next section, we will use the endogenous switching model to better control for the endogeneity of private financing and to evaluate the effect of receiving such funding on the exit choice.

Consistent with *H1*, industry turnover (*TOV)* has a positive effect on the probability of choosing IPOs over acquisitions over remaining private: the coefficient on *TOV* is positive and significant for both the IPO and acquisition regressions in all specifications and the coefficient on *TOV* in the IPO regression is significantly higher than that in the acquisition regression (at 1% for four out of five specifications and at 5% for the remaining one). Partially consistent with *H7*, we find that industry concentration (*HI*) only has a significantly positive effect on the probability of choosing acquisitions over remaining private, whereas the coefficient on *HI* in the IPO regression is insignificantly positive, though its magnitude is larger than that in the acquisition regression. Finally, industry risk (*INDRSK*) has no clear effect on firms' exit decisions.

The regressions in Table 3 also include industry-level information asymmetry variables.[39] The number of publicly listed firms in an industry (*LIST)*, which proxies for outsiders' ease of evaluation of firms, has a positive and significant coefficient in both IPO and acquisition regressions, and the coefficient on *LIST* in the IPO regression is significantly higher than that in the acquisition regression (at 1% level). This is consistent with *H1*, suggesting that firms operating in industries that are easier for outside investors to evaluate are more likely to go public than to be acquired. Also consistent with *H1*, the industry average number of analysts following *(NUMA)* has a positive effect on the probability of choosing IPOs over acquisitions over remaining private. This implies that the greater the information

[39] The information asymmetry proxies (except *LIST*) are constructed from I/B/E/S and start only from 1976. Therefore, our regressions that use these information asymmetry measures are based on the sample between 1976 and 2000.

asymmetry facing firms in an industry, the less likely they are to choose IPOs over acquisitions in the case of exit. Partial support for *H1* also comes from our results based on the industry average standard deviation in analysts' forecasts (*STDEV*) and the industry average analysts' forecast errors (*FORER)*: the coefficient on *STDEV* or *FORER* is negative and significant for the IPO regressions but is insignificant in the acquisition regression.

The second specification of Table 3 uses the *SP500* variable to control for market fluctuations instead of year dummies. The coefficient on *SP500* is positive and significant in the IPO regression but negative and significant in the acquisition regression, implying that firms are more (less) likely to exit via IPOs (acquisitions) if the stock market has achieved a higher level of return.

In summary, our regression results in Table 3 are generally consistent with the hypotheses presented in Section 2.1. We find that largest firms, those with highest total factor productivity, highest growth in output (sales), those with highest capital expenditure ratios, highest white-collar salary proportion, and those with highest market share, are likely to go public. Those firms with intermediate values of the above variables are likely to get acquired, and those firms with the lowest values of the above variables are likely to remain private. Further, firms that operate in industries characterized by highest stock liquidity and by the least information asymmetry are likely to go public, firms that operate in industries characterized by intermediate values of the above variables are likely to get acquired, and firms that operate in industries characterized by the lowest values of the above variables are likely to remain private. We also directly control for the effect of private funding (VC financing or bank loans) and demonstrate that, while access to private funding is an important factor that affects a firm's exit choice, it does not negate the effects of the various firm specific, industry, and information asymmetry variables as important determinants of the exit decision. These variables continue to be significant even after directly controlling for the access to private funding.

5. Robustness Tests: Propensity Score Matching and Endogenous Switching Model

5.1 Propensity score matching

To alleviate the concern that our above analysis may have included many small and poorly-run family businesses which have no intention (or ability) to exit successfully and compared them with higher-quality firms capable of a successful exit, we have used a propensity score matching algorithm to match across the three groups of firms (i.e., IPO firms, acquired firms, and firms remaining private throughout) along a set of important observable dimensions and follow them over time to see how changes in their product market characteristics relate to their exit outcomes. One key advantage of this approach is that we can now focus on the exit choice of a subset of private firms with similar observable quality several years prior to the exit event, which largely reduces the potential sampling bias. We use the propensity score matching methodology here to ensure that, several years before the exit, firms belonging to all three categories, namely, those that choose to exit through an IPO, an acquisition, or to remain private are truly similar in all observable dimensions. In other words, our propensity score matching method can be thought of as an extension to the simple two-dimensional characteristic matching of firms on size and industry.

Our propensity score matching procedures are similar to those adopted in Lemmon and Roberts (2010). However, in our case, we need to match three groups of firms on their propensities of exit, so we perform two separate sets of propensity score matching.[40] We first adopt a one-to-five nearest neighbor matching algorithm to match IPO firms and acquired firms at three years before the exit event (an IPO or an acquisition) on all available firm specific characteristics in our sample as well as on year and industry (2-digit SIC code) dummies.[41] More specifically, we take IPO firms and acquired firms at three years before their exit and run a probit regression of a dummy variable that equals 1 if the firm is an IPO firm and 0 if it is an acquired firm on all the control variables mentioned above. The results are presented in the first column of Panel A in Table 4, labeled “Pre-Match” under the matching “IPO and ACQ.” The results suggest that the specification has substantial explanatory power for the choice variable, as evidenced by a pseudo-R^2 of 28.1% and an extremely small p-value for a likelihood ratio test of the overall model fitness (well below 0.01). We then use the predicted probabilities, or propensity scores, from this probit estimation and perform a nearest-neighbor match with replacement. Since the number of

[40] We currently match IPO firms to acquired firms and then match acquired firms to firms remaining private. In un-tabulated analysis, we also match IPO firms simultaneously to both the acquired firms and those remaining private, and obtain qualitatively similar results.

[41] Matching IPO firms and acquired firms at five (instead of three) years before their exit yields similar (but weaker) results due to loss of observations.

potential control firms (acquired firms) is considerably larger than the number of treatment firms (IPO firms), we choose to find 5 controls for each treatment. This will allow us to avoid relying on too little information or including vastly different observations. However, our results are robust to any number of matches between 3 and 8. [42]

The second column of Table 4 Panel A under the matching “IPO and ACQ” shows the accuracy of the matching process. We repeat the same probit regression restricted to the matched sample, and label it “Post-Match.” None of the determinants are statistically significant. Further, if we compare the magnitudes of the coefficient estimates across the two columns, they decline significantly from the Pre-Match estimation to the Post-Match estimation, suggesting that our findings are not simply an artifact of a decline in the degree of freedom due to the drop in the sample size.[43] Finally, the pesudo-R^2 drops dramatically from 28.1% prior to the matching to 2.4% post-matching, and a likelihood ratio test for model fitness shows that we cannot reject the null hypothesis that all the coefficient estimates are zero (with a p-value close to 1).[44] In summary, the matching process has removed any meaningful observable differences from these two groups of firms.

We then take the matched acquired firms at three years before their exits and adopt a one-to-ten nearest neighbor propensity score matching algorithm to match them to firms that remain private throughout our sample on the same set of variables. Again, the matches are extremely accurate.[45] Our

[42] Following Lemmon and Roberts (2010), we match with replacement to improve the accuracy of our match. We also require that successful matches fall in the common support of estimated propensity scores. However, our results are robust to removing either of these two constraints.

[43] In addition, none of the year dummies and industry dummies is statistically significant in the Post-match probit regression whereas almost all of them are statistically significant in the Pre-Match regression. We do not report these findings to save space.

[44] The accuracy of the matching process can also be seen in the un-tabulated distribution of the estimated propensity scores. In fact, the majority of differences in the estimated propensity scores between the treatment (IPO) firms and their corresponding matches from the control group (acquired firms) are trivial: the maximal difference between the matched propensity scores is less than 0.01 across all five groups of matches (while the mean propensity score for the treatment and control firms is 0.187).

[45] For example, although all the matching product market variables are significant in the pre-match regression (under the matching “ACQ and PRV”), none of them are statistically significant in the post-match column. The pesudo-R^2 drops dramatically from 15.8% prior to the matching to 0.4% post the matching, and a likelihood ratio test for model fitness post the matching shows that we cannot reject the null hypothesis that all the coefficient estimates are zero (with a p-value close to 1). Moreover, the maximal difference between the matched propensity scores is less than 0.005 across all ten groups of matches.

final sample of propensity-score matched firms includes 236 IPO firms, 759 acquired firms, and 4763 firms remaining private.[46]

After the two sets of matches are done, we drop all observations before the matching year, i.e., only retain IPO and acquired firms from three years before their exits until their exit year, and only retain private firms from the year they are matched to the acquired firms. Panel B of Table 4 reports the results from a multinomial logit regression (in the same fashion of Table 3) only on the sample of propensity-score-matched firms. Most of our results in Table 3 (when we use the universe of private firms in the LRD) still hold when we focus on the group of propensity-score-matched firms. In particular, larger firms with higher total factor productivity, higher sales growth, higher capital expenditure ratios, larger market share, and more access to private funding (venture capital or bank loans) are more likely to go public than to get acquired. IPO firms still have a higher white-collar salary proportion than acquired firms, though the difference is not statistically significant. Further, firms that operate in industries characterized by a higher stock liquidity, a higher number of already listed firms, and lower information asymmetry are more likely to go public than to get acquired.

Overall, this robustness test shows that our baseline results in Section 4 are not driven by the fact that our sample includes small and low-quality firms that may not be capable of successfully exiting through an IPO or acquisition.

5.2 Endogenous switching model

In this subsection, we study whether our observed access to private funding may be capturing unobserved firm quality that directly affects the exit decision. For instance, higher quality firms are more likely to obtain funding from venture capitalists or banks, while at the same time more likely to go public (i.e., taking the more "successful" exit route) than to get acquired. Hence, to address this endogeneity concern, we have adopted a two-step Heckman-type (Heckman (1979)) endogenous switching model.

[46] In un-tabulated analysis, we also conduct univariate t-tests on the matching variables before and after the matching, and find that while almost all the matching variables are statistically different between the two groups (IPO vs. acquired, and acquired vs. private) prior to the matching, none of them have significant difference post the matching. These summary statistics of the matched firms can be provided to interested readers upon request.

Due to space limitations, we leave details of this robustness test and the corresponding tables to an Internet Appendix B (not to be published).

The results of our switching regression analysis show that private financiers such as VCs and banks rely on some unobservable criteria when they select firms to invest in, and these factors (that they condition the selection on) positively affect the more "desirable" exit choice (IPOs relative to acquisitions relative to remaining private) of firms receiving such financing. We also find that most of our baseline results in Section 4 hold after controlling for this selection effect: for both firms with and without private funding, larger firms with higher total factor productivity, higher sales growth, higher capital expenditure ratios, higher white-collar salary proportion, and in the high tech industries are more likely to go public than get acquired, and more likely to get acquired than remain private. Further, with or without private funding, firms operating in industries characterized by higher stock liquidity, higher industry concentration, and lower information asymmetry are more likely to go public than get acquired, and more likely to get acquired than remain private. We also perform a counterfactual analysis of privately-financed and non-privately-financed firms and find that, on average, firms with *actual* private funding are twice more likely to have a "preferred" outcome exit (i.e., IPO over acquisition over remaining private) than what the same firms would have achieved *had they not* received private financing, suggesting a monitoring (and advising) role rather than a selection (screening) role for private financiers (VCs and banks) in the exit decision.

In summary, we find that the various firm-specific, industry-specific, and information asymmetry variables affect the exit decision in a similar manner to that of our baseline findings even after explicitly accounting for the endogenous nature of private financing using a Heckman style switching model.

6. Dynamics of Firm Characteristics Before and After IPOs and Acquisitions

In this section, we analyze and compare the dynamic patterns of various firm specific product market characteristics five years before and after the dates of IPOs and acquisitions. The results are robust to 7-year and 3-year windows as well. In all specifications, we use the firms that remained private throughout our sample period as a benchmark.

As discussed in Section 2.2, various theories provide interesting implications for the dynamics of firm characteristics around IPOs and acquisitions. To study these firm dynamics, we employ a regression framework similar to that adopted in Chemmanur, He, and Nandy (2010):

$$Y_{it} = \alpha_i + \beta_t + \gamma X_{it} + \sum_{s=1}^{5} \delta_s BeforeExit_{it}^{s} + \sum_{s=1}^{5} \lambda_s AfterExit_{it}^{s} + \varepsilon_{it} \qquad (2)$$

, where Y_{it} is the variable of interest (e.g., *TFP*, sales, capital expenditures, etc.); X_{it} is a control for firm size (*SIZE*), which is time varying; $BeforeExit^{s}_{it}$ is a dummy variable equal to 1 if the firm goes public (or gets acquired) s years prior to the IPO (or the acquisition), where s = 1, 2, 3, 4, or 5 years; $AfterExit^{s}_{it}$ is a dummy variable equal to 1 if the firm goes public (or gets acquired) s years after the IPO (or the acquisition); i indexes firms, t indexes years, and α_i are firm fixed effects. Note that the benchmark (or control sample) in our analysis is the set of firms that remained private throughout. For such firms, the $BeforeExit^{s}_{it}$ and $AfterExit^{s}_{it}$ variables are always 0. As IPOs and acquisitions in our sample are spread over time, the specification also incorporates calendar-year dummies. Since the specification is estimated with firm fixed effects, we cluster the standard errors at the firm level as suggested by Petersen (2008).[47]

The dynamic pattern of the effect of an IPO (or an acquisition) on the variables of interest is captured by the coefficients δ_s and λ_s. To compare the dynamic pattern of a firm characteristic for an IPO firm and an acquired firm either before or after the event year, we also conduct (un-tabulated) Wald tests of $\sum_{s=1}^{5}\delta_s \,|_{IPO} = \sum_{s=1}^{5}\delta_s \,|_{Acq}$ and $\sum_{s=1}^{5}\lambda_s \,|_{IPO} = \sum_{s=1}^{5}\lambda_s \,|_{Acq}$, which test the combined change for a variable in all the years before (after) the event year relative to the control group for IPO versus acquisitions. In order to perform this joint test across equations, we first run a seemingly unrelated regression (SUR) with two

[47] The above specification corresponds to a difference-in-differences estimation strategy that has been used previously by Bertrand and Mullianathan (2003) and Schoar (2002), among others, to study firm performance around different events. In this specification, since the sample of IPOs and acquisitions are dispersed over time, the year fixed effects accounts for variations over time associated with market movements that may influence IPOs or acquisitions, such as IPO waves or merger waves. The *Before* and *After* year dummies in the specification, on the other hand, are event-time dummies around the exit year, which capture residual changes in the dependent variables around the IPO or acquisition after accounting for the calendar-time and firm fixed effects. In all the specifications, our base year is the exit year (year 0). Thus, the coefficients δ_s and λ_s reflect the deviations of the variables of interest with respect to the year of exit.

equations (for IPO and acquisition) for each product market variable and then compare the sum of δ_s or λ_s for the two forms of exits.[48]

We first examine the dynamic patterns of *TFP*, sales growth, and firm size over the five years before and after the exit event (IPO or acquisition). Table 5 presents the regression results. Consistent with Clementi (2002) and our predictions in Section 2.2, the *TFP* of both firms going public and firms getting acquired exhibit an inverted-U shape, which increases before the exit, reaches its peak at the exit year, and subsequently declines. Compared to the IPO year, the coefficients on all the *BeforeIPO* and *AfterIPO* dummies are negative, with the coefficients on $BeforeIPO^5$, $BeforeIPO^4$, $BeforeIPO^3$, $BeforeIPO^2$, and $BeforeIPO^1$ being significant, and the coefficients on $AfterIPO^3$, $AfterIPO^4$, and $AfterIPO^5$ being significant. The changes in *TFP* in the years prior to going public are also economically significant. The increase in *TFP* over the four years prior to going public (i.e., from year -5 to -1), of 5.8% translates to an increase in profits of roughly 29%.[49] Similarly, the decrease in TFP after going public (from the year of the IPO to four years after) of 4.6% corresponds to a decrease of 23% in profits. A similar, though weaker, pattern of TFP can also be seen for firms that are acquired. Compared to the acquisition year, the coefficients on most of the *BeforeACQ* and *AfterACQ* dummies are negative, with the coefficient on $BeforeACQ^5$, $AfterACQ^4$ and $AfterACQ^5$ being significant.[50] The un-tabulated Wald test of $\sum_{s=1}^{5}\delta_s|_{IPO}=\sum_{s=1}^{5}\delta_s|_{Acq}$ has a p-value of 0.00. The results of these comparisons are consistent with our hypothesis in Section 2.2 that the run-up in TFP prior to the exit will be less steep in an acquisition compared to that in an IPO. Finally, though the Wald test of $\sum_{s=1}^{5}\lambda_s|_{IPO}=\sum_{s=1}^{5}\lambda_s|_{Acq}$ does not show statistical significance, the p-value is 0.17 and we can still observe that the coefficients of $AfterIPO^s_{it}$ are

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[48] We have also jointly estimated the dynamic regressions for each variable for IPOs and acquisitions (i.e., including IPO firms, acquired firms, and firms remaining private in a single regression), and the results are similar (and available upon request). We show individual (separate) estimates for the dynamic patterns around IPOs and acquisitions (by benchmarking against firms remaining private) for ease of interpretation.

[49] 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.

[50] The changes in *TFP* in the years prior to being acquired are also economically significant. The increase in *TFP* over the four years prior to being acquired (i.e., from year -5 to -1), of 3.3% translates to an increase in profits of roughly 16.5%. Similarly, the decrease in *TFP* after being acquired (from the year of the acquisition to four years after) of 2.3% corresponds to a decrease of 11.5% in profits.

much more negative than $AfterACQ^{s}_{it}$, weakly supporting the hypothesis that the rate of fall in TFP subsequent to the acquisition is less compared to that after an IPO.

Table 5 also presents the results of sales growth, which show that almost all the *BeforeIPO* and *AfterIPO* coefficients are negative, implying that sales growth, like *TFP*, also reaches a peak in the year of the IPO. Other than the one year immediately before and after the IPO, the coefficients on all the other years are significant. Thus, we find that the sales growth of IPO firms exhibits an inverted-U shape. In contrast, we observe a weak inverted-U pattern for the sales growth of firms that are acquired not around the exit year, but two years before the exit. Two of the *BeforeACQ* coefficients are significantly positive, and the last two coefficients for *AfterACQ* are negative and significant. Moreover, both the test of $\sum_{s=1}^{5}\delta_s \mid_{IPO} = \sum_{s=1}^{5}\delta_s \mid_{Acq}$ and the test of $\sum_{s=1}^{5}\lambda_s \mid_{IPO} = \sum_{s=1}^{5}\lambda_s \mid_{Acq}$ show a p-value of 0.00. These findings are also consistent with our earlier cross-sectional results: unlike IPO firms, acquired firms typically experience a decline in their sales growth *before* their exit year, which may be part of the reason that these firms sell themselves to potential buyers who can help them in the product market (see Bayar and Chemmanur (2011) for a theoretical argument on how acquirers enhance the product market competitiveness of acquired firms after the acquisitions). In general, the dynamic patterns for sales growth seem to be consistent with that for *TFP*, indicating that acquired firms tend to experience less steep increases before and less steep decreases after the exit year in production efficiency compared to firms that go public.

Last, Table 5 presents the results of firm size (*SIZE*). We find that the coefficients on *SIZE* keep increasing throughout the years around the IPO or the acquisition. For IPO firms, all the coefficients on the *BeforeIPO* dummies are negative and significant at the 1% level, while all the coefficients on the *AfterIPO* dummies are positive and significant at the 1% level. This implies that the size of IPO firms is growing over the years around the IPO compared to their private peers. The analysis of *SIZE* for firms that are acquired shows a similar increasing pattern. However, the rate of change for coefficients on the *Before* dummies and *After* dummies seem to be greater for IPO firms than for firms that are acquired:

both the test of $\sum_{s=1}^{5}\delta_s |_{IPO} = \sum_{s=1}^{5}\delta_s |_{Acq}$ and the test of $\sum_{s=1}^{5}\lambda_s |_{IPO} = \sum_{s=1}^{5}\lambda_s |_{Acq}$ show a p-value less than 0.05. Overall, the results for firm size suggest that while both sets of firms experience an increase in size around their exits (either IPOs or acquisitions), IPO firms seem to grow faster (in terms of capital stock) than firms that are acquired both before and after the exit years.

In Table 6, we examine the dynamic patterns of sales, capital expenditure, and total employment. As hypothesized in Section 2.2, the coefficients on sales keep increasing throughout the years around the IPO: all the coefficients on the *BeforeIPO* dummies are negative and significant at the 1% level, while all the coefficients on the *AfterIPO* dummies are positive and significant at the 1% level. This implies that the sales of IPO firms are growing over the years around the IPO compared to their private peers. In contrast, the sales for acquired firms exhibit a weak inverted-U pattern. Almost all the coefficients on the *BeforeACQ* and *AfterACQ* dummies are negative (except for $AfterACQ^2_{it}$) and the coefficients on the $BeforeACQ^5$, $BeforeACQ^4$, $AfterACQ^5$, and $AfterACQ^4$ are significant at 1% level. Further, both the test of $\sum_{s=1}^{5}\delta_s |_{IPO} = \sum_{s=1}^{5}\delta_s |_{Acq}$ and the test of $\sum_{s=1}^{5}\lambda_s |_{IPO} = \sum_{s=1}^{5}\lambda_s |_{Acq}$ show a p-value of less than 0.01. These comparisons indicate that although both acquired firms and IPO firms have an increase in their output (sales) before their exit, the rate of increase in sales for the former is smaller than that for the latter. As discussed in Section 2.2, we are agnostic about the dynamic pattern for sales after the acquisition due to two countervailing forces: increased access to capital via the acquisition and possible competition for resources among different divisions within the combined (acquiring) firm. The decrease in sales after the acquisition seems to indicate that the latter force, namely, the internal competition within the combined firm, seems to dominate the positive impact an acquisition might exert on the output (sales) of the acquired firm. A caveat for the above interpretation of our results is that when we conduct the dynamics analysis, we controlled for firm size. This means that when we see sales go down after acquisitions, we are only showing that it does not increase in proportion to size (recall that firm size also increases before and after an acquisition). The results on the dynamic pattern of sales are also consistent with the cross-sectional results: since the most productive assets are taken public, it is not surprising that these acquired assets do not show increasing sales in proportion to the increase in their size.

The analysis of capital expenditures in Table 6 also shows an increasing pattern for IPO firms. Moreover, the coefficients on the *AfterIPO* dummies quickly reach the peak (after one or two years of IPO) and then remain steady at this high level or slightly decline, implying that IPO firms act fast enough to adjust their capital expenditures to the optimal level when their capital constraint is lifted. In contrast, there is no clear increasing pattern for the capital expenditures of firms that are acquired. The tests of the difference between coefficients on *BeforeExit* and *AfterExit* both show significance at 1% level. These results are in general consistent with our hypotheses about the dynamic patterns of capital expenditures for IPO firms and firms that are acquired (as outlined in Section 2.2).

The analysis of total employment shows that it increases over the years around the IPO. These results are consistent with Clementi's (2002) theoretical argument that the firm's scale of operations increases from before the IPO to after, which therefore leads to the continued increase in employment. In contrast, there is only a weak pattern of increase in total employment before acquisitions, and it tends to decrease in magnitude after the firms are acquired. The weak inverted-U pattern of total employment is consistent with that of sales for the acquired firms, implying that the internal competition for resources and capital within the combined firm actually results in a downscale of plants after they are acquired (and possibly an increase in the scale of acquirers' existing plants prior to the transaction).

In conclusion, our results on the dynamic pattern of firm characteristics are largely consistent with the predictions of various theories discussed in Section 2.2. *TFP* displays an inverted-U shape for both IPO firms and acquired firms, implying that it reaches its peak in the exit year, consistent with the predictions of Clementi (2002) and Spiegel and Tookes (2007). Moreover, the rate of changes for *TFP* before and after the exit year is more significant for IPO firms than for acquired firms. Sales growth exhibits a similar (inverted-U) pattern for IPO firms and for acquired firms, though the peak of the inverted-U pattern for the latter group occurs two years before the exit. While sales, capital expenditures, and total employment associated with the product and labor markets show gradually increasing patterns from 5 years before to 5 years after the IPO, these variables show either inverted-U patterns or no patterns from 5 years before to 5 years after the acquisition (after controlling for size and benchmarked against firms remaining private throughout).

7. Conclusion

In this paper, we made use of the Longitudinal Research Database (LRD) and the Ownership Change Database (OCD) of the U.S. Census Bureau to analyze the relationship between an entrepreneurial firm's product market characteristics and its exit decision. Our empirical results show that total factor productivity (*TFP*), size, sales growth, market share, capital expenditure ratio, human capital intensiveness, and access to private funding (venture capital or bank loans) significantly increase a private firm's likelihood of an IPO relative to an acquisition. Moreover, firms operating in industries with less information asymmetry and higher stock liquidity are also more likely to exit through an IPO relative to an acquisition. Our analysis of the dynamics of private firm characteristics around exit indicates that, while both forms of exit occur at the peak of a firm's productivity cycle, the rate of change of *TFP* before and after the exit year is more significant for IPO firms than for firms that are acquired.

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Table 1: Industry Distribution of the IPO and Acquired Firms: This table presents the 2 digit level SIC industry distribution of the sample of manufacturing firms in the LRD that either went public or got acquired during the period of 1972 to 2000. ND stands for Not Disclosed to comply with the U.S. Census Bureau's disclosure criteria.

2 Digit SIC	Industry Name	Number of IPO Firms	Number of Acquired Firms
20	Food and kindred products	50	1178
21	Tobacco products	ND	ND
22	Textile mill products	34	357
23	Apparel and other textile products	37	452
24	Lumber and wood products	27	422
25	Furniture and fixtures	24	274
26	Paper and allied products	24	275
27	Printing and publishing	43	841
28	Chemicals and allied products (Biotech)	83	505
29	Petroleum and coal products	ND	95
30	Rubber and miscellaneous plastics products	47	517
31	Leather and leather products	ND	95
32	Stone, clay, and glass products	34	410
33	Primary metal industries	110	418
34	Fabricated metal products	47	906
35	Industrial machinery and equipment (Computers)	201	1115
36	Electronic and other electric equipment (Telecom)	245	727
37	Transportation equipment	53	361
38	Instruments and related products	187	433
39	Miscellaneous manufacturing industries	ND	284

Table 2: Summary Statistics and Univariate Tests – Going Public vs. Getting Acquired vs. Remaining Private: This table presents summary statistics and univariate tests for firms that went public, firms that got acquired, and firms that remained private in the LRD between 1972 and 2000. The going public firms are those firms in the manufacturing sector (SIC 2000-3999) that went public between 1972 and 2000 as recorded in SDC. The acquired firms are those firms in the manufacturing sector (SIC 2000-3999) that were acquired between 1972 and 2000 either as recorded in SDC or as identified by the Ownership Change Database (OCD). The firms remaining private are all the firms in the LRD which neither had an IPO nor got acquired between 1972 and 2000, and which were not public prior to 1972. All statistics are firm-year observations, with the IPO sample being restricted to the years when the firms were private (prior to going public) and the Acquisition sample being restricted to the years when the firms were stand-alone (prior to being acquired). 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. 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 (arithmetic mean of) annual growth in sales (in real dollars) in the past three years. Percentage of Hi-tech is the percentage of firms in the sample that are high technology firms (i.e., belonging to 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. Venture capital backing is the percentage of firm-years that are backed by venture capitalists. Loan financing is the percentage of firm-years that the firms have bank loans. Private financing is the percentage of firm-years that are either backed by venture capitalists or financed by bank loans. White-collar salary proportion is the average proportion of total wages that is for white-collar workers in the past three years. Number of Listed Firms is the total number of firms in the same 3 digit SIC that are listed in the CRSP in the prior year. Number of Analysts Following is the lagged 3 digit SIC level mean of the number of analysts covering firms in an industry. Forecast Error is the lagged 3 digit SIC level mean of average analysts forecast errors across firms in the industry. Standard Deviation of Forecasts is the lagged 3 digit SIC level mean of the standard deviation in Analysts Forecast of EPS. Industry Stock Turnover is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the 3 digit SIC level in the prior year. Industry Risk is the one year lagged median of the 5 year standard deviation of sales at the SIC 3 level of all the firms covered in the LRD that year. Herfindahl Index is the lagged value of Herfindahl Index at the 3 digit SIC level. Panel A summarizes firm characteristics. Panel B summarizes industry characteristics. All the dollar values are in real terms. The last two columns report the *t*-stats for the tests of difference in means between the sample of firms going public and the sample of firms getting acquired, and between the sample of firms getting acquired and the sample of firms remaining private, respectively. ***, **, and * indicate significance at the 1, 5, and 10 percent levels respectively.

Panel A: Firm Characteristics

	Firms Going Public (1)			*Firms Getting Acquired (2)*			*Firms Remaining Private (3)*			*Test of Differences*	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	T-test for (1) - (2)	T-test for (2) - (3)
Capital Stock	66024.90	112154.10	3511	15314.58	40932.47	48894	4758.81	24262.08	858912	26.66***	56.46***
Total Employment	1288.92	1795.43	3511	386.24	692.76	48894	134.69	422.69	858912	29.63***	79.45***
Total Sales	187430.80	299209.50	3511	45484.95	104255.90	48894	15954.19	67309.07	858912	27.99***	61.90***
TFP	0.08	0.27	3501	0.04	0.26	48696	-0.01	0.29	810249	9.17***	38.73***
Sales Growth (%)	14	34	2875	8	27	39866	4	36	588546	9.58***	31.51***
Capital Expenditure	6475.59	11102.41	3511	1557.03	4250.82	48894	525.20	2539.60	858912	26.11***	53.14***
CAPEX Ratio (%)	13	13	3385	12	14	46485	12	18	623100	4.21***	-3.24***

Capital Intensity	46.49	51.35	3507	36.89	42.70	48610	23.38	35.73	823872	10.80***	68.32***
Market Share (%)	2.48	7.10	3511	0.56	1.86	48888	0.22	1.35	855425	15.96***	40.50***
Percentage of Hi-tech (%)	25	43	3511	7	25	48894	5	21	858912	24.40***	17.99***
Total Wage	38275.79	55621.36	3511	10196.81	20195.50	48894	3520.86	12511.82	858912	29.77***	72.31***
Average Wage	29.65	9.98	3507	26.47	9.46	48610	24.21	10.49	823872	18.29***	50.90***
Materials Cost	97057.28	161654.10	3508	26642.18	64259.8	48823	9366.00	40067.19	855549	25.65***	58.76***
Rental and Admin. Exp.	8000.23	12013.76	3511	1975.26	426392	48894	691.72	2680.76	858912	29.58***	65.83***
Venture Capital Backing	0.12	0.32	3511	0.01	0.10	48894	0.01	0.08	858912	19.68***	7.96***
Loan Financing	0.16	0.37	1636	0.02	0.12	16923	0.01	0.08	464430	75.79***	9.64***
Private Financing	0.18	0.38	3511	0.01	0.12	48894	0.01	0.10	858912	25.02***	10.26***
White-Collar Salary Prop.	0.37	0.17	3510	0.33	0.17	48843	0.31	0.17	848109	15.52***	24.38***

Panel B: Industry Characteristics and Information Asymmetry Variables

	Firms Going Public (1)			*Firms Getting Acquired (2)*			*Firms Remaining Private (3)*			*Test of Differences*	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	T-test for (1) - (2)	T-test for (2) - (3)
Number of Listed Firms	52.16	62.05	3440	26.90	35.11	47003	23.51	833.47	823182	23.60***	20.38***
Number of Analysts	5.66	2.98	3123	5.19	3.01	38414	4.86	2.73	691817	8.48***	20.70***
Forecast Error	1.19	2.06	3511	1.87	2.61	48894	1.64	2.50	858912	-18.56***	19.31***
Std. of Forecasts	0.58	1.23	3511	1.00	1.58	48894	0.94	1.55	858912	-19.23***	8.81***
Industry Stock Turnover	0.58	0.47	3439	0.45	0.44	46968	0.58	0.68	819664	16.38***	-60.15***
Industry Risk	0.01	0.06	3421	0.00	0.05	46238	0.03	0.11	832246	9.55***	-99.29***
Herfindahl Index	0.09	0.08	3511	0.08	0.08	48894	0.07	0.09	858912	9.36***	12.48***

Table 3: Determinants of the Exit Decision through IPOs vs. Acquisitions: Multivariate Analysis: This table presents the multinomial logit regressions of the effects that firm specific variables, industry characteristics, and information asymmetry variables have on a firm's decision to exit via an IPO or an acquisition using a sample of private firms from the LRD. The base model is: $EXIT_{it} = F\,(\beta_1 SIZE_{i,t-1} + \beta_2 TFP_{i,t-1} + \beta_3 SGTH_{\,i,t-1} + \beta_4 CAPR_{i,t-1} + \beta_5 WHITE_{i,t-1} + \beta_6 MSHR_{\,i,t-1} + \beta_7 AGE_{i,t-1} + \beta_8 HTEK_{\,i,t-1} + \beta_9 CAPINT_{i,t-1} + \beta_{10} TOV_{j,t-1} + \beta_{11} INDRSK_{j,t-1} + \beta_{12} HI_{j,t-1} + \beta_{13} LIST_{j,t-1} + \beta_{14} NUMA_{j,t-1} + \beta_{15} FORER_{j,t-1} + \beta_{16} STDEV_{j,t-1} \;\; \beta_{17} FINDUM_{i,t-1} + \beta_{18} SP500_{t-1}\,) + \varepsilon_{i,j,t}$, where *EXIT* is a categorical variable with three values: it equals 0 if the firm is private (the base category); it equals 1 if the firm goes public (IPO) in year *t*; and it equals 2 if the firm gets acquired (ACQ) in year *t*. *Size* is the lagged value of logarithm of capital stock; *Sales Growth (SGTH)* is the average (arithmetic mean of) annual growth sales in the past 3 years; *Market Share (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 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); *Capital Intensity (CAPINT)* is the lagged value of capital stock per worker; *AGE* is the natural logarithm of firm age, which is the number of years since the birth of the first plant of the firm as recorded in the Census data; *CAPEX Ratio (CAPR)* is the lagged value of capital expenditures over capital stock; *Hi-tech dummy (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; *Industry Risk (INDRSK)* is the one year lagged median of the 5 year standard deviation of sales at the SIC 3 level of all the firms covered in the LRD that year; *Herfindahl Index (HI)* is the lagged value of Herfindahl Index at the 3 digit SIC level; *LIST* is the total number of firms in the same 3 digit SIC that are listed in the CRSP in the prior year; *Turnover (TOV)* is the mean of stock turnover (calculated as trading volume over total number of shares outstanding) at the 3 digit SIC level in the prior year; *NUMA* is the lagged 3 digit SIC level mean of the number of analysts covering firms in an industry; *FORER* is the lagged 3 digit SIC level mean of average analysts forecast errors across firms in the industry; *STDEV* is the lagged 3 digit SIC level mean of the standard deviation in Analysts Forecast of EPS; *SP500* is the prior year's annual return of S&P's 500 Index; *Private financing* (*FINDUM*) is 1 if the firm is either backed by venture capitalists or financed by bank loans; *White-collar salary proportion* (*WHITE*) is the average proportion of total wages that is for white-collar workers in the past three years. All dollar values are in real terms. Heteroskedasticity corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance from the omitted category (remaining private) at the 1, 5, and 10 percent levels, respectively. †††, ††, and † represent statistical significance of the difference between coefficients in the *IPO* column and the *ACQ* column at the 1, 5, and 10 percent levels, respectively.

	Reg1		Reg2		Reg3		Reg4		Reg5		Reg6	
	IPO	ACQ	IPO	ACQ	IPO	ACQ	IPO	ACQ	IPO	ACQ	IPO	ACQ
SIZE	0.725	0.311	0.641	0.313					0.627	0.319	0.626	0.318
	***; †††	***	***;†††	***					***; †††	***	***; †††	***
	[0.031]	[0.008]	[0.028]	[0.008]					[0.029]	[0.008]	[0.029]	[0.008]
TFP	0.873	0.311	0.777	0.262	0.680	0.316	0.728	0.314	0.825	0.290	0.826	0.290
	***; †††	***	***;†††	***	***; †††	***	***; †††	***	***; †††	***	***; †††	***
	[0.150]	[0.042]	[0.155]	[0.043]	[0.138]	[0.038]	[0.132]	[0.038]	[0.164]	[0.043]	[0.164]	[0.043]
SGTH	0.824	0.140	0.967	0.253	0.961	0.220	0.974	0.228	0.790	0.163	0.787	0.162
	***; †††	***	***;†††	***	***; †††	***	***; †††	***	***; †††	***	***; †††	***
	[0.122]	[0.041]	[0.119]	[0.039]	[0.106]	[0.037]	[0.100]	[0.037]	[0.120]	[0.042]	[0.120]	[0.042]
CAPR	1.313	0.030	1.107	-0.070	0.716	0.030	0.770	0.030	1.462	0.080	1.460	0.070
	***; †††		***;†††		***; †††		***; †††		***; †††		***; †††	
	[0.313]	[0.096]	[0.303]	[0.095]	[0.255]	[0.084]	[0.241]	[0.083]	[0.299]	[0.096]	[0.299]	[0.096]
WHITE	1.544	0.496	1.664	0.540	0.801	0.516	1.377	0.591	1.788	0.628	1.782	0.621
	***; †††	***	***;†††	***	***	***	***; †††	***	***; †††	***	***; †††	***
	[0.328]	[0.082]	[0.292]	[0.080]	[0.287]	[0.074]	[0.264]	[0.073]	[0.295]	[0.079]	[0.295]	[0.079]
MSHR	2.276	-9.517	1.622	-10.218	6.959	0.710	5.997	0.340	1.967	-10.514	1.994	-10.333
	***; †††	***	*;†††	***	***; †††		***; †††		*; †††	***	**; †††	***

	[0.834]	[1.314]	[0.917]	[1.386]	[1.355]	[0.496]	[1.273]	[0.515]	[1.013]	[1.408]	[0.992]	[1.396]
AGE	-0.683	0.116	-0.314	0.116	-0.110	0.412	-0.130	0.407	-0.693	0.110	-0.691	0.111
	***; †††	***	***;†††	***	†††	***	†††	***	***; †††	***	***; †††	***
	[0.092]	[0.025]	[0.088]	[0.020]	[0.096]	[0.025]	[0.094]	[0.025]	[0.094]	[0.026]	[0.094]	[0.026]
HTEK	0.887	0.167	1.513	0.256								
	***; †††	**	***;†††	***								
	[0.191]	[0.071]	[0.142]	[0.052]								
CAPINT					0.002	0.003	0.002	0.003				
					*	***	**	***				
					[0.001]	[0.000]	[0.001]	[0.000]				
FINDUM					2.504	0.030	2.793	0.100	1.892	-0.220	1.889	-0.222
					***; †††		***; †††		***; †††	**	***; †††	**
					[0.152]	[0.098]	[0.139]	[0.098]	[0.139]	[0.098]	[0.139]	[0.098]
TOV			0.316	0.090	0.198	0.054	0.298	0.078	0.281	0.070	0.279	0.068
			***;†††	***	***; ††	***	***; †††	***	***; †††	***	***; †††	***
			[0.023]	[0.015]	[0.057]	[0.021]	[0.046]	[0.019]	[0.052]	[0.021]	[0.052]	[0.021]
INDRSK			-0.760	0.000	-2.554	-2.038	0.640	-1.454	2.599	-0.140	2.621	-0.090
					**	***	††	***	***; †††		***; †††	
			[0.961]	[0.275]	[1.085]	[0.293]	[0.833]	[0.282]	[0.876]	[0.279]	[0.882]	[0.280]
HI			0.880	0.469	2.201	1.140	1.188	0.891	1.106	0.635	1.112	0.654
				***	***; †	***	**	***	*	***	*	***
			[0.585]	[0.137]	[0.629]	[0.134]	[0.588]	[0.134]	[0.589]	[0.143]	[0.585]	[0.142]
LIST					0.519	0.148						
					***; †††	***						
					[0.065]	[0.016]						
NUMA							0.393	0.168				
							***; ††	***				
							[0.092]	[0.024]				
FORER									-0.091	0.000		
									*; †			
									[0.049]	[0.010]		
STDEV											-0.133	-0.020
											*	
											[0.073]	[0.014]
SP500			1.777	-0.658								
			***;†††	***								
			[0.294]	[0.078]								
Ind. Dummy	Yes		No		No		No		No		No	
Year Dummy	Yes		No		Yes		Yes		Yes		Yes	
Obs	495274		474469		469406		469406		474469		474469	
Pseudo R^2	0.083		0.049		0.059		0.057		0.082		0.082	

Table 4: Determinants of the Exit Decision through IPOs vs. Acquisitions: Multivariate Analysis on Propensity-score-matched Samples: This table presents the multinomial logit regressions of the effects that firm specific variables, industry characteristics, and information asymmetry variables have on a firm's decision to exit via an IPO or an acquisition using a sub-sample of propensity-score-matched private firms from the LRD. We first adopt a one-to-five nearest neighbor propensity score matching algorithm to match IPO firms and acquired firms at three years before the exit event (an IPO or an acquisition) on all firm specific characteristics considered in previous tables as well as on year and industry (2-digit SIC code) dummies. We then take the matched acquired firms at three years before their exits and adopt a one-to-ten nearest neighbor propensity score matching algorithm to match them to firms that remain private throughout our sample on the same set of variables. After the matching is done, we drop all observations before the matching year, i.e., only retain IPO and acquired firms from three years before their exits until their exit year, and only retain private firms from the year they are matched to the acquired firms. Panel A presents parameter estimates from the probit model used in estimating the propensity scores for the two sets of matching (IPO and ACQ, and ACQ and PRV). The dependent variable is one if the firm-year belongs to the treatment group (IPO in the first matching and ACQ in the second) and zero otherwise. All other variables are described in previous tables. The Pre-Match column contains the parameter estimates of the probit estimated on all firm-year observations available for matching, prior to matching. This model is used to generate the propensity scores for matching. The Post-Match column contains the parameter estimates of the probit estimated on the subsample of matched treatment and unique control firm-years, after matching. Panel B reports the results from a multinomial logit regression (in the same fashion of Table 3) only on the sample of propensity-score-matched firms. The dependent variable, *EXIT,* is a dummy variable representing three categories: it equals 0 if the firm is private (the base category); it equals 1 if the firm goes public (*IPO*) in year t; and it equals 2 if the firm gets acquired (*ACQ*) in year t. Heteroskedasticity corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. In Panel A, ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. In Panel B, ***, **, and * represent statistical significance from the omitted category (remaining private) at the 1, 5, and 10 percent levels, respectively. †††, ††, and † represent statistical significance of the difference between coefficients in the IPO column and the corresponding ACQ column at the 1, 5, and 10 percent levels, respectively.

Panel A: Diagnostics for the propensity score matching

	IPO and ACQ		ACQ and PRV	
Variable	Pre-Match	Post-Match	Pre-Match	Post-Match
SIZE	0.321***	0.070	0.256***	-0.002
	[0.034]	[0.044]	[0.012]	[0.019]
TFP	0.262**	0.253	0.097*	0.001
	[0.131]	[0.171]	[0.049]	[0.073]
SGTH	0.086	-0.020	0.112**	0.008
	[0.128]	[0.159]	[0.047]	[0.069]
CAPR	-0.064	-0.012	0.191*	0.118
	[0.309]	[0.420]	[0.110]	[0.170]
WHITE	0.916***	0.399	0.556***	0.010
	[0.237]	[0.307]	[0.090]	[0.132]
MSHR	3.078***	0.283	-1.237*	-0.254
	[1.109]	[1.700]	[0.650]	[0.909]
AGE	-0.113*	0.003	-0.178***	-0.030
	[0.062]	[0.080]	[0.024]	[0.035]
HTEK	0.553***	0.054	0.325***	0.114
	[0.149]	[0.181]	[0.056]	[0.077]
CAPINT	-0.002**	-0.001	-0.002***	0.0004
	[0.001]	[0.001]	[0.0004]	[0.001]
FINDUM	0.903***	0.230	0.127**	0.137
	[0.130]	[0.154]	[0.062]	[0.084]

Ind. Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Observations	4853	995	234588	7672
Pseudo R^2	0.281	0.024	0.158	0.004
LR Chi-square Test	599.24	26.13	1589.11	17.28
Chi-square p-value	0.000	1.000	0.000	1.000

Panel B: multinomial logit regression results

	Reg1		*Reg2*		*Reg3*		*Reg4*		*Reg5*		*Reg6*	
	IPO	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*	*IPO*	*ACQ*
SIZE	0.358	0.237							0.236	0.216	0.236	0.214
	***; †††	***							***	***	***	***
	[0.051]	[0.031]							[0.050]	[0.029]	[0.049]	[0.029]
TFP	0.839	0.322	0.735	0.311	0.632	0.272	0.629	0.262	0.757	0.287	0.759	0.286
	***; ††	**	***; †	**	***	**	***	**	***; ††	**	***; ††	**
	[0.192]	[0.131]	[0.188]	[0.124]	[0.198]	[0.129]	[0.202]	[0.130]	[0.200]	[0.134]	[0.200]	[0.134]
SGTH	0.813	0.235	0.898	0.238	0.902	0.310	0.931	0.333	0.834	0.263	0.833	0.262
	***; †††	*	***; †††	**	***; †††	**	***; †††	***	***; †††	**	***; †††	***
	[0.201]	[0.131]	[0.180]	[0.121]	[0.189]	[0.123]	[0.184]	[0.121]	[0.190]	[0.127]	[0.190]	[0.127]
CAPR	1.917	-0.014	1.247	-0.321	1.488	0.096	1.525	0.149	1.808	0.118	1.802	0.116
	***; †††		***; †††		***; †††		***; †††		***; †††		***; †††	
	[0.438]	[0.370]	[0.385]	[0.348]	[0.404]	[0.342]	[0.394]	[0.336]	[0.415]	[0.356]	[0.415]	[0.356]
WHITE	1.102	0.604	0.848	0.420	0.432	0.363	0.799	0.542	1.126	0.817	1.127	0.806
	**		**	*			**	**	***	***	***	***
	[0.432]	[0.258]	[0.378]	[0.236]	[0.396]	[0.237]	[0.385]	[0.231]	[0.398]	[0.236]	[0.397]	[0.235]
MSHR	1.624	-1.714	4.713	1.633	5.237	2.474	4.114	1.604	1.776	-2.197	1.841	-2.053
	†		***; ††	**	***; †	**	***		†		†	
	[1.572]	[1.407]	[1.147]	[1.036]	[1.440]	[1.079]	[1.484]	[1.102]	[1.648]	[1.509]	[1.602]	[1.504]
AGE	-0.258	-0.334	-0.305	-0.397	-0.073	-0.212	-0.124	-0.239	-0.294	-0.361	-0.288	-0.360
	***	***	***	***		***		***	**	***	**	***
	[0.117]	[0.067]	[0.094]	[0.055]	[0.119]	[0.067]	[0.118]	[0.066]	[0.120]	[0.066]	[0.120]	[0.066]
HTEK	0.429	0.449	0.646	0.576								
	**	***	***; †††	***								
	[0.218]	[0.140]	[0.170]	[0.108]								
CAPINT			-0.002	0.001	-0.004	0.001	-0.004	0.001				
			†		††		††					
			[0.002]	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]				
FINDUM					1.805	0.292	1.893	0.348	1.670	0.218	1.672	0.216
					***; †††	*	***; †††	**	***; †††		***; †††	
					[0.171]	[0.154]	[0.168]	[0.152]	[0.173]	[0.155]	[0.173]	[0.155]

TOV		0.255	-0.034	0.273	0.100	0.342	0.177	0.336	0.178	0.336	0.177
		***; †††		***; †		***; ††	***	***; ††	***	***; ††	***
		[0.069]	[0.077]	[0.070]	[0.064]	[0.062]	[0.051]	[0.064]	[0.051]	[0.064]	[0.051]
INDRSK		-2.643	-0.018	-4.001	0.287	-1.602	1.094	-0.340	1.763	-0.336	1.781
		**; ††		***; †††		††		†	***	†	***
		[1.088]	[0.659]	[1.372]	[0.787]	[1.089]	[0.690]	[1.035]	[0.678]	[1.043]	[0.676]
HI		1.335	0.466	1.792	0.785	1.222	0.532	1.248	0.422	1.242	0.440
		*		**	*						
		[0.749]	[0.476]	[0.781]	[0.472]	[0.779]	[0.468]	[0.821]	[0.473]	[0.807]	[0.475]
LIST				0.334	0.178						
				***; †	***						
				[0.073]	[0.044]						
NUMA						0.239	0.152				
						**	**				
						[0.120]	[0.075]				
STDEV								-0.157	0.024		
								**; ††			
								[0.073]	[0.031]		
FORER										-0.204	0.012
										**; ††	
										[0.103]	[0.045]
SP500		0.140	0.637								
			***								
		[0.414]	[0.249]								
Ind. Dummy	Yes	No		No		No		No		No	
Year Dummy	Yes	No		Yes		Yes		Yes		Yes	
Observations	33660	33179		33179		33179		33205		33205	
Pseudo R^2	0.07	0.02		0.07		0.07		0.07		0.07	

Table 5: Dynamic Characteristics of TFP, Sales Growth, and Firm Size around IPOs and Acquisitions: This table presents the dynamic pattern of TFP, Sales Growth, and Firm Size before and after IPOs and acquisitions. The dynamic pattern is estimated based on the following panel regression specifications: $Y_{it} = \alpha_i + \beta_t + \gamma X_{it} + \sum_{s=1}^{5} \delta_s BeforeExit_{it} + \sum_{s=1}^{5} \lambda_s AfterExit_{it} + \varepsilon_{it}$, where *Exit* can be IPO or acquisition. Y_{it} is *TFP*, Sales Growth, and Firm Size, respectively. Firm size is also used as a control variable for the analysis of TFP and Sales Growth. The sample includes all firm year observations in the LRD of firms that went public, got acquired, or remained private between 1972 and 2000; the dynamic pattern of these variables in firms going public (getting acquired) is benchmarked against those of firms that remain private. All the *Before* and *After* variables with superscripts are dummy variables. $BeforeExit^{s}_{it}$ is a dummy variable equal to 1 if the firm goes public (gets acquired) *s* years prior to the IPO (the acquisition), where *s* = 1, 2, 3, 4, or 5 years; $AfterExit^{s}_{it}$ is a dummy variable equal to 1 if the firm goes public (gets acquired) *s* years after the IPO (the acquisition). All other variables are described in previous tables. All dollar values are in real terms. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance from 0 at the 1, 5, and 10 percent levels, respectively.

	TFP		Sales Growth		Firm Size	
	IPO	ACQ	IPO	ACQ	IPO	ACQ
$BeforeExit^5$	-0.078***	-0.023**	-0.070**	0.000	-1.349***	-0.928***
	[0.020]	[0.011]	[0.031]	[0.000]	[0.137]	[0.056]
$BeforeExit^4$	-0.044**	-0.020	-0.074***	0.001	-1.016***	-0.839***
	[0.017]	[0.010]	[0.026]	[0.021]	[0.122]	[0.050]
$BeforeExit^3$	-0.046***	0.010	-0.085***	0.037**	-0.798***	-0.771***
	[0.014]	[0.011]	[0.023]	[0.018]	[0.099]	[0.043]
$BeforeExit^2$	-0.037***	0.010	-0.065***	0.038**	-0.633***	-0.434***
	[0.013]	[0.010]	[0.020]	[0.016]	[0.087]	[0.033]
$BeforeExit^1$	-0.020*	0.010	-0.020	0.020	-0.272***	-0.253***
	[0.011]	[0.008]	[0.015]	[0.011]	[0.060]	[0.021]
$AfterExit^1$	-0.010	0.000	0.000	0.001	0.360***	0.189***
	[0.011]	[0.009]	[0.015]	[0.012]	[0.061]	[0.019]
$AfterExit^2$	-0.020	-0.010	-0.031*	0.010	0.710***	0.304***
	[0.012]	[0.010]	[0.018]	[0.016]	[0.077]	[0.028]
$AfterExit^3$	-0.031**	-0.010	-0.073***	-0.010	0.857***	0.497***
	[0.014]	[0.010]	[0.022]	[0.018]	[0.106]	[0.034]
$AfterExit^4$	-0.046***	-0.023**	-0.098***	-0.029*	0.993***	0.699***
	[0.015]	[0.011]	[0.023]	[0.017]	[0.115]	[0.040]
$AfterExit^5$	-0.038**	-0.029**	-0.092***	-0.044***	1.185***	0.934***
	[0.016]	[0.012]	[0.025]	[0.017]	[0.130]	[0.053]
Size	-0.011***	-0.012***	-0.004***	-0.004***		
	[0.000]	[0.001]	[0.001]	[0.001]		
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	793238	801295	581831	589138	842073	850076
R^2	0.57	0.52	0.64	0.64	0.92	0.92

Table 6: Dynamic Characteristics of Sales, Capital Expenditure, and Total Employment around IPOs and Acquisitions: This table presents the dynamic pattern of Sales, Capital Expenditure, and total employment before and after IPOs and acquisitions. The dynamic pattern is estimated based on the following panel regression specifications: $Y_{it} = \alpha_i + \beta_t + \gamma X_{it} + \sum_{s=1}^{5} \delta_s BeforeExit_{it} + \sum_{s=1}^{5} \lambda_s AfterExit_{it} + \varepsilon_{it}$, where *Exit* can be IPO or acquisition. Y_{it} is Sales, Capital Expenditure, and total employment, respectively. The sample includes all firm year observations in the LRD of firms that went public, got acquired, or remained private between 1972 and 2000; the dynamic pattern of these variables in firms going public (getting acquired) is benchmarked against those of firms that remain private. All variables are described in previous tables. All dollar values are in real terms. All the regressions are ordinary least square regressions with firm fixed effect and calendar year dummies. Heteroskedasticity corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance from 0 at the 1, 5, and 10 percent levels, respectively.

	Sales		Capital Expenditure		Total Employment	
	IPO	ACQ	IPO	ACQ	IPO	ACQ
$BeforeExit^5$	-21,859.714***	-3,781.019***	-847.564***	48.710	-82.839***	-9.450
	[3,471.975]	[1,025.754]	[154.479]	[78.655]	[21.171]	[6.552]
$BeforeExit^4$	-16,981.701***	-2,426.555***	-733.453***	1.810	-68.100***	-3.790
	[2,912.481]	[864.230]	[141.424]	[66.749]	[18.267]	[5.269]
$BeforeExit^3$	-18,640.840***	-779.890	-827.778***	68.780	-82.050***	5.660
	[2,645.330]	[707.346]	[133.604]	[65.610]	[16.021]	[4.332]
$BeforeExit^2$	-16,474.984***	-176.200	-898.028***	33.470	-69.712***	4.400
	[2,154.966]	[584.078]	[121.274]	[53.525]	[12.212]	[3.282]
$BeforeExit^1$	-8,257.269***	-109.600	-534.752***	17.360	-22.090**	4.865*
	[1,417.177]	[435.559]	[94.582]	[47.984]	[8.738]	[2.531]
$AfterExit^1$	5,200.197***	-233.430	409.353***	34.650	25.765***	-5.391**
	[1,567.671]	[450.317]	[98.434]	[49.429]	[9.366]	[2.360]
$AfterExit^2$	10,075.623***	477.230	411.821***	60.480	63.502***	-6.674**
	[2,018.773]	[554.068]	[105.417]	[57.340]	[11.866]	[3.265]
$AfterExit^3$	12,701.448***	-405.170	390.374***	-42.800	81.100***	-15.793***
	[2,521.934]	[608.943]	[122.265]	[56.275]	[15.865]	[3.833]
$AfterExit^4$	14,988.102***	-2,172.900***	404.688***	-150.775***	95.861***	-26.499***
	[2,928.593]	[720.309]	[136.146]	[55.939]	[18.163]	[4.428]
$AfterExit^5$	16,336.545***	-3,912.164***	395.809***	-283.210***	101.514***	-37.909***
	[3,226.959]	[916.984]	[146.484]	[64.531]	[19.948]	[5.790]
Size	2,745.116***	2,676.888***	94.248***	92.548***	17.498***	17.079***
	[79.071]	[78.366]	[2.931]	[2.910]	[0.524]	[0.519]
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	842073	850076	842073	850076	842034	850076
R^2	0.89	0.89	0.74	0.73	0.90	0.90

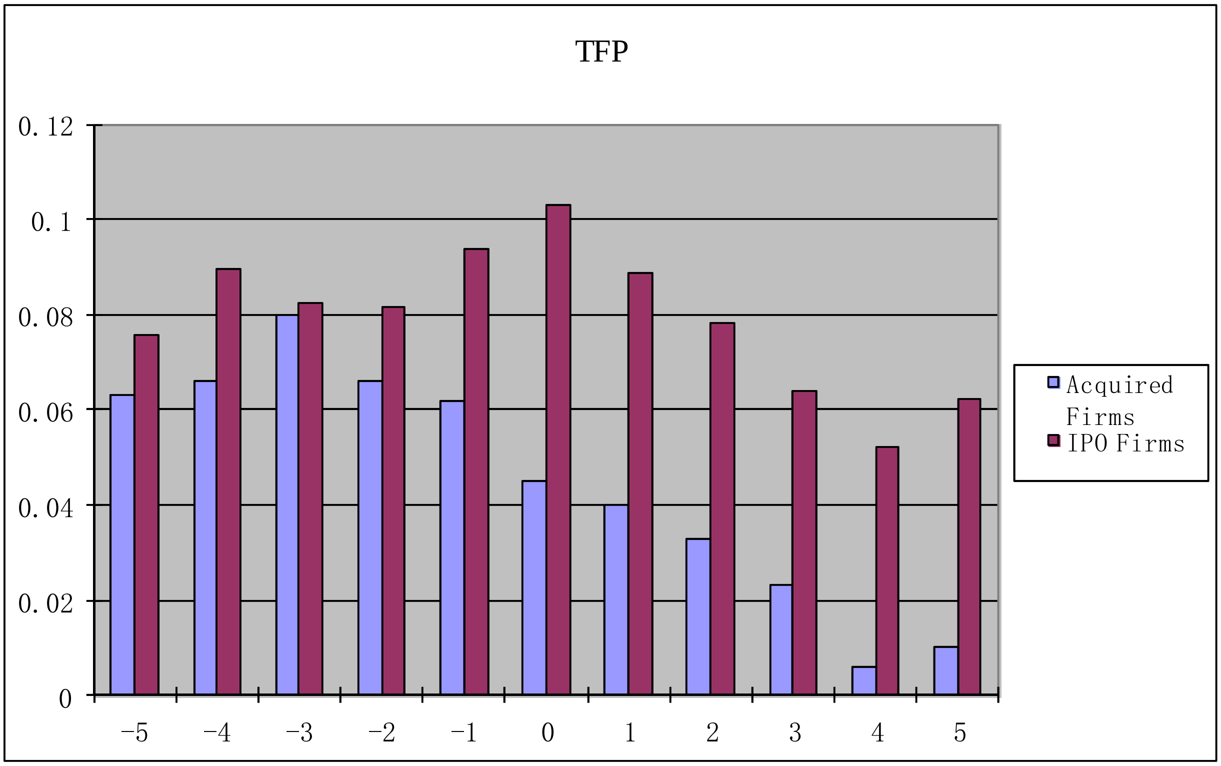

Figure 2: Dynamic pattern of TFP around the Exit

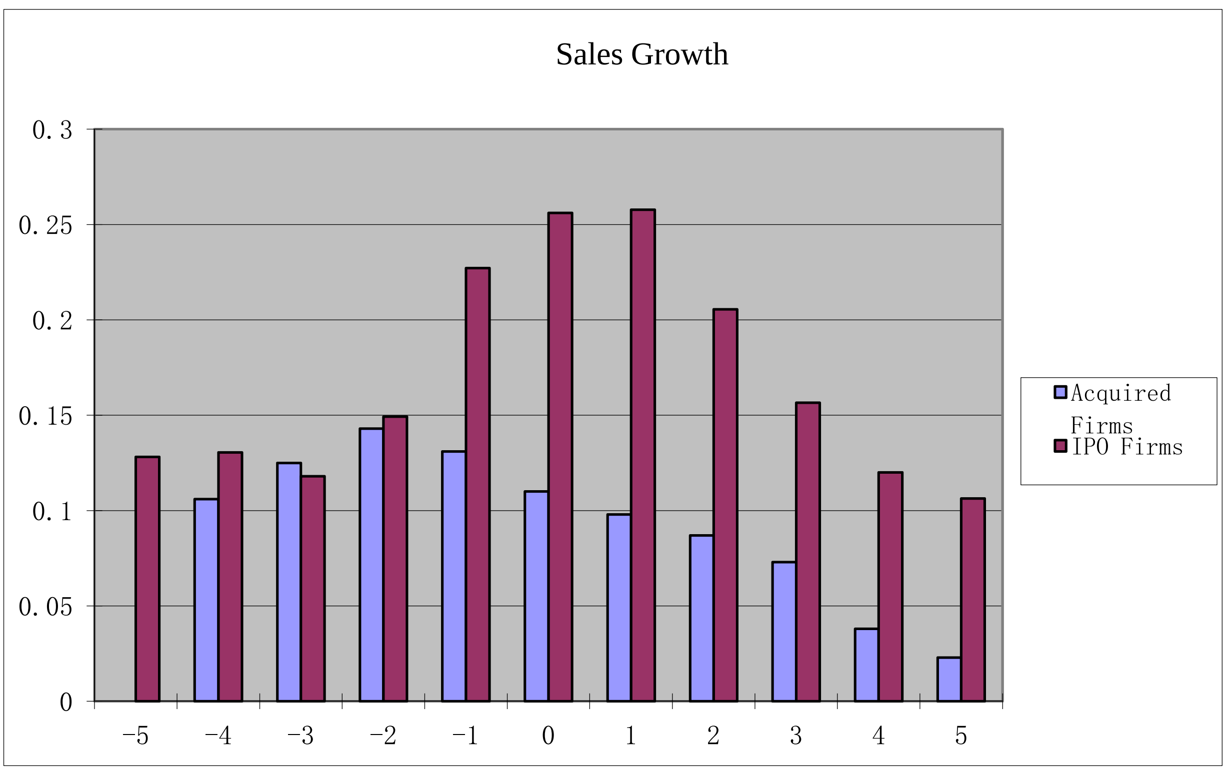

Figure 3: Dynamic pattern of Sales Growth around the Exit