Internet Appendix A (Not to Be Published):
Measurement of Total Factor Productivity (TFP)

Total Factor Productivity (TFP) is calculated from the LRD for each individual plant at the annual four digit (SIC) industry level using the entire universe of plants in the LRD as in Chemmanur, He, and Nandy (2010), and Chemmanur, Krishnan, and Nandy (2011). The total factor productivity of the firm is then calculated as a weighted sum of plant Total Factor Productivities (TFP) at the annual level. In particular, we obtain measures of TFP at the plant level by estimating a log-linear Cobb-Douglas production function for each industry and year. Industry is defined at the level of four-digit SIC codes.[1] Individual plants are indexed *i*; industries *j*; for each year *t,* in the sample:

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

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

Labor input (L) is defined as production worker equivalent man hours. This is the product of production worker man-hours, and the ratio of total wages and salaries to production worker wages. We also re-estimate the TFP regression by specifying labor input to include non-production workers, which yields qualitatively similar results. Values for the capital stock (K) are generated by the recursive perpetual inventory formula. We use the earliest available book value of capital as the initial value of net stock of plant capital (this is either the value in 1972, or the first year a plant appears in the LRD sample). These values are written forward annually with nominal capital expenditure (appropriately deflated at the industry level) and depreciated by the economic depreciation rate at the industry level obtained from the Bureau of Economic Analysis. Since values of all these variables are available separately for buildings and machinery, we perform this procedure separately for each category of assets. The resulting series are then added together to yield our capital stock measure. Finally, material input (M) is defined as expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased, adjusted for the change in the value of material inventories. All the variables are deflated using annual price deflators for output, materials, and investment at the four-digit SIC level from the Bartelsman and Gray NBER Productivity Database.[2] Deflators for capital stock are available from the Bureau of Economic Analysis.[3] Plant level TFP is then computed as the residuals of regression (1), estimated separately for each year and each four-digit SIC industry.

This measure of TFP is more flexible than the cash-flow measure of performance, as it does not impose the restriction of constant returns to scale and constant elasticity of scale. Also, since coefficients on capital, labor, and material inputs can vary by industry and year, this specification allows for different factor intensities in different industries. These production function estimates are pooled across the entire universe of manufacturing plants in the LRD, including plants belonging to both public and private firms and irrespective of whether they exit through IPOs or acquisitions, thus giving us an accurate measure of the relative performance of a plant within a particular 4-digit SIC industry in any given year. The TFP measure for each individual plant is the estimated residual of these regressions.

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[1] As a robustness check, we re-estimate the production function in several different ways. First, we use two and three-digit SIC industry classifications. Second, we estimate TFP with value added production function specifications and separate white and blue collar labor inputs. Third, we divide each annual four-digit SIC industry into two groups based on capital intensity, i.e., plants with capital intensity greater than the median capital intensity for that annual four-digit group are put in one group, while those with capital intensity less than the median are put in another group. We then estimate the production function for each group separately. In all cases we find similar results.

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

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

Thus, it is the difference between the actual output produced by the plant compared to its "predicted output". This "predicted output" is what the plant should have produced, given the amount of inputs it used and the industry production technology in place. Hence a plant that produces more than the predicted amount of output in any given year has a greater than average productivity for that year. Thus, TFP can be understood as the relative productivity rank of a plant within its industry in any given year. Since these regressions include a constant term, TFP only contains the idiosyncratic part of plant productivity.[4] Plant level TFP measures are then aggregated to the firm level by a sales-weighted approach.[5] The firm level TFP is winsorized at the 1st and 99th percentile.

[4] As a robustness check for our regression results, we use an alternative measure of productivity; namely, value added per worker, which is defined as total sales less materials cost of goods sold, divided by the number of workers. This measure has been used in previous studies such as McGuckin and Nguyen (1995). It does not have the desirable theoretical properties of TFP, but does have familiar statistical properties, since it is not computed from a regression. We find qualitatively similar results when using this measure of labor productivity.

[5] As a robustness check, we also used the ratio of its capital stock to the total capital stock of the firm and the ratio of plant employment to firm employment as weights. In all cases our results remain unchanged.

Internet Appendix B (Not to Be Published):
Endogenous switching model

In this subsection, we acknowledge the possibility that 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, the private financing dummy (*FINDUM*) in our multinomial logit regression may be endogenous. To address this concern, we adopt a two-step Heckman-type endogenous switching model.

This procedure is discussed in detail in Heckman (1979) and Maddala (1983) and is a generalized version of the traditional Heckman model and therefore accounts for the effect of unobservables (such as firm quality that affects a private firm's chance of receiving VC investment or bank loans) by using inverse Mills ratios. In particular, we use a first-stage probit regression to predict the probability of private funding and the inverse Mills ratios for firms with and without private financing. The inverse Mills ratio has been used in the prior literature as a measure of unobserved factors (such as firm quality) that affect the selection of firms for *treatment* (which is private funding in our context) as well as the *outcome* variable (which is the exit choice in our context). We then regress an exit choice variable on the inverse Mills ratio and all other product market variables in the second-stage OLS regression separately for firms with and without private financing. The reason for using probit (as opposed to OLS or logit) in the first stage and OLS (as opposed to multinomial or ordered probit/logit) in the second stage of our analysis is that the endogenous switching model is only valid under certain parametric assumptions (such as the joint normality distribution of errors in the two stages). To run OLS in the second stage, therefore, we construct a new exit choice variable (*EXIT)* that equals 2 if the firm goes public in that year, 1 if the firm gets acquired, and 0 if the firm is private. Finally, the predicted values of *EXIT* from the second-stage estimates are used to conduct a "what-if" analysis: what would the exit choice of a firm *with* private financing have been had it *not* received the financing? Similarly, what would the exit choice of a firm *without* private funding have been had it received the financing? Thus, the switching regression analysis measures the effect of the treatment (i.e., private funding) on the outcome variable (i.e., exit choice) through a "what-if" or counterfactual analysis rather than estimating it from a regression.[6]

In the first-stage probit regression, we control for all firm-level characteristics that could affect private financing, as well as industry (2-digit SIC code) fixed effects and financial market conditions (the S&P 500 return). In addition, we also include several well-received instruments (also used in Chemmanur, He, and Nandy (2010) and Chemmanur, Krishnan, and Nandy (2011)) that are correlated with the demand and supply of private financing (VC investment and/or bank loans) in the economy but are independent of the exit decisions of firms that obtained private funding—namely, the Increase in NSF Research Grants (*GRANT*), which is the average of the past five-year increase in the real National Science Foundation (NSF) research grants for both applied and basic research; AAA Spread (*AAA*), which is the spread of AAA bonds over five-year Treasury bonds in the current year; Number of Instate LPs (*NUMLP*), which is the logarithm of one plus the total number of venture capital limited partners (LPs) in the past five years that are located in the same state as the firm's headquarters. Note that while the first two instruments are at the year level (which is why we did not include year dummies in the first stage), the third instrument is at the firm-year level. These instruments provide us with exogenous variation in terms of both the supply of and the demand for private funding that affects the selection equation (i.e., the matching outcome between private financiers and entrepreneurial private firms) but do not directly affect firms' exit decisions several years later.

[6] This model has also been used in recent finance literature such as Dunbar (1995), Fang (2005), and Chemmanur, Krishnan, and Nandy (2011). Please see these papers for a more detailed description of this methodology.

The results of the switching regression analysis, reported in Panel A of Table B-1, show that firm size, *TFP*, sales growth, capital expenditure ratio, white-collar salary proportion, market share, firm age, market condition (*SP500*), and the high-tech dummy are all positive and significant determinants of receiving private financing. With regard to the instruments, we find that the coefficient on the increase in NSF research grants is positive and significant, suggesting that greater research grants may lead to an increase in entrepreneurial firm formation, thus leading to a greater demand for private funds either in the form of VC investment or bank loans. As expected, the coefficient on AAA spread, which captures the investment alternatives available to investors who may invest in such private funds, is negative and significant, suggesting that availability of funds to VCs and banks is an important criterion for private financing, consistent with Gompers and Lerner (1998). Finally, the coefficients on the number of instate LPs is positive and significant, suggesting a greater probability of receiving VC funding in the presence of a greater number of LPs nearby.

We then augment the second-stage OLS regressions for privately-financed and non-privately-financed firms with the inverse Mills ratios calculated from the first-stage to account for endogenous selection (based on unobservable factors). The second-stage results show that while the inverse Mills ratio is positive and significant for firms with private financing, it is insignificant for non-privately-financed firms. This suggests that private financiers such as VCs and banks may also 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. Therefore, properly controlling for this effect enables us to identify the relationship between *ex ante* product market variables and firms' exit choice in a more clear fashion. We find that most of our results in the main text hold: 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 industry are more likely to go public than get acquired than remain private. Market share has a positive effect and firm age has a negative effect on the above rank of exit choice only for firms with private financing. Further, with or without private funding, firms that operate in industries characterized by a higher stock liquidity, higher industry concentration, and lower information asymmetry are more likely to go public than get acquired than remain private.[7]

Panel B of Table B-1 presents the results of our counterfactual analysis of privately-financed and non-privately-financed firms. We obtain the counterfactual values of *EXIT* for firms with private financing as the predicted values of the non-privately-financed regression (by using privately-financed firm data), and vice versa. These results suggest that, on average, firms with 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 supportive (monitoring and/or certifying) rather than a selection role for private financiers (VCs and banks) in the exit decision. The second row shows a hypothetical improvement in the probability of a preferred exit (also twice as large) for non-privately-financed firms had the same firms received private financing, which is consistent with our earlier results presented in Table 3 of the main text.

In summary, the regression results in Table B-1 are consistent with our earlier results presented in Table 3 of the main text and are consistent with the hypotheses we discussed in Section 2.1 of the paper. We explicitly account for the endogenous nature of private financiers' selection of firms using a Heckman style two-stage model. While such selection affects the exit decisions of entrepreneurial firms, the various firm specific, industry specific, and information asymmetry variables that we discussed earlier are still important determinants of the exit decision even after controlling for such selection effects.

[7] To save space, we only present one specification with the number of listed firms in an industry (*LIST*) as a proxy for information asymmetry. Using the other three information asymmetry proxies (i.e., the number of analyst following, the average forecast error, and the standard deviation of analyst forecasts) does not change our results qualitatively.

Table B-1: Switching Regressions with Endogenous Switching for Firms with and without Private Financing: This table presents the results from an endogenous switching model in which the dependent variable in the first stage Probit regression is whether or not a firm gets private financing (venture capital or bank loans) in a given year (*FINDUM*) and the associated "what-if" analysis. Panel A reports the regression results. The time series for each firm that gets private financing terminates in the year of obtaining the financing. The instrumental variables in the first-stage regression are: *Increase in NSF Research Grants* (*GRANT*), which is the average of the past five-year increase in the real National Science Foundation research grants for both applied and basic research; *AAA Spread* (*AAA*), which is the spread of AAA bonds over five-year Treasury bonds in the current year; *Number of Instate LPs* (*NUMLP*), which is the logarithm of one plus the total number of venture capital limited partners (LPs) in the past five years that are located in the same state as the firm's headquarter. All other variables are described in previous tables. The dependent variable in the second-stage OLS regression, *EXIT,* is treated as a continuous variable: it equals 0 if the firm is private (the base category); it equals 2 if the firm goes public (*IPO*) in year t; and it equals 1 if the firm gets acquired (*ACQ*) in year t. The independent variables in the second-stage regressions are the Inverse Mills Ratio (*INVMILL*) from the first-stage and all the independent variables from the first-stage except for the three instrumental variables. Heteroskedasticity corrected clustered robust standard errors, clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Panel B reports the result of a "what-if" analysis based on the results of the switching regression model in Panel A. It reports the actual value of *EXIT* for firms with private financing, the fitted value of *EXIT* if private-financing-backed firms did not receive private financing, and the difference between actual and hypothetical values of *EXIT*. The table also reports the fitted value of *EXIT* for firms without private financing if they had received private financing, the actual value of *EXIT* of non-private-financing-backed firms, and the difference between the actual and hypothetical values of *EXIT*. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively, for t-test of mean difference.

Panel A: Endogenous switching regressions

First Stage		*Second Stage*		
Dep. Variable: Private Financing Dummy		*Dep. Variable: EXIT (=2 if IPO, 1 if ACQ, 0 if PRV)*		
			With Private Financing	*Without Private Financing*
GRANT	0.282***	*INVMILL*	0.465**	0.016
	[0.017]		[0.188]	[0.022]
AAA	-0.046**	*SIZE*	0.117***	0.004***
	[0.023]		[0.045]	[0.0001]
NUMLP	0.084***	*TFP*	0.107***	0.003***
	[0.009]		[0.034]	[0.001]
SIZE	0.250***	*SGTH*	0.072***	0.003***
	[0.007]		[0.021]	[0.001]
TFP	0.131***	*CAPR*	0.292***	0.004***
	[0.036]		[0.112]	[0.001]
SGTH	0.163***	*WHITE*	0.175***	0.006***
	[0.041]		[0.066]	[0.001]
CAPR	0.598***	*MSHR*	0.325**	-0.009
	[0.076]		[0.137]	[0.022]
WHITE	0.326***	*AGE*	-0.022***	0.0005
	[0.066]		[0.006]	[0.0004]
MSHR	0.503***	*HTEK*	0.133***	0.007***
	[0.150]		[0.046]	[0.001]
AGE	0.079***	*TOV*	0.019**	0.001***
	[0.018]		[0.009]	[0.0003]
HTEK	0.283***	*INDRSK*	0.141	-0.011***
	[0.043]		[0.088]	[0.004]
SP500	0.143**	*HI*	0.183**	0.013***
	[0.069]		[0.073]	[0.002]
		LIST	0.015*	0.001***
Ind. Dummy	Yes		[0.009]	[0.0002]
Observations	467301	Year Dummy	Yes	Yes
Pseudo R^2	0.22	Observations	13936	408150
Wald χ^2	3580.19	R^2	0.03	0.01

Panel B: Actual and hypothetical values of EXIT for firms with and without private financing

	Actual Value of *EXIT* for firms *with* Private financing	Value of *EXIT* for firms *with* Private financing if they had not obtained the financing	Difference
Mean	0.046	0.024	0.022***
	Actual Value of *EXIT* for firms *without* Private financing	Value of *EXIT* for firms *without* Private financing if they had obtained the financing	
Mean	0.012	0.024	-0.012***