Private and Public Merger Waves

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We examine the participation of public and private firms in merger waves and their outcomes. We show that public firms participate more in mergers and acquisitions than private firms and are more cyclical in their acquisitions. Public firms are also impacted more by macro factors including credit spreads and aggregate merger activities. Plants acquired on-the-wave realize more gain in productivity. We show that our results are not just driven by the fact that public firms have better access to capital. Using productivity data early in the firm's life, we find that better firms select to become public and that we can predict higher participation in productivity-increasing mergers and acquisitions ten and more years later after a firm's initial appearance. Our results suggest that a firm's potential can be identified early and that high potential firms become public in anticipation of accessing capital in the public markets when opportunities arise.

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ABSTRACT

We examine the participation of public and private firms in merger waves and their outcomes. We show that public firms participate more in mergers and acquisitions than private firms and are more cyclical in their acquisitions. Public firms are also impacted more by macro factors including credit spreads and aggregate merger activities. Plants acquired on-the-wave realize more gain in productivity. We show that our results are not just driven by the fact that public firms have better access to capital. Using productivity data early in the firm's life, we find that better firms select to become public and that we can predict higher participation in productivity-increasing mergers and acquisitions ten and more years later after a firm's initial appearance. Our results suggest that a firm's potential can be identified early and that high potential firms become public in anticipation of accessing capital in the public markets when opportunities arise.

1 Introduction

It is by now well established that the market for corporate assets is pro-cyclical. Mergers and acquisitions tend to cluster over a short period of time.[1] However, less is understood on what causes firms to participate in these waves and whether acquisitions that occur on the waves lead to the same efficiency outcomes than mergers that occur off the waves. Also unknown is the extent private firms participate in merger waves and whether their participation is affected by similar demand and supply factors that affect public firms. At one extreme, acquisitions waves may occur because investment opportunities also occur in waves. At the other extreme, waves are driven by changes in liquidity and investment climate which enable certain types of firms to obtain capital more easily or cheaper than other firms.

In this paper, we examine the impact of real and financial factors by comparing the participation of public and private firms in merger waves and their outcomes. Using plant-level data on a sample of about 40,000 firms over the period of 1977-2004, we find that public firms in general are more likely to participate in acquisitions than private firms. This is true after controlling for firm size and plant productivity. Moreover, there exists a notable difference between these two types of firms in their acquisition decisions over the business cycle. Public firms are almost twice more likely to buy assets in aggregate wave years than in non-wave years while the time-series of purchases by private firms are relatively much flatter. To a large extent, the observed aggregate merger and acquisition waves are mostly driven by higher participation of public firms.

The central contribution of this paper is to show how and why public and private firms behave differently in acquisitions. We take direct account of the fact that the decision to acquire public status is itself a choice variable. If public status confers advantages in financing mergers or accessing capital, firms may select into public status in anticipation of future acquisitions. Indeed, we find that firms with higher initial productivity at birth choose to become public, and later these firms are more sensitive to changes in their fundamentals and the aggregate investment climate in acquisition decisions. We find that firms with more "public" quality (as measured by the predicted probability of being public) also participate more in acquisitions and are more wave-driven. After controlling for the predicted probability of being public, the difference between public and private firms' acquisition behavior diminishes. Selection into public status based on initial productivity and size explains a significant portion of public firms' higher participation

[1] Mitchell and Mulherin (1996) and Harford (2005) analyze merger waves by public firms. See Andrade, Mitchell and Stafford (2001) and Betton, Eckbo, Thorburn (2008) for two surveys on the overall merger market.

in merger waves ten and more years later. Specifically, controlling for the "public" quality explains more than 90% of the difference in asset and whole firm sales, and 27% of the difference in purchases, between public and private firms.

We also analyze how macro factors may drive merger activity and especially how they affect public and private firms differently. Among the three factors we consider, credit market liquidity, as measured by the spread between Commercial and Industrial (C&I) loans and Fed Funds rate, has the greatest effect on merger intensity. We find that private firms are much less sensitive to credit spreads than public firms in acquisition decisions during merger waves. This suggests that they are either in general not constrained and the lower participation is explained by their lower productivity, or that financing constraints are sufficiently binding so that it is more efficient for private firms to change to public status before mergers.

We look further at how public firms with different levels of borrowing constraints respond to changes in liquidity on the market. When we split our sample of public firms based on credit ratings: investment grade (above BBB), below investment grade (BBB and below), and un-rated firms, we find that liquidity has the greatest impact for firms with below investment grade ratings. That is, firms with the intermediate access to credit markets are most affected by changes in market liquidity. This supports the notion that changes in the availability of credit are major driver of merger waves through the cost of accessing external financing.

However, our findings suggest that although public and private firms differ significantly in their acquisition decisions, the difference is not simply due to their difference in access to capital markets. Firms with higher productivity and greater anticipation of future growth choose to become public early in their life. Later, these firms participate more in acquisitions when opportunities become favorable. However, while better access or lower cost of capital which may help them participate in acquisitions, this is not the underlying reason why public firms and private firms acquisition patterns differ. There are difference in firm quality which enable some firms to grow through productivity increasing acquisitions, and these differences are reflected in their earlier choice to become public.

We find that acquisitions are efficiency improving, both on- and off-the-wave. Plants sold experience higher increases in productivity after transactions than similar plants that are kept. Productivity increases are higher for on-the-wave mergers, and in particular, when buyer and seller are both public firms. We do not find evidence that the increased occurrence of public mergers in waves leads to misallocation of assets. Instead, our finding suggests that periods of more frequent transactions may have been stimulated by higher efficiency improvement.

Our paper builds on the rapidly growing literature on merger waves. Clustering of mergers in time and industry has been studied by Mitchell and Mulherin (1996), Mulherin and Boone (2000), Andrade et al. (2001) and Harford (2005), among others. Maksimovic and Phillips (2001) point out the procyclicality of the market for acquisitions. More recently, Dittmar and Dittmar (2008) and Rau and Souraitis (2008) study wave characteristics of corporate financing events, including mergers. Shleifer and Vishny (2003) and Rhodes-Kropf, Robinson, and Viswanathan (2004) argue that merger waves are driven by overvaluation in public financial markets, while Harford (2005) places greater reliance on availability of liquidity. Schlingemann, Stulz, and Walkling (2002) study sales of industry segments using Compustat segment data. They find that firms are more likely to sell assets in periods of high industry liquidity. Eisfeldt and Rampini (2006) attribute liquidity as the reason why asset sales are pro-cyclical. Ahern and Harford (2010) show that industry ties predict inter-industry merger activities.

Our paper differs from the existing studies in several aspects. First, we study both public and private firms, using data from the Census. By comparing participation and outcomes of public and private acquisitions on and off the merger waves, we can directly address the effect of market valuation and liquidity shocks on firms with differential access to financial markets.

Second, we use detailed input and output data to estimate productivity for both public and private firms at the plant level. As a result, we can obtain estimates of the economic value created by mergers and are not affected by over- or under-payment between buyers and sellers. It gives us a better platform to compare efficiency implication of mergers on and off the wave, and by public and private firms.

Third, through the unique and separate plant and firm identifiers in the Census dataset, we are able to pin down exactly which plants within a firm have changed ownership so that we can directly access the outcome of an acquisition by comparing productivity changes for those plants. In comparison, most of existing studies draw their conclusions based on performance changes in the entire acquirer firm which confounds the performance changes of the acquired units with the pre-existing units.

Our paper is related to four recent papers. Yan (2006) and Duchin and Schmidt (2008) analyze the value created by on-the-wave and off-the-wave mergers. They find that on-the-waves are more likely to be value destroying. By contrast, we find that on average on-the-wave public mergers increase productivity of the acquired plants. The two findings are not inconsistent, in that acquiring firms may overpay for real synergies. Celikyurt, Sevilir, and Shivdasani (2008) and Hovakimian and Hutton (2008) show that a large percentage of firms engage in acquisitions in the period of three to five years after the IPO. While their finding does not prove that a primary motivation for IPOs is to enable firms to make acquisitions, they do suggest that for young firms, at very least, public status facilitates acquisitions. Our paper shows that the difference in public status significantly affects the probability of acquisitions, and especially so at the time of aggregate merger waves. Moreover, we show that growth and productivity of firms at the early pre-IPO stage predicts both public status and subsequent acquisition activities years afterwards.

In the next section, we present questions addressed by our study, together with theoretical predictions related merger waves. Section 2 describes our sample and variables and Section 3 describes merger waves. We estimate decisions to participate in mergers and acquisitions by public and private firms in Section 4. Section 5 examines changes in productive efficiency after mergers. Section 6 predicts the decision to become public and re-examines decisions to sell and buy assets. Section 7 concludes.

2 The Empirical Framework

A ready explanation for the phenomenon of procyclical merger waves is that the gains from the reallocation of assets across firms are also pro-cyclical. However, merger waves may also be driven by developments in the financial markets. Harford (2005) argues that waves occur in part because external capital is easier to raise and cheaper when the economy is improving. For public firms, periodic stock market misvaluation can be an alternative cause of merger waves. Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) suggest that higher valuation on the equity market makes equity-financed acquisitions more attractive. Using samples of publicly traded firms in the US, Harford (2005) and Rhodes-Kropf, Robinson and Viswanathan (2005) find support for liquidity and misvaluation hypotheses, respectively.

Much less is known about mergers by private firms. From our data (described in the next section), we are able to identify merger and acquisition decisions of both public and private firms. Figure 1 plots the time series for the rate of purchases and sales of US manufacturing plants over the period 1977-2004.

Insert Figure 1 here

There exists a remarkable difference between public and private firms in their acquisition decisions over the business cycle. As shown in Figure 1, purchases by public firms exhibit a clear wave pattern, whereas purchases by private buyers are relatively flat. Public firms are almost twice more likely to buy assets in aggregate wave years than in non-wave years while purchases by private firms are relatively much flatter. To a large extent, the observed aggregate merger waves are mostly driven by higher participation of public firms. This finding is consistent with the pattern found by Betton, Eckbo, and Thorburn (2008), using the publicly available data on the subsamples of public and non-public bidders.

2.1 Public Status and Participation in Merger Waves

By becoming public, a firm obtains better access to financial markets. More specifically, it acquires an option to obtain public financing at some future date at the prevailing rates, thereby lowering the cost of capital for acquisitions. This option is more valuable when a firm perceives greater future needs for external capital, either for investment or acquisitions. We outline a framework that permits us to empirically examine how access to public financial markets and investment opportunities affect mergers decisions given demand and financing shocks.

Firms are founded by entrepreneurs who differ in their vision, managerial talent or initial capital. Some firms have the potential to become significant players in their industries. Others, with less able entrepreneurs, niche products, or small-firm dominated industries will most likely stay small. Early in the life of the firm, the entrepreneur receives a signal about the firm's prospects and decides whether to become public through an IPO.[2] On one hand, public status offers financing advantages such that if the firm becomes public it has the option to access public markets at a future date. On the other hand, public status is costly to acquire initially (i.e. this is the direct and indirect cost of an IPO) and, due to reporting and governance regulations, has a per-period cost to maintain. Given these trade-offs, entrepreneurial firms that are initially larger, more productive, and in industries with higher capital intensity or significant growth opportunities are more likely to become public.

Since public firms may self-select for higher potentials, later, the acquisition activity of public firms will differ from those of private firms. In predicting the acquisition and restructuring behavior, it is important to separate out the following three distinct sources of differences between public and private firms.

First, we expect differences in acquisition activity purely on the basis of differences in fundamentals. Because larger and more productive firms select public status, we expect that a sample of public firms engages in more acquisitions, all other things being equal. This is purely a selection effect and will be reflected in the differences in the values of the explanatory variables in the subsample of public and private firms.

Second, public status may cause a differential in the elasticity of acquisition activity with respect to demand shocks in the industry. Maksimovic and Phillips (2001, 2002) and Yang (2008) argue that demand and productivity shocks cause firms' comparative advantage in an industry to shift. Specifically, positive demand shocks cause the optimal capacity of productive firms to expand relative to that of less productive

[2] The firm has option to postpone an IPO to a future date. This is inessential to our main argument and empirical tests. However, it is consistent the finding by Celikyurt, Sevilir, and Shivdasani (2008) and Hovakimian and Hutton (2008) that IPOs are frequently followedwithin a short span by acquisition activity.

firms. Thus, the demand for acquisitions by productive firms will increase relative to that of less productive firms in times of expansion. Less productive firms will sell assets to more productive firms. To the extent that the more productive firms self-select into public status, following a positive industry shock the rate of public acquisitions will increase, and the rate of sales will decrease, relative to private mergers.

Third, public and private firms will be affected differently by financial market shocks. This occurs because public firms have better option to access public financial markets, especially for long-term capital, at more favorable or easier terms than an otherwise identical private firm. Such access might be needed both to finance cash offers and to refinance the debt of target firms that comes due upon a change of control. Private firms rely more on short-term financing from financial intermediaries (Brav (2009)) and are unable to use equity as a medium of exchange in acquiring widely held firms. As a result, they will be differentially affected by changes in market liquidity. A priori, the differential effect could either be positive or negative. If increased liquidity in the market relaxes private firms' financing constraints more than those of public firms, then all else equal, macro liquidity shocks will have a greater effect on the participation of private firms. However, if liquidity shocks occur when private firms have fewer growth opportunities relative to public firms as a result of differences in their respective productivity, increases in market liquidity will be associated with an increase in the ratio of public to private acquisitions.

We use the following basic model to examine the asset purchase and sale decisions:

$$m_{it+1} = F(\delta_0 P_{it} + \delta_1 X_{it} + \delta_2 Z_t + \delta_3 (P_{it} X_{it}) + \delta_4 (P_{it} Z_t) + \varepsilon_{it}) \tag{1}$$

where m_{it+1} is 1 if firm i engages a purchase (sale) of assets at time $t+1$ and 0 otherwise. X_{it} includes firm-specific variables and industry variables. Z_t includes aggregate macro economic conditions or indicators for merger waves, and P_{it} is an indicator variable that takes the value of 1 for public firms and 0 for private firms. ε_{it} is a random error, and $F(.)$ is a non-linear limited dependent variable parametric form. Model (1) divides the difference in acquisition decisions between public and private firms into three distinct sources. First, public and private firm have different propensities to merge due to differences in fundamentals. Public firms tend to be larger and large firms may face lower fixed transaction costs and therefore are more likely to participate. This effect will be captured by the coefficient of δ_1. Second, public status may cause a difference in the elasticity of acquisition activity with respect to measured firm fundamentals or macro-economic shocks either due to their differences in access of capital or governance structure. These effects would be reflected in the coefficients of δ_3 and δ_4 , respectively. Third, public and private firms can be different in unmeasured factors. The coefficient δ_0 will pick up the average effect of public status on acquisition decisions based on factors that are not fully covered by our model.

2.2 Firm quality, Decision to Become Public and Participation in Merger Waves

The key to our framework is the prediction that firms' self-select into public status based on their potential for long-run profitable growth. We argue that the potential is evident early in the life of the firm and predicts future participation in the market for assets. To demonstrate this relation, we need to show that the firm's initial characteristics predict both selection into public status and merger activity in subsequent years.

We proceed in two steps. First, we take a subsample of firms that are born after the beginning of our sample, and use their characteristics at time t_{0i}, the date of firm i's first appearance as explanatory variables to predict whether the firms is public at time t. Time t lies in an interval between 5 years (or, alternatively, 10 years) after t_{0i} and the end of the sample. For some specifications, we also add lagged variables to account for industry and macro conditions on the decision to maintain public status. We use the following specification:

$$y_{it} = G\left(\pi_1 X_{it_{0i}} + \pi_2 Z_{i,t-1} + \nu_{it}\right) \tag{2}$$

and

$$\begin{aligned} P_{it} &= 1 \text{ if } y_{it} > P_{i^*} \\ P_{it} &= 0 \text{ if } y_{it} \leq P_{i^*} \end{aligned}$$

where P_{it} equals 1 if firm i is public at time t and zero otherwise, X_{it_0} captures the initial firm quality that is observable, and $Z_{i,t-1}$ includes contemporaneous market variables. $G\left(.\right)$ is a non-linear limited dependent variable parametric form.

In the second step, we replace P_{it} , the public status indicator in equation (1) with the predicted probability $\widehat{P_{it}}$ estimated from(2) to predict participation in the market for corporate assets:

$$m_{it+1} = F(\delta_0 \widehat{P}_i + \delta_1 X_{it} + \delta_2 Z_i + \delta_3(\widehat{P}_i X_{it}) + \delta_4(\widehat{P}_i Z_t) + \varepsilon_{it}). \tag{3}$$

By examining the significance of coefficients δ_0, δ_3,and δ_4, this specification allows us to analyze how initial conditions such as productivity and size affect a firm's decisions to buy or sell assets in subsequent years. The specification (2) also addresses two potential econometric problems. First, an estimate of the relation between contemporaneous public status and acquisition activity can be confounded by market shocks as firms may become public during a merger wave in order to more efficiently accomplish a specific planned transaction. This is suggested by Celikyurt, Sevilir, and Shivdasani (2008) and Hovakimian and

Hutton (2008). We can eliminate this problem by using firms' initial conditions at birth. It is unlikely that micro and macro shocks that occur at the time of the firm's initial appearance directly affect merger decisions five or ten years later. Second, public and private firms differ in size and productivity. A straight comparison of acquisition activity between these two groups may be confounded by differences in contemporaneous characteristics that are hard to control effectively using a standard econometric model. Replacing P_{it} by the predicted probability $\widehat{P_{it}}$ allows us to predict participation in the market for corporate assets based on initial conditions, rather than current public status, and thus mitigates this problem.

In addition, we also perform a matching exercise using the propensity score based on initial characteristics $\left(\widehat{P_{it}}\right)$. For firms with comparable propensity score, we estimate the average treatment effect due to the public status in participation of mergers and acquisitions on- and off-the-wave. This non-parametric approach provides an alternative way to further separate the effect due to selection from the effect due to public status.

So far, we have implicitly assumed that access all public firms have equal access to financial markets. As shown by Faulkender and Petersen (2006), firms with higher bond ratings have better access to public bond markets. To determine whether differences in access to credit markets has a significant effect on participation in the market for assets, we further separate public firms into three groups, investment grade, non-investment grade and non-rated, to examine their acquisition activity in response to firm, industry and macro conditions.

2.3 Gains in Productivity: Public and Private acquirers, and On- and Off-the-Wave

To gauge the economic outcome of public and private mergers on- and off-the-wave, we examine changes in productivity of the transacted plants around the acquisitions. Public and private acquisitions may have different outcomes because they differ in productivity. Since public firms are more productive, if they are also better able to deploy acquired assets, assets acquired by public firms will be associated with higher productivity gains.[3] Differences in outcome might also occur if public and private firms face different agency problems. To the extent that public status is associated with dispersed ownership and entrenched management, public firms are more likely to engage in empire building. If so, we would expect to see lower productivity gains for asset that are purchased by public acquirers than private acquirers. Thus, changes in productivity for acquired assets provide a measure of the relative importance between agency problems and inherent productivity characteristics in public and private firms.

[3] Rhodes-Kropf and Robinson (2006) provide evidence that synergies from mergers are the greatest when high productivity firms take over other high productivity firms. Public firms are more productive than private firms in general.

Changes in productivity in acquired assets might also depend on the timing of the transaction. When both liquidity and demand are high, firms find it easier to finance their purchases of assets. If acquisitions are motivated by empire building, we would expect to observe lower subsequent productivity gains during periods of high liquidity and demand. By contrast, if acquisitions are motivated by expected productivity gains, the gains will be highest during periods of high demand and high liquidity in the market for assets, i.e. on-the-wave. To test these hypotheses, we compare the post-merger productivity change for acquisitions done on-the-wave and off-the-wave of public and private firms.

3 Data and Basic Statistics

We use data from the Longitudinal Research Database (LRD) and Longitudinal Business Database (LBD), maintained by the Center for Economic Studies (CES) at the Bureau of the Census to identify and track mergers and asset sales for both public and private firms. The LRD tracks approximately 50,000 manufacturing plants every year from the Annual Survey of Manufactures (ASM). It contains detailed plant-level data on the value of shipments produced by each plant, investments broken down by equipment and buildings, and the number of employees.[4] The ASM covers all plants with more than 250 employees. Smaller plants are randomly selected every fifth year to complete a rotating five-year panel. Even though it is called the Annual Survey of Manufactures, reporting is mandatory for large plants and is mandatory for smaller plants once they are selected to participate. All data are reported to the government by law and fines are levied for misreporting.

The data we use covers the period from 1972 to 2004. To be included in our sample, firms must have manufacturing operations in SIC codes 2000-3999. We require each plant to have a minimum of three years of data. For each firm, we also exclude all its plants in an industry (at the three-digit SIC code) if its total value of shipments in that industry is less than $1 million in real 1982 dollars. Since we construct measures of productivity (described later) using up to 5 years of lagged data, our regressions cover the period 1977-2004. Since we compute the rate of capital expenditure by dividing capital expenditure on lagged capital stock and calculate change of sales using lagged sales, we lose the initial year a firm or a firm-segment enters the database and observations that are non-continuous. Our final sample has about 520,000 firm-industry years and more than 1 million plant years.

These Census databases keep unique identifiers for both firms and plants which allow us to track

[4] For a more detailed description of the Longitudinal Research Database (LRD) see McGuckin and Pascoe (1988) and also Maksimovic and Phillips (2002).

ownership change over time.[5] To identify public firms, we use an existing bridge file created by the CES staff that links the Census firm identifiers with identifiers of public firms in Compustat. To construct the bridge file, firms are matched by employer identification number (EIN) and name in each year from 1980 to 2005.

In our final sample, on average, public firms account for 20% of the firms in an industry and 35% of total output. Public firms are bigger - on average, public firms won 3.1 plants while private firms own 1.4 plants. The median value of shipment (in \$1982 dollar) is about \$9 million for private firms, and \$48 million for public firms. Public firms are also more productive than private firms, and have higher operating margin.

3.1 Global and Industry Merger and Acquisition Waves

We identify merger and acquisition waves at the aggregate economy level as well as on the industry level using the following procedure. For each industry, we first calculate the percentage of plants traded between firms in each year. Then, we calculate the standard deviation of this annual percentage over all years. Industry merger wave years are defined as years in which the percentage of plants traded is at least one standard deviation higher above the industry mean rate. For the aggregate wave years, we use similar method, except that the mean rate and the standard deviation are based on all plants in the economy. Aggregate merger wave years are years in which the percentage of plants traded is greater than one standard deviation above the aggregate mean rate.

Using data from 1977 to 2004 for all manufacturing industries (2,957 industry years), we have identified six aggregate wave years: 1986, 1987, 1996, 1998, 1999, and 2000, and 432 industry wave years. Table 1 presents summary statistics for these aggregate waves.

Insert Table 1 Here

First, public firms participate more in asset sales in general, and the number is even higher for on-the-wave years. On average, public firms operate 20% of the firms in manufacturing industries, and account for 37% of the total transactions. During the aggregate wave years, 42% of the buyers and 40% of the sellers are public firms, as compared to 35% and 30% off the wave, respectively.

[5] For example, if the plant #1000 is under firm #123 in year 2000, but firm #321 in year 2001, we identify it as a transaction from firm #123 to firm #321 in 2000. From communications with Census staff (Javier Mirinda) we understand that information on ownership transfers is updated in a timely manner for nearly all public and private transactions. The survey form is sent in December and companies are required by law to return the form back in 30 days to report any ownership changes during the reference year. For more detailed information on the survey, please refer to http://www.census.gov/econ/overview/mu0700.html.

Second, the number of public-to-public transactions increases more than any other types of transaction during aggregate wave years. On average, 1 out of 27 plants (3.7%) is sold during an off-the-wave year and 1 out of 17.5 plants (5.7%) during a wave year. Among all the transacted plants, 19% of the transactions are between a public buyer and a public seller on the wave, up from 12% off the wave. On the other hand, private-to-private transactions account for 37% all transactions on the wave, a sharp decrease from 48% off the wave.

Public firms buy more in a transaction on the wave – the average number of plants sold in a public-to-public transaction is 3.19 on the wave and 2.48 off the wave. About 26% of all public-to-public transactions on the wave involve full ownership transfer, while only 18% off the wave do so. In contrast, about three quarters of private-to-private transactions involve full ownership transfers, both on and off the wave.

Table 1B examines the relation between industry and global merger waves. Industry wave years and aggregate wave years are highly correlated. The probability of having an industry wave is about one third (33%) when the aggregate economy is on wave, and is less than one tenth (9.4%) in off-the-wave years. To further gauge the co-movement among different industries, we run a logit regression using the industry wave dummy as dependent variable in an industry-year panel. Our independent variable, Other_IW, indicates the fraction of other industries on wave in the same year. By construction, Other_IW is bounded from 0 to 1, and in our panel, this variable has a mean rate of 0.14 with a standard deviation of 0.12. We also include an industry fixed effect to account for differences in mean wave rate across industries. Table 1B shows that one additional industry being on the wave increases the odds ratio of other industries being on the wave by 6%.[6]

3.2 Public and Private Industries

In our sample, on average, public firms account for 20% of the firms in an industry. However, there exists a wide variation in percentage of public firms across industries. Table 1 presents the top and bottom ten industries based on their average percentage of public firms, together with the rate of transaction on and off the aggregate merger waves. Overall, the more "public" an industry is, the higher the participation in mergers and acquisitions - particularly so during the aggregate merger waves. All of the top ten public industries on our list have greater than average rate of transaction and the difference is even higher on the wave. By comparison, all of the "least" public industries with one exception, have transaction rate less than the average.

[6] We calculate the odds ratio as exp(6.440 * (1/105) = 1.063 based on the average number of industries in a year (105) and the estimated coefficient (6.44) from Table 1B.

For example, in the Search and Guide Instruments industry, public firms represent over 54% of the industry total output. Off the wave, 6.9% of the plants in the industry are involved in M&A activity, and on the wave, the percentage almost doubles to 11.6%. On the other hand, in Women's Outwear industry, public firms only represent 4.6% of the industry total output and the fraction of plants that involve in M&A activity are 1.8% off the wave and 2.3% on the wave.

Insert Table 2 here

3.3 Economy and Industry Conditions

We focus on supply and demand factors that might affect the rate of mergers over time. To capture the supply of capital, we use the spread between the rate on Commercial & Industrial (C&I) loans and the Fed Funds rate as a measure for aggregate liquidity following Harford (2005). Lown et al. (2000) find that this spread is strongly correlated with the tightening of liquidity measured from Federal Reserve Senior Loan Officer (SLO) survey. When credit spread is low, acquisitions become easier to finance and are more likely to be carried out. However, the comparative effect of narrowing credit spreads on private and public firms cannot be predicted a priori. On one hand, narrowing spread might allow public firms to take advantage of their access to public markets and increase their acquisition activity both absolutely and relative to private firms. On the other hand, the increased liquidity associated with low spreads might also make it cheaper for private firms to obtain loans. This second effect would increase the rate of private acquisitions relative to public acquisitions.

We use two variables to capture the level of demand and investment opportunities in the industry. When investment opportunities and demand increase and the supply of new capital is inelastic, highly efficient firms may choose to buy other firms instead of building new capacity. This relation is predicted by Maksimovic and Phillips (2001), Harford (2005), and Yang (2008), among others. We use the industry Tobin's q and the aggregate return on the S&P industrials index as a proxy for industry and aggregate level of investment opportunities respectively and examine their impact on merger activities. Tobin's q is calculated from Compustat data and is measured as the sum of the market value of equity and the book value of debt divided by the book value of assets.

Not surprisingly, these factors are correlated. For example, the correlation between credit spread and S&P industrial return is -47%. For robustness checks, we estimate the effects of these factors both separately and jointly in all of our specifications. For brevity, we only report results on joint estimation. Unless mentioned explicitly in the paper, results based on individual factors are qualitatively the same.

We also include the industry Herfindhal index in the specifications to control for the incentive to buy competitors to increase the firm's market power or the easiness to find a trading partner. It is calculated as the sum of squared firm-industry market shares using sales which are based on both public and private firms in the industry.

3.4 Productivity Calculations

We calculate the total factor productivity (TFP) of a plant as a measure of productive efficiency. TFP takes the actual amount of output a plant produces with a given amount of inputs and compares it to a predicted amount of output. A plant that produces more than the predicted amount of output has a positive TFP and a greater-than-average productivity.[7] To calculate the predicted output, we assume a translog production function. This functional form is a second-degree approximation to any arbitrary production function, and therefore takes into account interactions between inputs. For each industry, we estimate rolling regressions using the last five years of data for each plant to predict its output for the current year - thus the first year of our data for which we have calculated productivity is 1976. Specifically, we estimate the following model using an unbalanced panel with plant-level fixed effects:

$$\ln Q_{it} = A + f_i + \sum_{j=1}^{N} c_j \ln L_{jit} + \sum_{j=1}^{N}\sum_{k=j}^{N} c_{jk} \ln L_{jit} \ln L_{kit,} + \varepsilon_{it} \tag{4}$$

where Q_{it} represents output of plant i in year t, and L_{jit} is the quantity of input j used in production for plant i for time period t. A is a technology shift parameter, assumed to be constant by industry, f_i is a plant-firm specific fixed effect, ε_{it}, (if a plant changes owners a new fixed effect is estimated). We leave off the firm subscript for tractability), and $c_j = \sum_{i=1}^{N} c_{ji}$ indexes returns-to-scale. We deflate for industry price at the four digit level.

We obtain our measure of plant-level TFP from adding two components from the equation (4) above: a plant-firm fixed effect, f_i, and a plant residual term in each year. The fixed effect captures persistent productivity effects, such as those arising from managerial quality (Griliches (1957) and Mundlak (1978)), and a firm's ability to price higher than the industry average. The residual term measures the deviation of the actual output from the predicted output. For each industry year, we further standardize plant-level TFP by subtracting out the industry average and dividing by the standard deviation. This is to control for differences in precision with which productivity is estimated within industries. This correction is analogous to a simple measurement error correction and is similar to the procedure used to produce standardized

[7] This measure does not impose the restrictions of constant returns to scale and constant elasticity of scale that a "dollar in, dollar out" cash flow measure would require.

cumulative excess returns in event studies.[8]

In computing changes of TFP, we control for predictable time series variation by subtracting the predicted change from the actual change.[9] We estimate the predicted change of TFP by regressing future changes in TFP on initial TFP levels for all plants during the same time period. This procedure is analogous to obtaining a coefficient of mean reversion.

We use over one million plant years (approximately 40,000 plants each year) in our TFP estimation, and include three different types of inputs, capital, labor, and materials as explanatory variables. All of the variables are available on the plant level. However, our productivity calculations do not capture any headquarters or divisional level costs that are not reported at the plant-level (i.e. overhead, research and development). The ASM only shows the value of shipments, but does not state the actual quantity shipped by each plant. We thus deflate the value of shipments by 1982 price deflators to get the real value. For all inputs and outputs measured in dollars, we adjust for inflation by using four-digit SIC deflator data from the Bartelsman and Gray (1994) database. Each input has to have a non-zero reported value to be included. Kovenock and Phillips (1997) describe these inputs and the method for accounting for inflation and depreciation of capital stock in more detail.

4 Endogenizing Public Status

The summary statistics we have presented show that public firms are more likely to engage in asset transactions and that the aggregate merger wave is largely driven by higher participation from public acquirers and targets. But the decision to acquire public status is itself a choice variable. Thus, if public status confers advantages in financing mergers, then firms could select into public status prior to a merger. In this section, we analyze this selection process and re-examine firms' decisions to buy or sell asset controlling for self-selection.

We first examine the decision of being public using initial conditions only. Then, we include the lagged firm and industry variables to account for cases that firms may change their public status over time and the timing of the decision. However, this is not crucial for our later results. Initial conditions are very persistent over time and explain a great deal on whether the firm will become public later. For example, ten years after the first appearance, 44% of the firms that started in the smallest quintile will remain in

[8] This standardization does not affect the results we report. The results have similar levels of significance when we do not standardize productivity in this manner.

[9] The literature on operating performance, e.g., Barber and Lyon (1996) and Lie (2001) emphasizes the importance of this correction. For instance, Lie finds that the failure to correct for this introduces bias into ex-post performance statistics.

the smallest quintile and 90% of the firms that started in the largest quintile will remain in the largest quintile. Productivity is also persistent over time although not as much as size Ten years after the first appearance, 36% (40%) of firms that started out in the least (most) productive quintile remain in the same productivity quintile.

4.1 Predicting Public Status

Model (3) predicts a firm's public status based on its initial conditions. We examine how initial productivity and size from five to ten years before a given year influences whether firms select to be public. The selection explanation emphasizes that firms that are of sufficient quality to engage in merger and acquisition activity, preposition themselves by selecting to go public as they are more likely to have the demand for financing available in the public market.

Since our sample with productivity measure starts from 1976, to accurately capture the initial status, we only include firms which appeared in the database after 1976. We cross-check with the LBD to reconfirm the year of the initial appearance.[10] For the purposes of predicting the firm's public status and whether it firm participates in an asset sale or purchase we also create either a five or a ten year exclusion window. Specifically, we exclude the firm from our sample in the first five (ten) years after it first appears in the database. Thus, in the tables on participation in the market for assets presented below there is at least a five-(ten-)year gap between the firm's initial year, and the data on its initial conditions, and the years we analyze. In columns 1 through 3, we predict a firm's public status five years and later from the firm's initial appearance in our database (which as stated earlier should be very close or equal to a firm's birth year), while in columns 4 through 6, we predict public status 10 years after the initial appearance. Thus, we exclude observations within five and ten years of a firm's initial appearance, respectively.

Insert Table 3 Here

Table 3 shows our result on predicting the public status. We run probit models using a firm's public status as dependent variable and its long-term lags of size and productivity, along with other demand shock variables, as explanatory variables. In column 1, we include the initial size and productivity (from at least 5 years before the current observation, Size_0, TFP_0) and their square terms ($\text{Size}_0 2$, $\text{TFP}_0 2$) to measure the early quality of a firm, and use the change of aggregate industry shipment in the past 25 years(CDTVS_{25}) to measure the long-term growth in industry demand. The five year lag period removes the concern that

[10] LBD is constructed from the Business Registry and covers all firms with any paid employees. As a result, it is less subject to sample selection than the LRD.

contemporaneous shocks affect both the incentives to be public and trade assets. Instead, the specification captures the fundamental quality of a firm which affects both the incentives to go public as well as the incentives to trade assets. Both linear and square terms of productivity and size are significant, suggesting that initially large and more productive firms become public later in life. Firms with initial size and TFP both in the highest quintile have a 27% probability of being public five years after the initial appearance, while the smallest and least productive firms have less than 1% of the probability of being public. The industry long-term growth in demand also plays an important role. Firms in industries with increasing long-term demand, as proxied by growth in shipments, are more likely to be public than other firms in industries with declining demand. The initial conditions, together with the industry long-term demand explain about 18% of the total variation in firms' public status five years after the initial appearance.

In column 2, we add industry and macro variables, lagged one year, to further predict public status. Firms in industries with higher capital expenditure rates and more growth opportunity may have higher demand for capital. Thus, we add industry characteristics such as industry capital expenditure rate (I_Capex) and industry Tobin's q (I_Tobinq). Industry structure such as concentration ratio may also affect a firm's decision to become public. We use the Herfindhal index (HERF) as our measure of concentration which is defined using sales from both public and private firms. Some industries may be more suitable for small private firms than others due to the nature of business. We use the percentage of firms with less than 50 employees, S50, as a proxy to measure industry business condition.[11] Becoming public may be more likely for initially productive firms if productivity is persistent over time. We include in our regression a measure for productivity persistence (Persistence) based on the rank correlation between the lagged and the current TFP for all firms within the industry. A higher persistence indicates that firms that are productive now are more likely to stay productive in the future. Lastly, to account for the cost of becoming public especially due to changes in macroeconomic conditions, we include the log number of IPOs in a year. This series was calculated based on data provided on Jay Ritter's website.[12] All of the industry and annual variables are lagged.

In column 3 we break up the initial size into quintiles and interact it with firm's initial productivity. There is a monotone effect on size and TFP across all quintiles. Firms that are initially large with high productivity are more likely to become public later in their lives. In columns 4 through 6, we estimate the same specification using initial firm quality and firm size from at least 10 years prior to subsequent years. The results from these specifications are similar to the one with initial quality and size from five

[11] We use the employment number provided in LBD to compute this percentage.

[12] http://bear.cba.ufl.edu/ritter/ipoisr.htm

years prior.

If decisions of being public are largely driven by firm and industry conditions which also affect merger waves, then we should take into account this endogenous choice when we estimate the participation of public firms in merger waves. In the next section, we will first compare the participation of public and private firms in merger waves and then re-examine the question, explicitly taking account of the choice of being public.

5 Participation in Merger Waves: Public and Private Firms

5.1 Probability of Buying and Selling Assets

Table 4 examines the probability of buying and selling assets for both public and private firms over indicators of credit market conditions and merger waves. Our dependent variable, D_Buy, takes the value of 1 if a firm buys assets in the next period and 0 otherwise, and D_Sell, takes the value of 1 if a firm sells any asset. We first estimate our equations separately for public and private firms, and then later (in Table 7) match firms by the estimated probability of being public. All regressions are run on the firm-industry-level. Panel A examines the decision to buy assets and Panel B examines the decision to sell assets. In both panels, columns 1 to 2 estimate specifications that include aggregate economy-wide variables and Columns 4 and 5 examine specifications with our global wave indicator variable.[13] Column 3 and 6 report the p-value for testing the difference between public and private firms.

We include the firm size, measured as total value of shipment across all industries in which it operates, as large firm may have higher financing capacity when it comes to acquire assets. We also include the productivity of the firm and the Tobin's q of the industry to control for demand for assets, and use Herfindhal index to control for industry structure.

Insert Table 4 Here

Public firms are more likely to engage in asset transactions. In our sample, in a given year, about 7.36% (7.91%) of all public firms bought (sold) assets while less than 1.75% (4.08%) of all private firms bought (sold) any asset. For both groups, size is positively related with buying and selling asset, while productivity has a positive effect on purchases, but a negative effect on sales. The sensitivity of purchase and sales to productivity, on the other hand, is much higher for public firms. The estimated marginal

[13] This variable is equal to one for the six aggregate wave years: 1986, 1987, 1996, 1998, 1999, and 2000, and zero otherwise.

effect of TFP is ten times larger in buy decisions, and 5 times larger in sell decisions for public firms than that for private firms. Public firms are also much more sensitive to credit spreads and to aggregate wave indicator. In both panels, the difference between two groups is significant at one percent level. Similar patterns are documented when we use the aggregate wave indicator. For both groups, higher stock returns lead to higher rate of transactions (in purchases and sales). Private firms are slightly more likely to sell assets when returns are high, while the difference is not statistically significant in purchase decisions.

To better understand factors that are driving the observed differences between public and private firms in their decisions to buy assets, we calculate economic effects based on the estimated model. We predict rate of purchases and sales by varying the credit spread variable from the 10th to the 90th percentile and also our global wave indicator variable from zero to one while holding all other variables at their sample median. In a different run, we also use the estimated coefficients from the private firm regressions and apply them on the median data of public firms. This way, we can decompose the differences in the outcome variable (in this case, rate of purchases or sales) between two groups (private and public firms) into a part that is due to differences in the explanatory variables and a part that is due to differences in sensitivity to those explanatory coefficients. For example, public firms may participate more in acquisitions because they are more sensitive to aggregate economic conditions, or because they are bigger and bigger firms are better equipped to absorb the fixed transaction costs. These results are presented in Table 5.

Insert Table 5 Here

The rate of purchase is vastly different between public and private firms at every percentile of the credit spread data. For example, when credit spread is at its median, the rate of purchases is 7.32% for public firms, but only 0.77% for private firms. Public firms are also more sensitive. For public firms, the rate of purchase increases from 6.50% to 8.45% when credit spread moves from its 90^{th} to the 10^{th} percentile. In comparison, for private firms, the change is much flatter - from 0.75% to 0.80%.

However, this difference does shrink remarkably when we apply the estimated coefficients from the private firm regressions to data based on public firms. For the median credit spread, the predicted rate of purchases by private firms is 11% that of public firms. However, when we apply the estimated coefficients from the private regression (column 2) to the public firm data, we find that differences in firm characteristics explain about 87% of the observed difference between public and private firms. Thus, differences in the characteristics of public and private firms explain a significant portion of the observed difference in purchases. Public firms are larger and more productive, and large and more productive firms are more likely to buy assets. However, a sizable gap (13%) still remains even after we control for firm characteristics and is attributable to public and private firms' differences in sensitivity to these characteristics. More interestingly, this gap is bigger when credit spreads are low and when global wave indicator is equal to one, suggesting that public and private firms have different sensitivity to macro conditions.

We find similar patterns in decisions to sell assets. When credit spread moves from the 90th to the 10th percentile, the rate of sales increases from 3.45% to 3.55% for private firms, and from 6.72% to 9.33% for public firms. When we apply the estimated coefficients from the private regression (column 2) to the public firm data, we find that differences in firm characteristics explain about 84% of the observed difference between public and private firms. Controlling for firm characteristics, credit matters less when credit spreads are low and when aggregate acquisition activity is high.

As an alternative robustness check for the size effect, we divide our sample into quintiles based on firm size, and repeat our analysis above in Table 4 using only firms in the largest quintile. Not surprisingly, most of the public firms are in the largest quintile. Compared to the overall sample, the largest quintile has a much more balanced panel of public and private firms - 43% of the firms in the largest size quintile are public firms and the rest are private firms. Our results remain qualitatively the same. Among firms in the largest size quintile, public firms are still more sensitive to liquidity in capital market and the aggregate merger activity in their decisions to buy assets than private firms.[14]

So far, we have shown that public firms are more sensitive to their own productivity and macro conditions such as credit spreads and aggregate merger activity when it comes to buy or sell assets. However, the difference in sensitivity may depend on the nature of the transaction (horizontal versus diversifying or mergers versus partial sales). To make sure that our findings above are not driven by a certain type of transactions, we run two sets of multinomial probit models as robustness checks. In the first set, we split purchases into horizontal and diversifying purchases; and in the second set, we separate full purchases (mergers) from partial asset purchases. Table 6 presents the marginal effects from our estimation. In all specifications, large, more productive public firms are more likely to buy assets and the effect of credit spreads on acquisitions is stronger on public firms. This is true for both within- and across-industry purchases and for mergers as well as for partial asset purchases. The estimated marginal effect of credit spreads is higher for horizontal acquisitions (as compared to diversifying acquisitions) and for mergers (as compared to partial sales).

In addition, we find that industry growth opportunity (measured by industry Tobin's q) has different effect for public firms in different transactions – positive for horizontal acquisitions and negative for

[14] In the interest of space, we do not report the tables using only firms in the largest size quintile. Results are available upon request.

diversifying acquisitions. This suggests that horizontal purchases may be driven by increasing growth opportunity in the industry while firms buy assets in other industries when their existing industries face declining growth. Examining partial versus full sales, we find that Tobin's q has a positive effect for partial sales, but a negative effect for full sales.[15]

Insert Table 6 Here

5.2 Endogenous Selection: Reexamining the Probability of Selling and Buying

As pointed out earlier, firms with higher productivity and greater anticipation of future growth may choose to become public to participate more in acquisitions when opportunities rise. In this section, we control for the endogeneity of public status and reexamine decisions to buy assets.

We take a two-step approach. First, using the firm's initial conditions we predict whether a firm will be public in subsequent years, omitting the firm's first five years (column 1 of Table 3). Then, based on the predicted probability of being public, we separate firms into quartiles and identify firms in the lowest quartile as our "private-like" sample and firms in the highest quartile as our "public-like" sample. Less than 2% of the firms in the "private-like" sample are public, and 27% of the firms in "public-like" sample are public. To accurately identify initial conditions, we exclude firms that appeared before 1976 (the first year that our TFP measure is available) from our prediction of being public. As a result, our sample with predicted public status is more representative of younger firms.[16]

Next, we use the same specification as in Table 4 to re-estimate decisions to buy (and sell) assets for "public-like" and "private-like" firms. Table 7 presents the estimation results.

Insert Table 7 Here

"Public-like" firms are more likely to buy and sell assets than "private-like" firms, and the gap in both sales and purchases is bigger when credit spreads are low and when global wave indicator equals to one. These results parallel our earlier findings using samples of firms which were actually public and private, respectively. The finding that sample splits based on predicted public status gives similar results as those based on actual public status suggests that a large portion of the difference in observed acquisitions and

[15] We define partial sales as transactions in which seller sells a portion of its asset to the buyer and remains existing and full sales (or mergers) as cases in which seller sells all of its assets and exits.

[16] Since public firms tend to be older, the restriction of first year appearance after 1976 yields more missing value for public firms than for private firms. 15% of public firms and 29% of private firms have non-missing vlaue for predicted public probability.

sales between public and private firms is indeed driven by differences in fundamentals early in the life of the firm. Larger and more productive firms select to become public, and later, these firms participate more in asset purchases and sales when opportunity rises.

Controlling for selection effect, does public status still matter when it comes to acquisitions? To answer this question, we focus on the subsample of firms with high probability of being public ("public-like" sample) and divide firms based on their actual public status. Private "public-like" firms are those firms that we predict, based on fundamentals when the firm firms appears in our data base, to be public in future years, but are in fact private when observed, five or more years later. For acquisition decisions, these private "public-like" firms have higher sensitivity to macro conditions, such as credit spreads or global wave indicator, than private firms, but lower sensitivity than "public-like" firms that are, in fact, public. Given that the difference between public and private firms in the "public-like" subsample is smaller than the difference between public and private firms overall, it suggests that actual public status affects acquisitions decisions but to a smaller degree after accounting for selection. We find even smaller differences between public and "public-like" private firms for asset sales decisions. "Public-like" private firms have a much higher sensitivity to credit spreads and to the global wave indicator than do the full sample of private firms. The marginal effect of credit spreads on sales decisions for "public-like" private firms is much closer to public firms.

To further examine the magnitude between the selection and treatment effect due to public status, we perform a matching exercise. We match firm based on the predicted probability of being public using specification in Table 3 column 2, and then estimate the average treatment effect in the rate of purchase and sales by the actual public status. By matching, we can better control for the selection effect due to initial conditions, and the resulting average treatment effect then describes the difference due to actual public status. Table 8 presents the result.

Insert Table 8 Here

On the purchase side, matching based on initial quality explains about 27% of the difference between public and private firms. When we separate our sample periods into wave and non-wave years, we find that public status matters more during merger waves (matching explains 22% on-the-wave and 33% off-the-wave). On the sales side, most of the differences between public and private firms can be explained by initial selection. Controlling for the propensity of being public, public firms public are no longer more likely to sell assets than private firms. The initial quality selection explains almost all of the differences for off-the-wave sales and 80% of the differences in on-the-wave years.

Two factors may explain our findings. First, through the initial quality (such as size and productivity), we are able to capture the capacity to become public, but not the willingness. Some entrepreneur firms may have all the initial quality for being public, but choose to stay private for control or quiet life (Bertrand and Mullainathan, 2003). In that case, the public status is a signal of both quality and preference. Alternatively, our results can also suggest that being public does make a difference when it comes to financing. Public firms have better access to capital markets in general, and benefit even more when credit become more readily available. Therefore, they are more likely to engage in acquisitions in presence of good opportunities. The asymmetry in our findings between sales and purchases suggests that the advantage of being public through better access to capital is more prominent for acquisitions.

5.3 Credit Ratings

Our results so far show that private firms are less sensitive to credit spreads than public firms in acquisition decisions. This suggests that private firms are either in general not constrained, or that, the financing constraints are sufficiently binding that it is more efficient for private firms to change to public status before the merger.

One way to shed light on this question is to look at how public firms with different levels of borrowing constraints respond to changes in liquidity on the market. We split our sample of public firms into three groups based on S&P long-term debt ratings (Compustat data item 280): firms with investment grade credit rating (above BBB), below investment grade (BBB and below), and un-rated firms. Within our sample, 28% of the public firms have investment grade rating (HR), 14% have below investment grade rating (LR), and the rest are un-rated (NR). We then run regressions to predict decisions to buy and to sell assets for each rating group. Table 9 reports our results.

Insert Table 9 Here

For all public groups, credit spreads have a significant negative effect on acquisition decisions, and they affect the LR firms the most. The estimated marginal effect of credit spread on acquisitions is almost three times as high as the marginal effect for HR or NR firms. On the sales side, LR firms, especially those with lower productivity, are also more likely to sell assets when credit spreads are low. Liquidity appears to have double effect on LR firms: On one hand, more liquidity on the market helps to relax the constraints faced by LR firms and enables them to borrow more or at lower rate to finance acquisitions. On the other hand, liquidity may also affect LR firms on the sale side by lifting covenants on previous bank loans which prevent them from selling assets.

Table 10 presents the economic significance by rating group. For LR firms, the probability of buying (selling) assets increases by 61% (64%) when credit spread moves from the 90th to the 10th percentile. In comparison, the increases are 18% and 31%, respectively for HR firm, and 28% and 38% respectively for NR firms. It is worth noting that among all three public groups, HR firms have the highest purchase rate. The observation that HR firms engage in more acquisitions while LR firms are most sensitive to liquidity conditions suggests that even within the category of public firms there exist material differences in the access to funding for acquisitions. The more financially constrained firms are affected more when credit condition improves. In addition, firms with anticipated needs for capital may choose to attain credit ratings, and the lower sensitivity of NR firms may be driven by selection rather than financial constraints.

6 Post-Sale Performance of Merger Waves: Private and Public Firms

In this section, we examine changes in productivity for transacted plants around acquisition for both off- and on-the-wave mergers. Since firms may choose to sell a certain type of plants, later we also account for the endogeneity of selling decisions. We measure plant-level changes of productivity by adding annual TFP at the plant level using three windows, (-1, 1), (-1, 2) and (-1, 3) with year 0 being the transaction year.

Insert Table 11 Here

Table 11 presents these results in three panels. Panel A shows that on average transacted plants have bigger improvements in productivity than non-transacted plants. The coefficients for D_Sale, the indicator for whether the plant is sold, is significantly positive at 1% level in all of our specifications, with or without controlling for size and productivity. Acquisitions are indeed value enhancing.

In Panel B, we include an indicator variable for aggregate merger wave (D_GW) and an interaction term between D_Sale and D_GW (SALE_GW). Not only do acquired plants have bigger improvement in productivity, the increases are also higher for deals done on the wave. Two years after the acquisition, transacted plants have a 3.3% increase in productivity compared to non-transacted plants, and a 3% additional increase if the deal is done in aggregate wave years.

Yan (2006) and Duchin and Schmidt (2008) show that on-the-wave horizontal mergers are followed by poor stock and operating performance. On the contrary, we find that on-the-wave transactions create bigger efficiency gains. There are several notable differences between our and their studies. First, we examine efficiency gains rather than stock returns. The two findings are not inconsistent, in that acquiring firms may overpay for real synergies. Second, due to the unique feature of the Census dataset, we are able to track the transacted plants before and after the acquisition whereas the other studies examine changes of operating performance for all of the assets managed by the acquirer.

Panel C presents results when we divide transactions based on the public status of the buyer and the seller. Except for private-to-private transactions (PrvtoPrv), all other three types of transactions have positive productivity gains significant at 1% level. Across the groups, changes in productivity following on-the-wave acquisitions are positive and either significantly higher than or statistically indistinguishable from changes in productivity following off-the-wave acquisitions. In particular, on-the-wave transactions between public firms consistently bring additional improvement - plants sold between public firms increase productivity by 7% to 10% in the next three years. Both results, on-the-wave merger generating more efficiency gains and public-to-public transactions having bigger improvement in productivity, suggest that the higher incidence of such mergers may the consequence of higher expected synergies. In addition, our findings provide implication on corporate governance in public and private firms. Acquisition decisions made in public firms are more value-enhancing and this can be due to higher efficiency in management.

6.1 Robustness Checks: Change of TFP

A plant has to exist after the acquisition in order for us to capture changes in productivity. Hence, there is a potential concern that our results may be driven by sample selection such that plants that do not improve in efficiency are closed after the acquisition. To address this issue, we run a Heckman selection model to correct for sample selection bias. Since size is the most significant factor for survival, we include size in our first stage selection model to predict whether a plant will continue to operate one, two, and three years after the transaction, respectively. Then, in the second stage, we predict changes in productivity one, two, or three years later using the indicator for transaction (D_Sale), together with the inverse mills ratio from the first stage prediction. Results are shown in Table 12 Panel A. The estimated coefficients for the transaction indicator, D_Sale, remains positive and significant at 1% level for all of three time windows.

Insert Table 12 Here

Decisions to sell assets are not made in random. If shocks that affect a plant to be sold is also correlated with shocks that affect changes in productivity after the transaction, then estimating changes in productivity on transaction indicator can lead to biased result. We perform two alternative analyses to address this concern.

First, we use the predicted probability that a plant will be sold and as an instrumented variable to replace the actual transaction status in the regression. To estimate the probability of being sold, we use similar specifications as in Table 4, column1 and 2 (but on the plant level), estimating the model separately for public and private firms to allow for difference sensitivity to firm, industry and macro factors. We then apply the same probability to all plants of the firm in the industry and use it as an instrumented variable. Panel B presents our results. The coefficient on the predicted sales probability remains significant and positive at 1% level. The coefficients are bigger in magnitude since the instrumented variable has a mean around 4.7%.

Next, we perform a propensity score matching. We match plants based on their predicted probability of being sold (again using specifications similar to that in Table 4 column 1 and 2) and compare changes in productivity by the actual transaction status. Panel C presents the estimated average treatment effect. Controlling for the probability of being sold, transacted plants experience 0.6% to 2.0% higher improvement in productivity. Further, consistent with our earlier analysis, on-the-wave transactions provide even higher gains in productivity. Plants sold during merger waves have 2.0% to 2.9% higher increase in productivity compared to plants that are kept with existing owners, controlling for probability of being sold. The estimated average treatment effect is significant at 1% level for all three time windows.

We conclude that mergers and acquisitions enhance efficiency on average and especially so during merger waves. The acquired plants improve productivity after the ownership change. While liquidity and aggregate waves may indeed facilitate transactions, transactions that occur during higher liquidity periods and aggregate merger wave years lead to even bigger efficiency improvement.

6.2 Robustness Checks: Misvaluation and Public Merger Activity

Several authors have recently argued that a significant fraction of merger activity of public firms can be explained by misvaluation. For example, Rhodes-Kropf, Robinson and Viswanathan (2005) argue that while economic shocks might be fundamental determinants of merger activity, misvaluation by public markets may determine who buys whom and how mergers are clustered in time. This raises the possibility that our equations above which do not take potential firm misvaluation into account, are mis-specified due to omitted variable bias.

Misvaluation can occur at the firm level (contemporaneous misvaluation relative to other firms in the same sector) or at the sector level (misvaluation of the sector relative to its historic or future valuations). Given our results above that on-the-wave mergers are more frequent and productive, examination at the firm level is more likely to uncover clean evidence of the effect of misvaluation. We adopt a variant of the Rhodes-Kropf, Robinson and Viswanathan (2005) measure of firm-specific misvaluation and check whether the addition of this variable affects our findings for public firms.[17] To calculate the firm specific misvaluation measure (MISV), we use model (3) from Rhodes-Kropf, Robinson and Viswanathan (2005), as updated by Hoberg and Phillips (2010). First, we regress log market value of equity on log book value of equity, net income, an indicator for negative net income and leverage ratio by industry using a historical 10-year rolling window. Then, we use the estimated industry-specific regression coefficients to compute the predicted market value of equity assuming that a firm's market value at time t is a function of its current characteristics and the industry specific value of characteristics estimated from past years. Following Hoberg and Phillips, we use only lagged data in the calculation of these coefficients to avoid any look ahead bias.

In Table 13 Panel A, we add MISV to the public firm specifications that predict purchases and sales shown in Table 4.[18] The signs and significances of the original variables are not affected and the increase in explanatory power is modest. The coefficient of MISV is positive and significant, indicating that firms with higher estimated misvaluation are more likely to both buy and sell plants. As MISV moves from its 25th percentile to the 75th percentile, the average rate of acquisitions for a public firm increases from 6.98% to 7.84%. The effect is stronger on the wave, where the corresponding increase is from 9.29% to 11.09%. The probability of a sale also increases as MISV moves from its 25th percentile to the 75th percentile, but the increase is much smaller than for acquisitions. While economic factors such as productivity and liquidity drive merger waves, misvaluation to some extent affects who buys whom. Our finding that higher misvaluation measure leads to higher probability in both purchase and sales is consistent with the relative overvaluation prediction of Rhodes-Kropf, Robinson and Viswanathan (2005). They predict that on the wave more overvalued firms buy from less over-valued firms. It is also worth noting that the misvaluation measure used here (based on Rhodes-Kropf, Robinson and Viswanathan (2005)) can either capture deviation from the true value or market expectation on the unmeasured productivity. The higher valuation of the acquiring and target firms in respect to their current performance may well be driven by the expected gain in future productivity.

Insert Table 13 Here

[17] As discussed by Rhodes-Kropf, Robinson, and Viswananthan (2005), the key to investigating these effects is obtaining a good measure of misvaluation. Measures of misvaluation are of necissity valuation anomalies relative to a model of market expectations. While intendeded to misvaluation they may also pick up the market's expectation of future performance. The discussion of the valuation models in general is beyond the scope of this paper.

[18] The number of observation in Table 13 Panel A is slightly smaller than that in Table 4 due to missing value in misvaluation variable.

Rhodes-Kropf and Robinson (2008) suggest that the difference in market-to-book between acquirer and target firms widens on the wave due to impatience to consummate the merger. A natural question to ask is whether mergers with higher spread in valuation lead to different outcome. In Panel B of Table 13, we examine changes of productivity based on the relative valuation between the acquiring and the target firms. Using the difference in MISV between the acquirer and target firms (RMISV), we define two binary variables, Low_RMISV and High_RMISV, to split public transactions into two groups based on sample median. We set both variables equal to zero for plants that are not in transaction. We regress changes of TFP on these two indicators, the aggregate wave indicator, and their interactions. On average, both transaction groups have significant gain in productivity, compared to non-transacted plants. For example, two years after the transaction, transacted plants in Low_RMISV group increase TFP by 3.76% while transacted plants in High_RMISV group increase TFP by 5.67%. On the wave, transactions with low relative MISV consistently generate higher gains while transactions with high relative MISV do not lead to additional improvement. In unreported regressions, we have considered alternative specifications, using the acquirer's misvaluation in the equation to predict TFP changes around a merger, and find similar results.

In sum, adding misvaluation to the specifications provides new insights on the matter, but does not change any of our previous results. Misvaluation, for both the buyer and the seller, predicts higher participation in the market for assets. Changes of TFP for transacted plants remain to be positive, both on and off the wave although the effect is relatively weaker for on-the-wave transactions with higher relative misvaluation.

7 Conclusions

We examine the participation of public and private firms in merger waves. We find that public firms participate more in the market for assets, especially during merger waves, than private firms. Acquisitions by public firms are more likely to lead to an increase in productivity of acquired assets, especially when the assets are acquired from other public firms. Public firms also acquire and sell assets more when they are productive and when there is increased liquidity in the financial market.

However, differences in participation are not just driven by liquidity and access to capital market. First, we find that acquisition activity differs between public and private firms because of their fundamentals differ. Larger and more productive firms select public status, and these firms also engage in more acquisitions in the long run, all other things being equal. Using initial productivity from over five and ten years prior to the transaction, we show that better firms select to become public and later participate more in acquisitions. Second, public status causes a differential in response to measured firm fundamentals or macro-economic shocks. Public firms participate more because they have the option to access public financial markets at more favorable or easier terms than otherwise identical private firms. These effects are reflected in the differences in the estimated coefficients between public and private firms.

Our paper provides several implications to the understanding of mergers and acquisitions, especially across different organization forms and over the business cycle. Consistent with the neoclassical theories, we find that mergers that occur on the waves are associated with greater increases in productivity. In particular, acquisitions by public firms on-the-wave are associated with high gains. We find little evidence that merger waves are causing economic inefficiency in the market for corporate control, although we do not know whether these reallocations create sufficient value to the acquiring firms' shareholders to cover the premiums usually paid. On the corporate governance side, we find that public firms make better acquisition decisions than private firms judged by efficiency gains despite of the potential conflicts due to separation of ownership and control in public firms.

Our results also show that the future acquisition behavior of firms can thus be predicted by firm characteristics early in their lives. Productive firms select to become public and later participate more in the market for corporate assets in ways that increase the productivity of the acquired assets. These findings are related to the recent study by Lemmon, Roberts and Zender (2006) that shows that a firm's later financial policies are predictable from before they become public. Together, these studies suggest that there are deep differences between firms that persist over many years and affect their behavior and value creation. Mergers are in part driven by deep firm characteristics which are set when the firm is created by the entrepreneur.

Overall, our work suggests that an active market for corporate assets is important in facilitating the growth of the most productive firms. Regulations that make mergers more difficult during waves are likely to be socially costly.

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Figure 1 Transaction Over Time

This figure plots the time series for the rate of acquisition among U.S. manufacturing firms in the period of 1977 to 2004. The two lines present percentage of transactions made by public firms (diamond) and private firms (square), respectively. The bars show the number of industries having industry-wide merger waves. Industry merger waves are defined as years when the rate of transaction within an industry is at least one standard deviation above it sample mean rate.

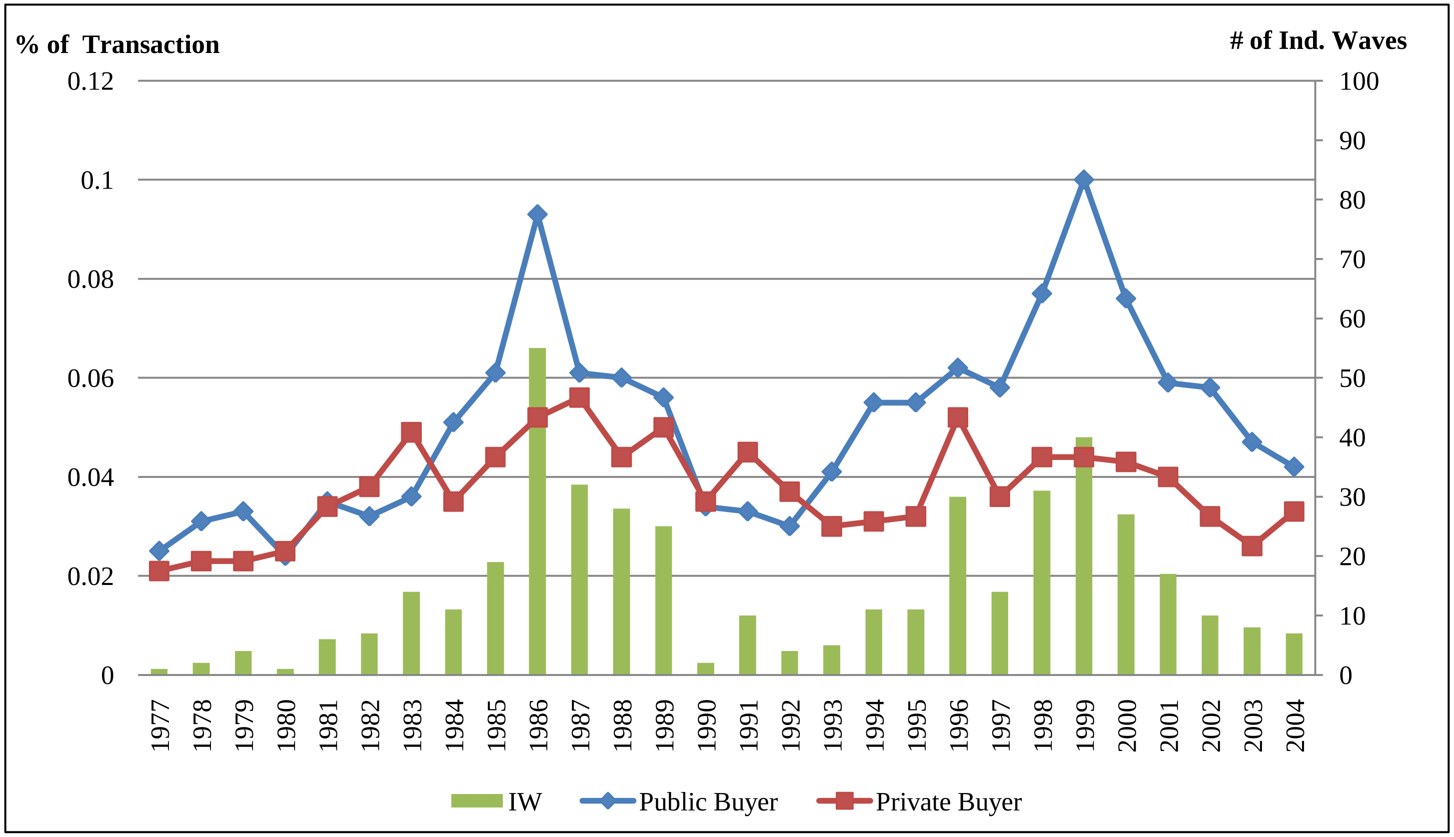

Table 1A: Summary Statistics - Public and Private Merger Waves

This table presents summary statistics on participation over the merger waves. GW is an indicator variable that equals to 1 for aggregate merger wave years and zero otherwise. Panel A presents the percentage of plants in transaction by the public status. We use the number of plants owned by public (private) firms as denominator to calculate the rate for public (private) buyers and sellers. Panel B shows the breakout of the transaction sample by wave dummy (GW), and by public status of the buyer and seller. Panel C presents summary statistics on transaction size and the percentage of mergers.

Panel A: Percentage of Plants in Transaction

GW	Public Buyer	Private Buyer	Public Seller	Private Seller
0	4.16%	3.74%	3.39%	4.21%
1	7.41%	5.06%	5.94%	6.27%
Average	4.88%	4.03%	3.95%	4.66%

Panel B: Number of Transactions

Buyer Public	GW=0		GW=1	
0	22,470	(65%)	8,374	(58%)
1	11,892	(35%)	6,179	(42%)
Total	34,362		14,553	

Seller Public	GW=0		GW=1	
0	24,127	(70%)	8,787	(60%)
1	10,235	(30%)	5,766	(40%)
Total	34,362		14,553	

Transaction	GW=0		GW=1	
Public Buyer Public Seller	4,129	(12%)	2,726	(19%)
Public Buyer Private Selle	7,763	(23%)	3,453	(24%)
Private Buyer Public Selle	6,106	(18%)	3,040	(21%)
Private Buyer Private Sell	16,364	(48%)	5,334	(37%)
Total	34,362		14,553	

Panel C: Transaction Size and Nature

	Number of Plants Bought		Percent of Mergers	
Transaction	GW=0	GW=1	GW=0	GW=1
Public Buyer Public Seller	2.48	3.19	18%	26%
Public Buyer Private Selle	2.01	2.13	72%	78%
Private Buyer Public Selle	1.74	1.94	8%	11%
Private Buyer Private Sell	1.42	1.38	74%	74%
Average	1.67	1.84	58%	57%

Table 1B: Summary Statistics - Global and Industry Merger Waves

Panel A shows shows the percentage and the number of industries (in paratheses) in transaction by global wave indicator (D_GW) and by industry wave indicator (D_IW). Panel B presents results from a Logit regression using the industry-year panel. The dependent variable is the industry wave indicator (D_IW) which equals 1 if an industry in on the wave and zero otherwise. The explanatory variable (Other_IW) captures the percentage of industries on the wave during that year. The industry fixed effects are included and the robust standard errors are reported. Industries are defined based on 3-digit SIC.

Panel A: Global and Industry Waves

	D_IW	
D_GW	0	1
0	90.6%	9.4%
	(2090)	(217)
1	66.9%	33.1%
	(435)	(215)
Total	85.4%	14.6%
	(2525)	(432)

Panel B: Logit Regression with Industry Fixed Effects

Dependent Variable: D_IW

	Coef.	Std. Err.	z	P>|z|
Other_IW	6.440	0.447	14.42	0.000
Constant	-2.928	0.099	-29.49	0.000
Industry FE	Yes			
Number of Obs	2957			
Wald Chi2	207.87			
p-value	(0.000)			

Table 2: Merger Waves by Industry

This table lists the most public and the most private industries in our sample based on percentage of output produced by public and private firms. It also presents the percentage of transaction in each industry on- and off-the-wave.

Most "Public" Industries

Industry	Number of Firms	Number of Establishments	% of Public Firms	% of Output by Public Firms	% of Trans. off-the-wave	% of Trans. on-the-wave
Guided Missiles & Space Vehicle	34	66	61%	70%	5.7%	7.4%
Search & Guide Instruments	108	179	44%	54%	6.9%	11.6%
Paperboard Mills	58	152	42%	59%	6.4%	9.2%
Engines and Turbines	72	125	40%	56%	5.1%	8.7%
Communication Equip	342	501	39%	49%	5.6%	7.4%
Primary Smelting	53	88	39%	54%	6.8%	7.0%
Petroleum Refining	85	189	39%	55%	7.5%	12.8%
Industrial Organic Chemicals	188	417	39%	55%	6.5%	10.1%
Rubber Products	36	68	39%	56%	7.7%	21.6%
Computer & Office Equip	344	460	38%	46%	5.0%	5.6%
Average					6.3%	10.1%

Least "Public" Industries

Industry	Number of Firms	Number of Establishments	% of Public Firms	% of Output by Public Firms	% of Trans. off-the-wave	% of Trans. on-the-wave
Wood Containers	180	205	3%	4%	1.7%	3.5%
Women's Outwear	528	654	5%	12%	1.8%	2.3%
Concrete	721	1496	5%	14%	3.7%	5.0%
Jewelry	166	181	6%	9%	2.0%	2.5%
Commercial Printing	1067	1385	8%	17%	2.6%	3.3%
Meat Products	476	843	8%	30%	3.8%	5.1%
Newspapers	280	715	8%	32%	4.9%	8.7%
Misc Industrial Machinery	658	747	8%	13%	2.3%	3.1%
Millwork, Veneer, and Plywood	490	731	8%	22%	3.1%	3.9%
Sawmills and Planning Mills	477	778	9%	27%	3.2%	4.1%
Average					2.9%	4.2%

Table 3: Predicting Public Status

This table reports the estimated marginal effects(in %) of probit models predicting the public status. The dependent variable, D_Pub, is equal to 1 for public firms and 0 for private firms. TFP0 and TFP02 represent the linear and square terms of initial TFP, respectively, and Size0 and Size02 measure the linear and square terms of initial size, respectively. CDTVS25 measures the change in long-run shipments in the industry (in 25 years). I_CapEx, I_Tobinq and HERF represent the industry capital expenditure, Tobin's q, and Herfindahl Index (based on sales), respectively. Small Firms measures the percentage of small firms in the industry (with less than 50 employees). Persistence measures the persistence of TFP within the industry based on rank correlation. Ln(N_IPO) is the log number of annual IPOs. Q2(Size0) - Q5(Size0) are indicators for the second to fifth quintile based on Size0, respectively. For column (1) to (3), we only include firms that are at least five years after their birth, and for column (4) to (6), we only include firms that are ten years after their birth. All time-varying variables are lagged. Robust standard errors are computed allowing clustering at the industry level. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Dependent Variable:	Five Years after Birth			Ten Years after Birth		
D_Pub	(1)	(2)	(3)	(4)	(5)	(6)
TFP0	0.29	1.98 ***	-0.89	0.52	2.90 ***	1.00
	(0.20)	(0.30)	(0.90)	(0.40)	(0.50)	(1.50)
TFP02	11.48 ***	10.04 ***		17.16 ***	15.58 ***	
	(0.60)	(0.60)		(1.00)	(1.00)	
SIZE0	1.80 ***	1.25 ***		1.90 **	1.46 *	
	(0.50)	(0.50)		(0.80)	(0.80)	
SIZE02	0.18 ***	0.19 ***		0.22 ***	0.22 ***	
	(0.00)	(0.00)		(0.00)	(0.00)	
CDTVS25	0.31 ***	0.21 ***	0.22 ***	0.42 ***	0.28 ***	0.28 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I_CapEx		12.08 ***	11.72 ***		19.91 ***	19.95 ***
		(0.70)	(0.70)		(1.30)	(1.30)
I_Tobinq		9.56 ***	10.92 ***		14.23 ***	14.94 ***
		(1.40)	(1.40)		(2.30)	(2.30)
HERF		7.20 ***	7.78 ***		4.13 ***	4.37 ***
		(0.70)	(0.70)		(1.10)	(1.20)
Small Firms		-12.41 ***	-14.80 ***		-16.79 ***	-19.41 ***
		(0.60)	(0.60)		(1.00)	(1.00)
Persistence		1.70 ***	1.83 ***		1.94 ***	2.09 ***
		(0.10)	(0.10)		(0.10)	(0.10)
Ln(N_IPO)		0.24 ***	0.06		0.42 ***	0.36 ***
		(0.10)	(0.10)		(0.10)	(0.10)
Q2(Size0)			1.43 ***			1.42 ***
			(0.30)			(0.50)
Q3(Size0)			5.70 ***			6.72 ***
			(0.40)			(0.60)
Q4(Size0)			10.86 ***			11.95 ***
			(0.40)			(0.60)
Q5(Size0)			30.05 ***			30.51 ***
			(0.60)			(0.80)
Q2(Size0)*TFP			-2.99 **			-6.12 ***
			(1.20)			(2.00)
Q3(Size0)*TFP			-0.75			-3.24 *
			(1.10)			(1.80)
Q4(Size0)*TFP			1.45			0.21
			(1.00)			(1.70)
Q5(Size0)*TFP			5.62 ***			4.83 ***
			(1.00)			(1.60)
R-square	0.180	0.191	0.169	0.165	0.178	0.167
Number of Obs	187,581	187,581	187,581	88,934	88,934	88,934

Table 4: Decision to Buy or Sell Assets

This table reports the estimated marginal effects(in %) from probit models. In Panel A, the dependent variable, D_Buy, equals to 1 if a firm buys at least one plant and zero otherwise. In Panel B, the dependent variable, D_Sell, equals to 1 if a firm sells at least one plant and 0 otherwise. Size is the log of total value of shipments (in 1987 dollars), and TFP is the total factor productivity. I_Tobinq is the industry Tobin's q and HERF measures the industry Herfindahl Index based on sales. Credit Spread is the spread between C&I loan rate and Fed Funds rate. S&P is the return of S&P Industrial Index. D_GW is an indicator variable which equals 1 for wave years and zero for non-wave years. Column 2 and 5 are estimated using public firms and Column 3 and 6 are estimated using private firms. Column 4 and 7 reports the p-value for the difference between public and private firms which we estimate using the combined sample with interaction between the public status dummy and all other explanatory variables. Robust standard errors allow clustering at the industry level and are reported in parentheses. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Decision to Buy (Dependent Variable = D_Buy)

Variable	Public	Private	P-value for Difference	Public	Private	P-value for Difference
Size	0.70 ***	0.62 ***	<0.001	0.69 ***	0.62 ***	<0.001
	(0.00)	(0.00)		(0.00)	(0.00)	
TFP	0.35 ***	0.03 *	0.070	0.35 ***	0.03 *	0.072
	(0.10)	(0.00)		(0.10)	(0.00)	
I_Tobinq	-0.08	-0.09 ***	0.136	-0.18	-0.11 ***	0.100
	(0.10)	(0.00)		(0.10)	(0.00)	
HERF	-0.39	0.61 *	0.046	-1.21	0.52	0.030
	(1.90)	(0.30)		(1.90)	(0.30)	
Credit Spread	-2.75 ***	-0.09 **	<0.001			
	(0.30)	(0.00)				
S&P	2.66 ***	0.51 ***	0.892			
	(0.60)	(0.10)				
D_GW				3.29 ***	0.32 ***	<0.001
				(0.20)	(0.00)	
Pr(D_Buy)	7.36%	1.75%				
R-square	0.01	0.13	0.13	0.01	0.13	0.13
Number of Obs	99,121	420,944	520,065	99,121	420,944	520,065

Panel B: Decision to Sell (Dependent Variable = D_Sell)

Variable	Public	Private	P-value for Difference	Public	Private	P-value for Difference
Size	1.06 ***	1.38 ***	<0.001	1.07 ***	1.38 ***	<0.001
	(0.00)	(0.00)		(0.00)	(0.00)	
TFP	-0.89 ***	-0.18 ***	<0.001	-0.89 ***	-0.18 ***	<0.001
	(0.10)	(0.00)		(0.10)	(0.00)	
I_Tobinq	-0.42 ***	-0.16 ***	0.379	-0.50 ***	-0.15 ***	0.124
	(0.10)	(0.00)		(0.10)	(0.00)	
HERF	-8.48 ***	2.89 ***	<0.001	-8.86 ***	2.92 ***	<0.001
	(2.00)	(0.60)		(2.00)	(0.60)	
Credit Spread	-3.66 ***	-0.15 *	<0.001			
	(0.30)	(0.10)				
S&P	1.73 ***	1.83 ***	0.021			
	(0.60)	(0.20)				
D_GW				3.70 ***	0.34 ***	<0.001
				(0.20)	(0.10)	
Pr(D_Sell)	7.91%	4.08%				
R-square	0.01	0.04	0.04	0.01	0.04	0.04
Number of Obs	107,645	557,470	665,115	107,645	557,470	665115

Table 5: Economic Significance: Decision to Buy or Sell and Credit Spreads

This table shows the estimated probabilities of purchases and sales for public and private firms at the 10th, 25th, 50th, 75th, and 90th percentile for credit spread and on- and off-the-wave. We compute the estimated probabilities using coefficients from probit regression ins Table 4. Throughout, all other variables are held at the sample median for respective sample (public and private firms).

Panel A: Probability of Purchases

	Credit Spread					D_GW	
	p10	p25	p50	p75	p90	0	1
(1) Public firms	8.45%	7.84%	7.32%	7.04%	6.50%	6.50%	9.81%
(2) Private firms	0.80%	0.79%	0.77%	0.77%	0.75%	0.70%	0.90%
(3) Private firms using medians of data from public firms	6.53%	6.45%	6.38%	6.34%	6.25%	5.94%	7.36%
Ratio (unadjusted): (2)/(1)	0.09	0.10	0.11	0.11	0.12	0.11	0.09
Ratio (adjusted for size): (3)/(1)	0.77	0.82	0.87	0.90	0.96	0.91	0.75

Panel B: Probability of Sales

	Credit Spread					D_GW	
	p10	p25	p50	p75	p90	0	1
(1) Public firms	9.33%	8.51%	7.81%	7.44%	6.72%	6.89%	10.61%
(2) Private firms	3.55%	3.52%	3.50%	3.48%	3.45%	3.35%	3.67%
(3) Private firms using medians of data from public firms	6.66%	6.62%	6.57%	6.55%	6.50%	6.32%	6.85%
Ratio (unadjusted): (2)/(1)	0.38	0.41	0.45	0.47	0.51	0.49	0.35
Ratio (adjusted for size): (3)/(1)	0.71	0.78	0.84	0.88	0.97	0.92	0.65

Table 6: Decision to Buy Assets - Robustness Checks

This table reports the estimated marginal effects(in %) from probit models. In Panel A, the dependent variable equals to 1(2) if a firm buys at least one plant in the existing (new) industry, and zero otherwise. In Panel B, the dependent variable equals to 1 if a firm buys at least one plant and the seller continues to exist after the acquisition, 2 if the seller exits completely (i.e. mergers), and 0 otherwise. Size is the log of total value of shipments (in 1987 dollars), and TFP is the total factor productivity. I_Tobinq is the industry Tobin's q and HERF measures the industry Herfindahl Index based on sales. Credit Spread is the spread between C&I loan rate and Fed Funds rate. S&P is the return of S&P Industrial Index. D_GW is an indicator variable which equals 1 for wave years and 0 for non-wave years. In each panel, Column 2 and 4 are estimated using public firms and Column 3 and 5 are estimated using private firms. Robust standard errors allow clustering at the industry level and are reported in parantheses. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Within and Diversifying Purchases

Variable	Public	Private	Public	Private
1 (Buy - in Existing Inds)				
Firm Size	0.78 ***	0.36 ***	0.78 ***	0.36 ***
	(0.00)	(0.00)	(0.00)	(0.00)
TFP	0.20 ***	0.01	0.20 ***	0.01
	(0.10)	(0.00)	(0.10)	(0.00)
I_Tobinq	0.41 ***	-0.02	0.37 ***	-0.03
	(0.10)	(0.00)	(0.10)	(0.00)
HERF	-7.46 ***	-1.30 ***	-7.85 ***	-1.33 ***
	(1.60)	(0.30)	(1.60)	(0.30)
Credit Spread	-1.65 ***	-0.11 ***		
	(0.20)	(0.00)		
S&P	1.17 **	0.24 ***		
	(0.50)	(0.10)		
D_GW			1.740 ***	0.170 ***
			(0.200)	(0.000)
2 (Buy - In New Inds)				
Firm Size	-0.08	0.25 ***	-0.08	0.25 ***
	(0.00)	(0.00)	(0.00)	(0.00)
TFP	0.15 **	0.02 *	0.14 **	0.02 *
	(0.10)	(0.00)	(0.10)	(0.00)
I_Tobinq	-0.58 ***	-0.07 ***	-0.63 ***	-0.08 ***
	(0.10)	(0.00)	(0.10)	(0.00)
HERF	6.03 ***	1.64 ***	5.61 ***	1.59 ***
	(1.20)	(0.20)	(1.20)	(0.20)
Credit Spread	-1.08 ***	0.02		
	(0.20)	(0.00)		
S&P	1.47 ***	0.28 ***		
	(0.40)	(0.10)		
D_GW			1.520 ***	0.150 ***
			(0.100)	(0.000)
Pr(D=1)	4.43%	1.02%		
Pr(D=2)	2.93%	0.73%		
Chi2	830	9387		
N	99,121	420,944		

Panel B: Partial and Full Purchases

Variable	Public	Private	Public	Private
1 (Buy - Partial Sale)				
Firm Size	0.39 ***	0.29 ***	0.39 ***	0.29 ***
	(0.00)	(0.00)	(0.00)	(0.00)
TFP	0.14 **	0.02	0.13 *	0.02
	(0.10)	(0.00)	(0.10)	(0.00)
I_Tobinq	-0.18 *	-0.04 **	-0.23 **	-0.05 ***
	(0.10)	(0.00)	(0.10)	(0.00)
HERF	1.18	0.31	0.82	0.25
	(1.30)	(0.20)	(1.30)	(0.20)
Credit Spread	-0.81 ***	-0.05		
	(0.20)	(0.00)		
S&P	1.09 **	0.17 ***		
	(0.40)	(0.10)		
D_GW			1.200 ***	0.190 ***
			(0.100)	(0.000)
2 (Buy - Full Sale)				
Firm Size	0.31 ***	0.32 ***	0.30 ***	0.32 ***
	(0.00)	(0.00)	(0.00)	(0.00)
TFP	0.21 ***	0.02	0.21 ***	0.02
	(0.10)	(0.00)	(0.10)	(0.00)
I_Tobinq	0.09	-0.05 **	0.05	-0.05 ***
	(0.10)	(0.00)	(0.10)	(0.00)
HERF	-1.65	0.30	-2.10	0.26
	(1.50)	(0.20)	(1.50)	(0.20)
Credit Spread	-1.98 ***	-0.04		
	(0.20)	(0.00)		
S&P	1.56 ***	0.35 ***		
	(0.50)	(0.10)		
D_GW			2.090 ***	0.130 ***
			(0.200)	(0.000)
Pr(D=1)	3.53%	0.84%		
Pr(D=2)	3.83%	0.92%		
Chi2	500	9300		
N	99,121	420,944		

Table 7: Decision to Sell and Buy Assets w/ Endogenous Selection

This table reports the estimated marginal effects(in %) of probit models on decisions to buy (Panel A)or to sell assets (Panel B) using "public-like" and "private-like" samples. We define "public-like" and "private-like" firms as firms with the predicted probability of being public in the highest and lowest quartile, respectivly. The predicted probability of being public is estimated based on column 1 in Table 3. In Panel A, the dependent variable, D_Buy, equals to 1 if a firm sells at least one plant in the next year and 0 otherwise, and in Panel B, the depependent variable, D_Sell, equals to 1 if a firm buys at least one plant in the next year and 0 otherwise. In both panels, column (1) and (3) are estimated using public-like firms, column (2) and (4) are estimated using private-like firms only, column (5) and (7) are bases on public public-like firms and column (6) and (8) are based on private public-like firms. Robust standard errors allow clustering at the industry level and are reported in parentheses. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Decision to Buy Assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Public-like Firms Only			
Variable	Public-like	Private-like	Public-like	Private-like	Public	Private	Public	Private
Firm Size	1.16 ***	0.21 ***	1.15 ***	0.21 ***	1.31 ***	0.91 ***	1.31 ***	0.90 ***
	(0.10)	(0.00)	(0.10)	(0.00)	(0.10)	(0.10)	(0.10)	(0.10)
TFP	-0.06	-0.01	-0.06	-0.01	-0.02	-0.12	0.02	-0.12
	(0.10)	(0.00)	(0.10)	(0.00)	(0.20)	(0.10)	(0.20)	(0.10)
I_Tobinq	-0.14	-0.03	-0.15	-0.03	-0.16	-0.23 *	-0.14	-0.25 **
	(0.10)	(0.00)	(0.10)	(0.00)	(0.30)	(0.10)	(0.30)	(0.10)
HERF	-5.68 ***	-0.71	-5.95 ***	-0.70	-18.96 ***	-2.11	-19.47 ***	-2.31
	(2.10)	(0.50)	(2.10)	(0.50)	(5.90)	(2.10)	(5.90)	(2.00)
Credit Spread	-1.09 ***	0.02			-3.71 ***	-0.38		
	(0.40)	(0.10)			(1.10)	(0.30)		
S&P	1.13 **	0.15			1.57	0.83		
	(0.50)	(0.10)			(1.40)	(0.50)		
D_GW			0.82 ***	0.01			1.61 ***	0.58 ***
			(0.20)	(0.00)			(0.50)	(0.20)
Pr(D_Buy)	3.22%	0.40%			5.61%	2.33%		
R-square	0.05	0.18	0.05	0.18	0.03	0.04	0.03	0.04
Number of Obs	39,336	36,190	39,336	36,190	10675	28661	10675	28661

Panel B: Decision to Sell Assets

Variable	(1) Public-like	(2) Private-like	(3) Public-like	(4) Private-like	(5) Public-like Firms Only: Public	(6) Public-like Firms Only: Private	(7) Public-like Firms Only: Public	(8) Public-like Firms Only: Private
Firm Size	0.67 ***	0.85 ***	0.66 ***	0.85 ***	0.52 ***	0.78 ***	0.51 ***	0.77 ***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.20)	(0.10)	(0.20)	(0.10)
TFP	-0.34 **	-0.25 ***	-0.34 **	-0.25 ***	-0.56 **	-0.25	-0.55 **	-0.25
	(0.10)	(0.10)	(0.10)	(0.10)	(0.20)	(0.20)	(0.20)	(0.20)
I_Tobinq	-0.17	-0.16	-0.21	-0.14	-0.44	-0.03	-0.63 **	-0.01
	(0.20)	(0.10)	(0.20)	(0.10)	(0.30)	(0.20)	(0.30)	(0.20)
HERF	-9.39 ***	3.86 **	-9.38 ***	3.91 ***	-16.03 **	-6.63 *	-15.96 **	-6.54 *
	(3.30)	(1.50)	(3.30)	(1.50)	(6.50)	(3.70)	(6.40)	(3.70)
Credit Spread	-3.54 ***	0.07			-4.48 ***	-3.21 ***		
	(0.60)	(0.30)			(1.10)	(0.70)		
S&P	0.39	0.42			0.54	0.31		
	(0.80)	(0.40)			(1.50)	(0.90)		
D_GW			1.99 ***	-0.11			3.33 ***	1.47 ***
			(0.30)	(0.10)			(0.60)	(0.30)
Pr(D_Sell)	6.55%	1.71%			6.85%	6.43%		
R-square	0.01	0.03	0.01	0.03	0.01	0.01	0.01	0.01
Number of Obs	40,066	40,071	40,066	40,071	10786	29280	10786	29280

Table 8 : Decisions to Buy or Sell Assets - Propensity Score Matching

This table shows the difference in estimated probabilities in purchases (Panle A) and sales(Panel B) between public and private firms before and after matching. We match firms based on the predicted probability of being public using the specification in Table 3 column 1.

Panel A: Probability of Purchases

	All	Off-the-Wave (GW = 0)	On-the-Wave (GW = 1)
Public firms	5.37%	4.83%	6.47%
Private firms	1.11%	1.03%	1.28%
DIF	4.27%	3.80%	5.19%
DIF(Matching)	3.10%	2.56%	4.00%
% Explained by matching	0.27	0.33	0.23
# of Treatment	16,656	11,138	5,518
# of Control	143,576	99,735	43,841
T-stat (from bootstrap)	(16.36)	(13.31)	(9.64)

Panel B: Probability of Sales

	All	Off-the-Wave (GW = 0)	On-the-Wave (GW = 1)
Public firms	6.63%	5.88%	8.16%
Private firms	3.42%	3.21%	3.90%
Dif	3.22%	2.68%	4.26%
Dif(after matching)	0.30%	0.03%	0.85%
% Explained by matching	0.91	0.99	0.80
# Treatment	16,656	11,138	5,518
# Control	143,576	99,735	43,841
T-stat (from bootstrap)	(1.07)	(0.13)	(1.91)

Table 9 Decisions by Credit Rating

This table reports the estimated marginal effects(in %) from probit models on decision to buy (Panel A) or sell assets (Panel B) by credit rating status. The dependent variable, D_Buy (D_Sell), equals to 1 if a firm buys (sells) at least one plant and 0 otherwise. "No Rating" refers to public firms that are not rated, "Low Rating" refers to public firms that have BBB or below credit ratings, and "High Rating" refers to public firms that have above BBB ratings. Size is the log of total value of shipments (in 1987 dollars). TFP is the total factor productivity. I_Tobinq is the industry Tobin's q and HERF measures the industry Herfindahl Index based on sales. Credit Spread is the spread between C&I loan rate and Fed Funds rate. S&P is the return of S&P Industrial Index. D_GW is an indicator variable which equals 1 for wave years and 0 for non-wave years. All explanatory variables are lagged. Robust standard errors are computed allowing clustering at the industry level and reported in parentheses. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Decisions to Buy Assets

Variable	No Rating		Low Rating		High Rating		Private Firms		"Public-like" Private Firms	
Size	0.74 ***	0.75 ***	-0.45 ***	-0.47 ***	-0.15	-0.16	0.60 ***	0.60 ***	0.91 ***	0.90 ***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.00)	(0.00)	(0.10)	(0.10)
TFP	0.280 ***	0.28 ***	0.210	0.23	0.400 **	0.36 **	0.040 ***	0.04 **	-0.140	-0.15
	(0.10)	(0.10)	(0.20)	(0.20)	(0.20)	(0.20)	(0.00)	(0.00)	(0.10)	(0.10)
I_Tobinq	-3.32	-3.70 *	9.86 **	8.53 *	5.06	3.43	0.93 ***	0.85 ***	-2.05	-2.26
	(2.00)	(2.00)	(4.40)	(4.40)	(3.70)	(3.70)	(0.30)	(0.30)	(2.00)	(2.00)
HERF	-0.63 ***	-0.64 ***	-0.47	-0.55	1.25 ***	1.00 ***	-0.06 **	-0.08 ***	-0.22 *	-0.24 **
	(0.20)	(0.20)	(0.40)	(0.30)	(0.30)	(0.20)	(0.00)	(0.00)	(0.10)	(0.10)
Credit Spread	-2.16 ***		-6.03 ***		-2.17 ***		-0.11 **		-0.34	
	(0.30)		(0.90)		(0.60)		(0.00)		(0.30)	
S&P	3.88 ***		2.86 *		0.92		0.45 ***		0.91 *	
	(0.80)		(1.70)		(1.40)		(0.10)		(0.50)	
D_GW		2.39 ***		5.82 ***		3.60 ***		0.33 ***		0.57 ***
		(0.30)		(0.60)		(0.50)		(0.00)		(0.20)
Pr (D_Buy)	6.10%		8.89%		9.37%		1.71%		2.32%	
R-square	0.01	0.01	0.01	0.01	0.00	0.01	0.14	0.14	0.04	0.04
Number of Obs	58,655	58,655	14,773	14,773	25,693	25,693	392,379	392,379	28,565	28,565

Panel B: Decisions to Sell Assets

Variable Name	No Rating		Low Rating		High Rating		Private Firms		"Public-like" Private Firms	
Size	1.23 ***	1.22 ***	0.84 ***	0.85 ***	0.81 ***	0.81 ***	1.40 ***	1.40 ***	0.77 ***	0.77 ***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.00)	(0.00)	(0.10)	(0.10)
TFP	-0.750 ***	-0.75 ***	-1.000 ***	-0.98 ***	-1.270 ***	-1.27 ***	-0.170 ***	-0.17 ***	-0.250	-0.25
	(0.10)	(0.10)	(0.20)	(0.20)	(0.20)	(0.20)	(0.00)	(0.00)	(0.20)	(0.20)
I_Tobinq	-0.55 ***	-0.71 ***	-0.65 *	-0.58 *	0.10	0.15	-0.18 ***	-0.16 ***	-0.01	0.01
	(0.20)	(0.20)	(0.30)	(0.30)	(0.30)	(0.20)	(0.00)	(0.00)	(0.20)	(0.20)
HERF	-8.85 ***	-9.26 ***	-7.54	-7.73	-5.68	-6.07	3.40 ***	3.46 ***	-6.67 *	-6.58 *
	(2.40)	(2.40)	(5.10)	(5.00)	(4.50)	(4.50)	(0.60)	(0.60)	(3.70)	(3.70)
Credit Spread	-3.37 ***		-5.56 ***		-3.34 ***		-0.09		-3.18 ***	
	(0.30)		(0.80)		(0.60)		(0.10)		(0.70)	
S&P	1.31 *		-0.16		4.02 ***		1.89 ***		0.34	
	(0.80)		(1.50)		(1.20)		(0.20)		(0.90)	
D_GW		4.24 ***		3.48 ***		2.52 ***		0.30 ***		1.46 ***
		(0.30)		(0.50)		(0.40)		(0.10)		(0.30)
Pr (D_Sell)	7.47%		8.05%		8.87%		3.94%		6.44%	
R-square	0.01	0.02	0.01	0.01	0.01	0.01	0.04	0.04	0.01	0.01
Number of Obs	64,985	64,985	15,620	15,620	27,040	27,040	528,287	528,287	29,183	29,183

Table 10 : Economic Significance: Decisions By Rating Group

This table shows the estimated probabilities of purchases and sales for public firms with different ratings and "public-like" private firms at the 10th, 25th, 50th, 75th, and 90th percentile for credit spread and in non-wave and wave years. We compute estimated probabilities using the coefficients from the probit regressions in Table 9. All other variables are held at the sample median for respective sample.

Probability of Purchases

	Credit Spread					Ratio (p10/p90)	D_GW		Ratio (1/0)
	p10	p25	p50	p75	p90		1	0	
High-Rating Firms	9.92%	9.48%	9.08%	8.87%	8.44%	1.18	11.76%	8.22%	1.43
Low-Rating Firms	11.06%	9.69%	8.54%	7.95%	6.85%	1.61	12.94%	7.17%	1.80
No-Rating Firms	6.95%	6.48%	6.06%	5.84%	5.41%	1.28	7.83%	5.43%	1.44
"Public-Like" Private Firms	2.39%	2.30%	2.22%	2.18%	2.10%	1.14	2.03%	2.66%	0.76

Probability of Sales

	Credit Spread					Ratio (p10/p90)	D_GW		Ratio (1/0)
	p10	p25	p50	p75	p90		1	0	
High-Rating Firms	10.22%	9.48%	8.85%	8.50%	7.80%	1.31	10.63%	8.11%	1.31
Low-Rating Firms	10.30%	8.90%	7.80%	7.31%	6.27%	1.64	10.67%	7.14%	1.49
No-Rating Firms	8.82%	8.06%	7.41%	7.07%	6.41%	1.38	10.68%	6.39%	1.67
"Public-Like" Private Firms	7.58%	6.87%	6.27%	5.95%	5.35%	1.42	3.51%	3.23%	1.09

Table 11: Changes of TFP

This table reports regression estimates on changes of TFP on the establishment level. D_Sale is an indicator variable that equals to 1 if the establishment is sold and 0 otherwise. D_GW is an indicator variable which equals to 1 for aggregate merger wave years and 0 otherwise. PrvtoPrv indicates transactions between private firms, and PubtoPub indicates transactions between public firms. PrvtoPub indicates transactions between private sellers and public buyers, and PubtoPrv indicates transactions between public buyers and private sellers. TFP(-1, 1) is the change of TFP from t-1 to t+1 with t being the current year. Similarly, TFP(-1,2) and TFP(-1,3) measure change of TFP from t-1 to t+2 and t+3, respectively. We control for industry fixed effects and robust standard errors are reported in the parentheses. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A

Dependent Variable	TFP (-1,1)		TFP(-1,2)		TFP(-1,3)	
Variable Name	(1)	(2)	(3)	(4)	(5)	(6)
D_Sale	0.030 ***	0.025 ***	0.042 ***	0.038 ***	0.031 ***	0.030 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Ln(Output)		0.055 ***		0.066 ***		0.067 ***
		(0.00)		(0.00)		(0.00)
TFP		-0.021 ***		-0.032 ***		-0.035 ***
		(0.00)		(0.00)		(0.00)
Constant	-0.017 ***	-0.609 ***	-0.024 ***	-0.737 ***	-0.032 ***	-0.763 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Obs	809,070	809,070	663,753	663,753	549,279	549,279
R-Square	0.001	0.01	0.001	0.012	0.002	0.012

Panel B

Dependent Variable	TFP (-1,1)		TFP(-1,2)		TFP(-1,3)	
Variable Name	(1)	(2)	(3)	(4)	(5)	(6)
D_Sale	0.018 ***	0.015 ***	0.033 ***	0.031 ***	0.020 ***	0.021 ***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
D_GW	0.000	-0.005 ***	0.005 **	-0.009 ***	0.01 ***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D_Sale * GW	0.038 ***	0.032 ***	0.030 ***	0.027 ***	0.036 ***	0.032 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
TFP		-0.021 ***		-0.034 ***		-0.037 ***
		(0.00)		(0.00)		(0.00)
Ln(Output)		0.057 ***		0.067 ***		0.068 ***
		(0.00)		(0.00)		(0.00)
Constant	-0.012 **	-0.62 ***	-0.021 ***	-0.748 ***	-0.03 ***	-0.774 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Obs	769,431	769,431	643,675	643,675	529,646	529,646
R-Square	0.001	0.011	0.001	0.013	0.002	0.012

Panel C

Dependent Variable	TFP (-1,1)		TFP(-1,2)		TFP(-1,3)	
Variable Name	(1)	(2)	(3)	(4)	(5)	(6)
PrvtoPrv	-0.002	-0.005	0.004	-0.003	-0.009	-0.013
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PrvtoPub	0.036 ***	0.02 **	0.032 ***	0.029 ***	0.034 ***	0.032 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PubtoPrv	0.064 ***	0.057 ***	0.089 ***	0.094 ***	0.055 ***	0.045 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PubtoPub	0.069 ***	0.043 ***	0.099 ***	0.082 ***	0.098 ***	0.066 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
D_GW		0.000		0.005 **		0.010 ***
		(0.00)		(0.00)		(0.00)
PrvtoPrv_GW		0.013		0.032 **		0.017
		(0.01)		(0.02)		(0.02)
PrvtoPub_GW		0.045 ***		0.013		0.011
		(0.02)		(0.02)		(0.02)
PubtoPrv_GW		0.019		-0.018		0.016
		(0.02)		(0.02)		(0.02)
PubtoPub_GW		0.059 ***		0.041 *		0.073 ***
		(0.02)		(0.02)		(0.02)
Constant	-0.017 ***	-0.012 **	-0.024 ***	-0.021 ***	-0.033 ***	-0.031 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Obs	809,070	769,431	663,753	643,675	549,279	529,646
R-Square	0.001	0.001	0.001	0.001	0.002	0.002

Table 12: Robustness Checks - Changes of TFP and Selection Effect

This table reports results from three robustness checks for change of TFP regression. Panel A provides estimation results from Heckman's selection model. Panel B shows the instrument variable approach in which we use the predicted probability of being sold (D_Sale). Panel C shows the estimated average treatment effects given the predicted probability of being sold. TFP(-1, 1) is the change of TFP from t-1 to t+1 with t being the current year. Similarly, TFP(-1,2) and TFP(-1,3) measure change of TFP from t-1 to t+2 and t+3, respectively. Robust standard errors are computed allowing clustering at the industry level and are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Heckman Selection Model

Variable Name	TFP(-1,1)		TFP(-1,2)		TFP(-1,3)	
D_Sale	0.016	***	0.029	***	0.025	***
	(0.00)		(0.00)		(0.01)	
Constant	0.100	***	0.130	***	0.140	***
	(0.00)	***	(0.00)	***	(0.00)	***
Selection						
Size	0.337	***	0.383	***	0.412	***
	(0.00)		(0.00)		(0.00)	
Constant	-2.557	***	-3.361	***	-3.933	***
	(0.01)		(0.01)		(0.01)	
Mills Ratio						
Lamda	-0.229	***	-0.216	***	-0.188	***
	(0.00)		(0.00)		(0.00)	
Number of Obs	1,146,914		1,146,914		1,146,914	
Number Censored	337,844		483,161		549,279	

Panel B: Instrument Variable Approach (using predicted probability of being sold)

Variable Name	TFP(-1,1)		TFP(-1,2)		TFP(-1,3)	
Pr_Sale	1.225	***	1.420	***	1.388	***
	(0.02)		(0.03)		(0.03)	
Constant	-0.088	***	-0.107	***	-0.108	***
	(0.01)		(0.01)		(0.01)	
Number of Obs	751,521		629,151		517,433	
R-Square	0.002		0.003		0.001	

Panel C: Average Treatment Effect: Change of TFP (Matching on Pr_Sale)

Variable Name	TFP(-1,1)			TFP(-1,2)			TFP(-1,3)		
D_GW	0	1	BOTH	0	1	BOTH	0	1	BOTH
ATT	0.0%	2.0%	0.6%	1.6%	2.9%	2.0%	0.9%	2.5%	1.5%
Std. Error	(0.5%)	(0.8%)	(0.4%)	(0.6%)	(0.9%)	(0.5%)	(0.7%)	(1.0%)	(0.5%)
T- stat	-0.01	2.55	1.46	2.68	3.20	4.03	1.39	2.58	2.82
# Treatment	25,063	11,212	36,275	21,420	9,364	30,784	17,477	8,296	25,773
# Control	533,274	181,874	715,233	452,950	145,314	598,363	364,501	127,066	491,656

Table 13: Robustness Checks - Market Valuation

Panel A reports the estimated marginal effects(in %) from probit models. In column (1) to (3), the dependent variable, D_Buy, equals to 1 if a firm buys at least one plant and zero otherwise. In column (4) to (6), the dependent variable, D_Sell, equals to 1 if a firm sells at least one plant and 0 otherwise. Size is the log of total value of shipments (in 1987 dollars), and TFP is the total factor productivity. I_Tobinq is the industry Tobin's q and HERF measures the industry Herfindahl Index based on sales. Credit Spread is the spread between C&I loan rate and Fed Funds rate. S&P is the return of S&P Industrial Index. We calculate MISV using the procedure of Rhodes-Kropft, Robinson and Viswanathan (2005) as updated by Hoberg and Phillips (2009). Panel B reports regression results in which the dependent varaible is change of TFP. D_RMISV is an indicator variable that equals 1 if the difference in MISV between buyer and seller is higher than median transactions and 0 otherwise.The Robust standard errors allow clustering at the industry level and are reported in parentheses. *, ** and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Marginal Effects

Variables	D_Buy			D_Sell		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Output)	0.76 ***	0.72 ***	0.71 ***	1.02 ***	1.01 ***	1.02 ***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
TFP	0.34 ***	0.27 ***	0.28 ***	-0.9 ***	-0.92 ***	-0.92 ***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
I_Tobinq	-0.86	-0.57	-1.29	-0.32 *	-0.32 *	-0.37 **
	(3.40)	(3.40)	(3.20)	(0.20)	(0.20)	(0.20)
Herfindahl Index	0.03	-0.03	-0.25	-8.37 ***	-8.28 ***	-8.77 ***
	(0.20)	(0.20)	(0.20)	(2.40)	(2.40)	(2.40)
Credit Spread	-2.68 ***	-2.52 ***		-3.29 ***	-3.26 ***	
	(0.40)	(0.40)		(0.40)	(0.40)	
Industrial Return	2.21 ***	2.37 ***		2.86 ***	2.91 ***	
	(0.90)	(0.80)		(0.80)	(0.80)	
MISV		1.44 ***	1.05 ***		0.31 *	0.34
		(0.20)	(0.20)		(0.20)	(0.20)
GW			3.63 ***			3.29 ***
			(0.30)			(0.30)
MISV_GW			1.34 ***			0.00
			(0.40)			(0.40)
Number of Obs	77894	77894	77894	83854	83854	83854
R-square	0.010	0.011	0.015	0.013	0.013	0.014

Panel B: Change of TFP

Dependent Variable	TFP (-1,1)		TFP(-1,2)		TFP(-1,3)	
Variable Name	(1)	(2)	(3)	(4)	(5)	(6)
D_Sale = 1 & D_RMISV=0	0.0243 ***	0.0152 ***	0.0376 ***	0.0299 ***	0.0297 ***	0.0185 ***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
D_Sale = 1 & D_RMISV = 1	0.0371 **	0.0207	0.0567 ***	0.0580 **	0.0608 ***	0.0930 ***
	(0.018)	(0.024)	(0.021)	(0.027)	(0.023)	(0.030)
D_GW		-0.0048 ***		-0.0088 ***		-0.0021
		(0.002)		(0.002)		(0.002)
(D_Sale = 1 & D_RMISV=0) * D_GW		0.0310 ***		0.0276 ***		0.0364 ***
		(0.008)		(0.010)		(0.011)
(D_Sale = 1 & D_RMISV=1) * D_GW		0.0415		0.0005		-0.0761
		(0.037)		(0.042)		(0.046)
TFP	-0.0207 ***	-0.0207 ***	-0.0343 ***	-0.0344 ***	-0.0375 ***	-0.0375 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Output)	0.0565 ***	0.0565 ***	0.0670 ***	0.0672 ***	0.0679 ***	0.0679 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.6211 ***	-0.6201 ***	-0.7481 ***	-0.7481 ***	-0.7742 ***	-0.7734 ***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.012)
Number of Obs	769,431	769,431	643,675	643,675	529,646	529,646
R-Square	0.011	0.011	0.013	0.013	0.012	0.012