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# Private and Public Merger Waves

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**ABSTRACT**

We document that public firms participate more than private firms as buyers and sellers of assets in merger waves and their participation is affected more by credit spreads and aggregate market valuation. Public firm acquisitions realize higher gains in productivity, particularly for on-the-wave acquisitions and when the acquirer's stock is liquid and highly valued. Our results are not driven solely by public firms' better access to capital. Using productivity data from early in the firm's life, we find that better private firms subsequently select to become public. Initial size and productivity predict asset purchases and sales 10 and more years later.

PRIOR RESEARCH ESTABLISHES THAT the market for corporate assets is procyclical. Mergers and acquisitions tend to cluster in time.[1] However, what causes firms to participate in these waves, and whether acquisitions that occur on the waves lead to the same efficiency outcomes as mergers that occur off the waves, remain open questions. The extent to which private firms participate in merger waves and whether their participation is affected by similar demand and supply factors that affect public firms also remain unanswered. At one extreme, acquisition waves may occur because investment opportunities also occur in

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[1] Mitchell and Mulherin (1996) and Harford (2005) analyze merger waves by public firms. Netter, Stegemoller, and Wintoki (2011) show that when including small deals and private acquirers this pattern is much smoother than the pattern with only large and public deals. See Andrade, Mitchell, and Stafford (2001) and Betton, Eckbo, and Thorburn (2008) for two surveys on the overall merger market.

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waves. At the other extreme, waves may be driven by changes in liquidity and investment climate that allow certain types of firms to obtain capital more easily or cheaper than other firms. Thus, public firms may take advantage of high valuations in the stock market to buy assets.

The central contribution of this paper is to show how and why real and financial factors affect public and private firms differently in their acquisition and asset sale behavior. 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 approximately 40,000 firms over the 1977 to 2004 period, we compare how public and private firms participate in merger waves and the outcomes of the mergers. We find sharp differences between these two groups. Public firms purchase and sell assets at a higher intensity than private firms. This is true even after controlling for firm size and plant productivity. Moreover, there exists a notable difference between these two types of firms' acquisition decisions over the business cycle. Public firms are almost twice as likely to buy *and* sell assets in wave years than in nonwave years, while the transactions of private firms are much flatter over time. To a large extent, the observed merger and acquisition waves are driven by higher participation of public firms.

Both efficiency and valuation affect acquisition decisions. Firms with higher productivity are more likely to buy assets and firms with lower productivity are more likely to sell assets. The productivity–acquisition relation is stronger for public firms than for private firms. In addition, for public firms, acquisition decisions are also influenced by stock market conditions. Public firms with higher unexplained valuation (or misvaluation) and stock liquidity participate more in acquisitions.

We show that credit market liquidity, as measured by the spread between Commercial and Industrial (C&I) loans and the Fed Funds rate, has a significant effect on merger intensity. In addition to productivity, private firms are less sensitive to credit spreads than public firms, suggesting that, while productivity matters, private firms' financing constraints may also be sufficiently binding and cannot be relaxed even at times of high liquidity.

To further study how the credit spread interacts with financial constraints in affecting acquisition decisions, we divide our sample of public firms into groups based on the level of potential borrowing constraints. We use credit rating status (investment grade, below investment grade, and nonrated) to measure a firm's liquidity in the debt market and use stock liquidity (based on the Amihud illiquidity index) to measure the firm's liquidity in the stock market. We find that public firms with intermediate access to financial markets (debt or equity) have the highest sensitivity. However, public firms that are more likely to be constrained (nonrated and with a high illiquidity index) have greater sensitivity to industry-level financial factors than private firms. Thus, our finding suggests that access to the financial market and market liquidity are important drivers for merger waves through the cost of accessing external financing.

We also 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 self-select into public status in anticipation of future acquisitions. Indeed, we find that firms that are larger and more productive at birth choose to go public, participate more in acquisitions, and are more wave-driven. Controlling for the probability of being public (or "public quality") based on initial conditions, the difference in participation rates between public and private firms declines. Specifically, public quality explains more than 27% of the difference in acquisitions and 91% of the difference in asset sales between public and private firms.

Our results show that the difference in public and private firms' acquisition activity is not simply due to the public firms' better access to financial markets. While better access to markets and lower cost of capital may help public firms participate in acquisitions, they are not the fundamental reasons why public and private firms differ in their acquisition behavior. Rather, differences in firm quality enable some firms to grow through productivity-enhancing acquisitions, and these differences are reflected in their earlier choice of obtaining public status.

We find that acquisitions are efficiency improving, both on and off the wave. Plants acquired gain more in productivity compared to similar plants that are not sold. Productivity increases are higher for on-the-wave mergers, and in particular, when the buyer and seller are both public firms and when the buyer is highly valued with more liquid stock. We thus do not find evidence that the increased occurrence of public mergers in waves leads to misallocation of assets. Instead, our findings suggest that periods of more frequent transactions and greater stock valuation are associated with ex post efficiency improvements. The evidence is consistent with public buyers paying for synergies as they are more likely to buy with highly valued stock but still make productivity improvements ex post.

We find that firms with high unexplained valuation relative to current fundamentals are indeed more likely to buy assets. This result is consistent with the notion in Rhodes-Kropf and Viswanathan (2004) that firms cannot tell the difference between overvalued stock and high productivity of other firms and therefore high valuations facilitate acquisitions, even if potentially at the wrong price. We find that acquirers with high unexplained valuation also experience greater subsequent productivity gains following the acquisitions. Thus, while acquirers may pay or fund their purchases with highly valued equity, the purchases are not without merit and improve the allocation of resources in the economy.

As a robustness check, we also separate transactions into partial- and whole-firm acquisitions and find that firms with high unexplained valuation are equally likely to engage in partial-firm purchases as they are whole-firm acquisitions. Since the former are more likely to be paid in cash and less affected by stock valuation, our finding supports the idea that firms with high valuation face better opportunities and are more likely to engage in acquisitions.

Our paper builds on the rapidly growing literature on merger waves. Clustering of mergers by public firms in time and industry has been studied by Mitchell and Mulherin (1996), Mulherin and Boone (2001), Andrade, Mitchell, and Stafford (2001), and Harford (2005). Netter, Stegemoller, and Wintoki (2011) examine a large sample of mergers that includes small deals and private acquirers, and find that these deals are smoother over time. Dittmar and Dittmar (2008) and Rau and Stouraitis (2011) show that corporate financing events including mergers come in waves. Shleifer and Vishny (2003) and Rhodes-Kropf, Robinson, and Viswanathan (2005) argue that merger waves are driven by misvaluation in financial markets, while Harford (2005) places greater reliance on availability of liquidity. Schlingemann, Stulz, and Walkling (2002) find that firms are more likely to sell assets in periods of high industry liquidity. Moeller, Schlingemann, and Stulz (2006) show that acquisitions made during merger waves create value for acquiring shareholders on average despite a small number of acquisitions with extremely large losses. Eisfeldt and Rampini (2006) identify liquidity as the reason why asset sales are procyclical.

Our paper differs from existing studies in several respects. First, we study both public and private firms using a comprehensive data set from the Census Bureau. By comparing participation and outcomes of public and private acquisitions on and off the wave, we can directly analyze the effect of market valuation, liquidity, and access to the financial market on acquisition decisions.

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

Third, the unique and separate plant and firm identifiers in the Census data set allow us to pin down exactly which plants within a firm have changed ownership, and thus we can directly assess the outcome of an acquisition by comparing productivity changes for those plants. In comparison, most existing studies draw their conclusions based on performance changes in the entire acquirer firm, which confounds the performance changes of the acquired units with those of the acquirer's own units.

Our work is related to several recent papers. Yan (2006) and Duchin and Schmidt (2008) analyze the value created by on- and off-the-wave mergers. They find that on-the-wave mergers are more likely to be value destroying as reflected by acquirer stock returns. By contrast, we find that on average on-the-wave mergers of public firms increase productivity of the acquired plants. The two findings are not inconsistent, in that acquiring firms may overpay for real synergies. However, our results show that the transactions increase overall efficiency in the economy.

Our results are also related to several papers that document higher acquisition activity for firms that recently had IPOs (Brau and Fawcett (2006), Hovakimian and Hutton (2008), and Celikyurt, Sevilir, and Shivdasani (2010)). While this finding does not prove that a primary motivation for IPOs is to enable firms to make acquisitions, it does suggest that, for young firms at the very least, public status facilitates acquisitions. Our paper complements and extends these papers in several important ways. Consistent with these papers, we also find that firms undertake more acquisitions in the first 5 years after going public. In addition, we find that acquirers that recently went public realize similar productivity gains on their purchased plants, compared to other public firms, on or off the wave. Different from these papers, we show that initial conditions in the early pre-IPO stage can predict both public status and subsequent acquisition activities years afterwards. Furthermore, we analyze decisions to sell assets, and find significant differences between public and private firms based on fundamentals and financial conditions consistent with our arguments.[2]

Our paper joins the emerging literature on private firms. Brav (2009) examines financing decisions of private firms and Asker, Farre-Mensa, and Ljunqvist (2010, 2011) compare investment decisions of public and private firms. However, these studies are not able to control for self-selection into public status. They match firms based on recent size data, which may imply matching successful private firms with less successful public firms. In contrast to the Asker et al. studies, we find a benefit of public market status. We show that public firms increase the productivity of the assets they purchase more than private firms. We thus contribute to the literature by providing evidence on acquisition decisions between public and private firms and the differential effect over the business cycle.

The remainder of the paper proceeds as follows. Section I presents our empirical framework including research questions addressed by our study, our estimation strategy, and theoretical predictions related to merger waves. Section II provides a description of the data, variables, and summary statistics. We endogenize the decision to be public in Section III. Section IV compares decisions to participate in mergers and acquisitions by public and private firms. Section V examines changes in productivity around transactions, and Section VI concludes.

## I. Empirical Framework

One explanation for the phenomenon of procyclical merger waves is that the gains from the reallocation of assets across firms are also procyclical. However, merger waves may also be driven by conditions in the financial markets. Harford (2005) argues that waves occur in part because it is easier to raise external capital at a lower cost 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)

[2] Our empirical results are not driven by mergers of recently public firms. We do find that recently public firms have a higher acquisition rate. However, such transactions are only a small portion of our sample of public firm acquisitions and the outcomes of those transactions are not different from those of the rest of the sample.

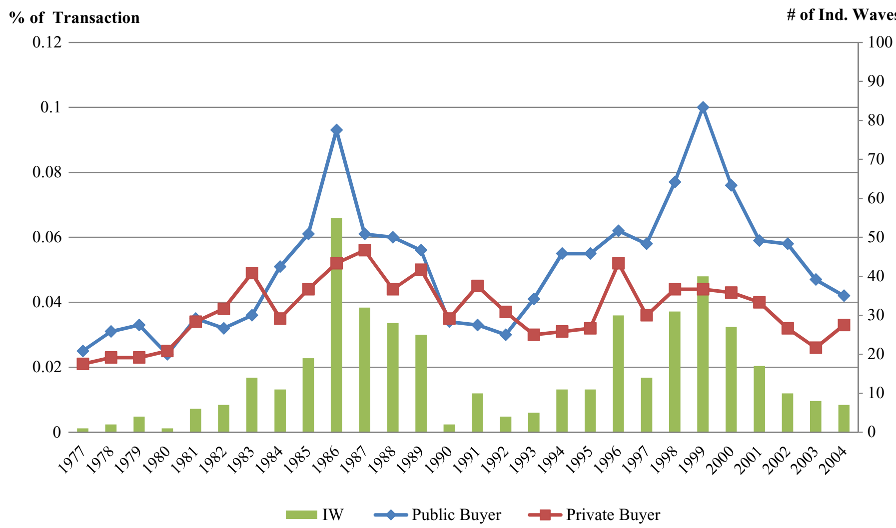


**Figure 1. Transactions over time.** This figure plots the time series for the rate of acquisitions among U.S. manufacturing firms over the 1977 to 2004 period. The two lines present the percentage of transactions made by public firms (diamond) and private firms (square). The bars show the number of industries having industry-wide merger waves. Industry merger waves are defined as years when the rate of transactions within an industry is at least one standard deviation above its sample mean.

suggest that higher valuations in the equity market make equity-financed acquisitions more attractive. Using samples of publicly traded firms in the United States, 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.[3] Comparing acquisition activities of public and private firms over the business cycle helps us shed light on how fundamentals and financial markets may affect firms' decisions. From our data (described fully 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 U.S. manufacturing plants over the 1977 to 2004 period.

There exists a remarkable difference between public and private firms in their acquisition rates over the business cycle. As shown in Figure 1, public firms are almost twice as likely to buy assets in aggregate wave years than in nonwave years while purchases by private firms are much flatter. The observed aggregate merger waves are driven to a large extent by higher participation of public firms. This finding is consistent with the pattern found by Betton, Eckbo, and Thorburn (2008) using publicly available data on public and nonpublic bidders.

[3] Brav (2009) shows that British public and private firms differ systematically in their financial and investment policies, but does not address their merger activity.

### *A. Initial Statistics: Public and Private Participation in Merger Waves*

In this section we provide basic summary statistics on merger and acquisition activities of both public and private firm using our data—described fully in the next section—from U.S. manufacturing industries.

We identify merger and acquisition waves at the aggregate economy level as well as at the industry level using the following procedure. For each industry, based on three-digit SIC code, we first calculate the percentage of plants traded between firms each year. We then 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 than the industry mean rate. To identify aggregate wave years, we use a similar method, except that the mean rate and the standard deviation are calculated using 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 Census data for 2,957 industry-years from 1977 to 2004, we identify six aggregate wave years, 1986, 1987, 1996, 1998, 1999, and 2000, and 432 industry wave years.

Table I presents summary statistics on aggregate merger waves.

First, public firms participate in acquisitions more than private firms in general, with a larger difference in on-the-wave years. On average, public firms operate 20% of the firms in our sample, but account for 37% of the total transactions. During aggregate wave years, 42% of buyers and 40% of sellers are public firms, as compared to 35% and 30%, respectively, off the wave.

Second, the number of public-to-public transactions increases more than any other type of transaction during aggregate wave years. In particular, 19% of all transactions on the wave are between public firms, up from 12% off the wave. In contrast, private-to-private transactions account for 37% all transactions on the wave, a sharp decrease from 48% off the wave.

The increase in the proportion of public buyers is consistent with the conjecture that during waves financial constraints on public firms are relaxed. However, the proportion of transactions from public firms to private firms increases from 18% to 21%, whereas the reverse flow, from private sellers to pubic buyers, increases by only 1%, from 23% to 24%. Thus, we do not find evidence that more assets transfer from private to public firms during merger waves. On-the-wave transactions cannot therefore be explained just by a relative increase in access to capital by public firms relative to private firms—they may also be affected by changes in relative productivity between public and private firms.

Public firms also engage in bigger transactions than private firms—the average number of plants sold in a public-to-public transaction is 3.19 on the wave and 2.48 off the wave, compared to 1.38 and 1.42 in private-to-private transactions. About 26% of all public-to-public transactions on the wave involve full ownership transfer (mergers), while only 18% off the wave do so. In contrast, about three-quarters of all private-to-private transactions are mergers, both on and off the wave.

**Table I**

## Summary Statistics: Public and Private Merger Waves

This table presents summary statistics on participation over the merger waves. Panel A presents the percentage of plants in transactions by public status. We use the number of plants owned by public (private) firms as the denominator to calculate the rate for public (private) buyers and sellers. Panel B shows the composition of all transactions and Panel C presents summary statistics on the size and type of transactions. *D_Wave* is an indicator variable that equals one for aggregate merger wave years and zero otherwise. Aggregate wave years are years in which the percentage of plants traded is greater than one standard deviation above the aggregate mean. We classify all transactions into two categories: asset acquistions and mergers.

Panel A: Percentage of Plants in Transactions

| | Public Firms | | Private Firms | |
|---|---|---|---|---|
| *D_Wave* | Buyers | Sellers | Buyers | Sellers |
| 0 | 4.16% | 3.39% | 3.74% | 4.21% |
| 1 | 7.41% | 5.94% | 5.06% | 6.27% |
| Average | 4.88% | 3.95% | 4.03% | 4.66% |

Panel B: Number of Transactions

| Buyer | $D\_Wave = 0$ | | $D\_Wave = 1$ | |
|---|---|---|---|---|
| Private | 22,470 | (65%) | 8,374 | (58%) |
| Public | 11,892 | (35%) | 6,179 | (42%) |
| Total | 34,362 | | 14,553 | |
| **Seller** | $D\_Wave = 0$ | | $D\_Wave = 1$ | |
| Private | 24,127 | (70%) | 8,787 | (60%) |
| Public | 10,235 | (30%) | 5,766 | (40%) |
| Total | 34,362 | | 14,553 | |
| **Transaction** | $D\_Wave = 0$ | | $D\_Wave = 1$ | |
| Public buyer public seller | 4,129 | (12%) | 2,726 | (19%) |
| Public buyer private seller | 7,763 | (23%) | 3,453 | (24%) |
| Private buyer public seller | 6,106 | (18%) | 3,040 | (21%) |
| Private buyer private seller | 16,364 | (48%) | 5,334 | (37%) |
| Total | 34,362 | | 14,553 | |

Panel C: Size and Type of Transactions

| | Number of Plants Bought | | Percent of Mergers | |
|---|---|---|---|---|
| Transaction | $D\_Wave = 0$ | $D\_Wave = 1$ | $D\_Wave = 0$ | $D\_Wave = 1$ |
| Public buyer public seller | 2.48 | 3.19 | 18% | 26% |
| Public buyer private seller | 2.01 | 2.13 | 72% | 78% |
| Private buyer public seller | 1.74 | 1.94 | 8% | 11% |
| Private buyer private seller | 1.42 | 1.38 | 74% | 74% |
| Average | 1.67 | 1.84 | 58% | 57% |

Industry wave years and aggregate wave years are highly correlated. The aggregate waves are driven by many industries having waves at the same time. 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. Moreover, one additional industry on the wave increases the odds ratio of other industries being on the wave by 6%.

### *B. Public Status and Participation in Merger Waves*

The fact that public firms' merger activity is more cyclical suggests that access to financial markets facilitates merger waves. However, public status is endogenous. Firms may choose to go public to have better access to financial markets. More specifically, by going public a firm 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 need for external capital, either for investment or acquisitions. Thus, the observed difference between public and private firms in acquisition can also reflect the difference in initial firm quality. In this section, we outline a framework that permits us to empirically examine how access to public financial markets and investment opportunities affect mergers decisions given initial firm quality and 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 go public now or later with a high probability. On the one hand, public status offers financing advantages such that if the firm goes public it has the option to access public markets at a future date and acquire other firms at a lower cost.[4] On the other hand, public status is costly to acquire initially (i.e., including direct and indirect costs 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 go public.

Since public status is an endogenous choice, to compare public and private firms in their acquisition decisions it is important to separate out the following three distinct sources of differences between them.

First, we expect differences in acquisition activity purely on the basis of differences in fundamentals. Because larger and more productive firms may select public status, we expect a sample of public firms to engage in more

[4] The firm has the option to postpone an IPO to a future date. This is not essential to our main argument and empirical tests. However, it is consistent with the finding by Celikyurt, Sevilir, and Shivdasani (2010) and Hovakimian and Hutton (2008) that IPOs are frequently followed by acquisition activity within a short span.

acquisitions, all other things being equal. This is purely a selection effect and will be reflected in differences in the values of the explanatory variables in the subsamples of public and private firms.

Second, public status may cause a disparity 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 firms. As a result, assets will flow from less to more productive firms following the positive demand shock. To the extent that more productive firms self-select into public status, following a positive industry shock the rate of public acquisitions will increase relative to private acquisitions.

Third, public and private firms may be affected differently by financial market shocks. Public firms can access public financial markets, especially for long-term capital, at more favorable or easier terms while private firms rely more on short-term financing from financial intermediaries (Brav (2009)). Faulkender and Peterson (2006) show that public firms with higher bond ratings also have better access to public bond markets. Such access might be needed both to finance cash offers and to refinance the debt of target firms that comes due upon a change in control. Public firms' incentives to merge may also be driven by mispricing in public markets, analyzed by Rhodes-Kropf and Viswanathan (2004), possibly in conjunction with agency problems (Shleifer and Vishny (2003)). In addition, public firms, especially those with liquid stock, can use equity as a medium of exchange to finance their acquisitions while the same option usually is not available for privately held firms.

However, the comparative effect of shocks such as the narrowing credit spreads on private and public firms cannot be predicted a priori. 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 decision to buy or sell assets:

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

where $m_{it+1}$ is one if firm $i$ engages in a purchase (sale) of assets at time $t+1$ and zero otherwise; $X_{it}$ includes firm-specific variables (including productivity, size, stock market valuation, and liquidity) together with industry variables; $Z_t$ includes macroeconomic conditions or indicators for merger waves; $P_{it}$ is an indicator variable for public status, which we predict later with firm initial conditions at firm birth; $\varepsilon_{it}$ is a random error; and $F(.)$ is a nonlinear limited dependent variable in parametric form.

Model (1) divides the difference in acquisition decisions between public and private firms into three distinct sources as mentioned above. First, the coefficient $\delta_1$ captures the effect of firm characteristics, such as size and productivity firms. These characteristics will differ across the population of private and public firms as firms self-select to go public. Second, public status may cause a difference in the elasticity of acquisition activity with respect to measured firm fundamentals or macroeconomic shocks. These effects will be reflected in the coefficients of $\delta_3$ and $\delta_4$, respectively. Lastly, the coefficient $\delta_0$ will pick up the marginal effect of public status on acquisition decisions based on factors that are not fully covered by our framework.

### *C. Firm Quality, Decision to Be 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, and that the difference in firm quality, rather than actual public status, may explain the difference in their participation in acquisitions. To establish this link, we need to separate the latent quality of a firm from its public status. If this potential is evident early in the life of the firm, then initial characteristics can predict both the selection into public status and merger activity in subsequent years.[5]

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 firm is public at time $t$, where $t$ ranges from 5 (or alternatively 10) years after the initial appearance to the end of the sample. We use the following specification:

$$y_{it} = G\left(\pi_1 X_{it_{0i}} + \nu_{it}\right) \tag{2}$$

and

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

where $P_{it}$ equals one if firm $i$ is public at time $t$ and zero otherwise, $X_{it_0}$ captures the initial firm characteristics that are observable at birth. $V_{it}$ is a random variable and $G(.)$ is a nonlinear 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 $\delta_0$, $\delta_3$, and $\delta_4$, specification (3) allows us to analyze how initial conditions such as productivity and size affect

[5] Lemmon, Roberts, and Zender (2008) show that firms' leverage ratios are driven by an unobserved time-invariant effect that can be traced to periods prior to the IPO.

a firm's decisions to buy or sell assets in subsequent years. 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 go public during a merger wave in order to more efficiently accomplish a specific planned transaction (Celikyurt, Sevilir, and Shivdasani (2010) 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 5 or 10 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 for effectively using a standard econometric model. To avoid these issues, we also perform a matching exercise using the propensity score based on initial characteristics and the predicted probability of going public ($\widehat{P_{it}}$). For firms with comparable propensity score, we estimate the average treatment effect due to public status in participation of mergers and acquisitions on and off the wave. This nonparametric approach provides an alternative way to separate the effect due to selection from the effect due to public status.

### *D. Gains in Productivity: On- and Off-the-Wave Mergers*

Comparing changes in productivity for transacted plants in public and private acquisitions helps us to study the relative importance of fundamentals, financial access, and agency problems. If merger waves occur because growth opportunities also come in waves, then we should observe greater improvement in economic efficiency in periods when there are more transactions. Moreover, if the higher participation of public firms on the wave is driven by their difference in productivity and growth opportunities, then acquisitions of public firms should perform at least as well as (or better than) acquisitions by private firms. Better access to financing by public firms can facilitate transactions by these firms.

On the other hand, since public status is associated with dispersed ownership and potentially entrenched management, public firms may be more likely to engage in empire building. If so, we would expect to see lower productivity gains for assets acquired by public firms compared to those purchased by private firms. As such, changes in productivity for acquired assets provide a measure of the relative importance between agency problems and inherent quality (i.e., productivity) in public and private firms.

The timing of the transaction may also drive changes in productivity for acquired assets. Merger waves often coincide with higher liquidity and valuation in the financial market. If waves are largely driven by valuation or liquidity in the financial market, then large transaction volume would not necessarily lead to higher operational efficiency. Moreover, if public firms acquire more on the wave to take advantage of more favorable access to financial markets rather than to realize synergies, then we should observe worse performance from public acquirers on the wave. In contrast, if merger waves are driven by expected productivity gains, we should observe greater productivity gains in periods when there are more transactions, that is, on the wave. To test these hypotheses, we compare changes in productivity for plants bought by public and private firms on and off the wave.

## II. Data and Basic Statistics

### *A. Plant-Level Census Data*

We use data from the Annual Survey of Manufactures (ASM), Census of Manufactures (CMF), 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 Census data track approximately 50,000 manufacturing plants every year, and contain detailed plant-level data on the value of shipments produced by each plant, investments broken down by equipment and buildings, and labor input such as number of employees and hours worked.[6] The ASM covers all plants with more than 250 employees. Smaller plants are randomly selected every fifth year to complete a rotating 5-year panel. Even though it is called the ASM, 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 cover the period from 1972 to 2004. To be included in our sample, firms must have manufacturing operations in SIC codes 2000 to 3999. We require each plant to have a minimum of 3 years of data. For each firm, we also exclude all its plants in an industry (at the three-digit SIC code level) 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 from 1977 to 2004. We lose the initial year that a firm or a firm-segment enters the database and observations that are noncontinuous since we use lagged capital stock to compute the rate of capital expenditure and we use lagged sales to compute sales growth. Our final sample has about 665,000 firm-industry-years and more than one million plant-years.

The Census databases keep unique identifiers for both firms and plants that allow us to track ownership changes over time. For example, if plant #1000 is under firm A in 2000 but firm B in 2001, we identify it as a transaction from firm A to firm B during 2001. Census staff (Javier Miranda and Ron Jarmin) confirmed to us that information on ownership transfers is updated in a timely manner for nearly all public and private transactions in the company organization survey. The survey form is sent in December and companies are required by law to return the form in 30 days to report any ownership changes during the

[6] We access the ASM and CMF data using the Longitudinal Research Database (LRD). For a more detailed description of the LRD, see McGuckin and Pascoe (1988) and Maksimovic and Phillips (2002).

reference year.[7] 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, 20% of the plants are owned by public firms, and together they produce about 35% of total output. Public firms are bigger—on average, public firms operate 3.1 plants compared to 1.4 plants owned by private firms. The median value of shipment (in 1982 dollars) 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 margins. Using these data we calculate productivity for each plant using a translog production function. Kovenock and Phillips (1997) describe the productivity calculations, the data used as inputs, and the method for accounting for inflation and depreciation of capital stock in more detail.

### B. Economy and Industry Conditions

We focus on supply and demand factors that may affect acquisition decisions 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 of aggregate liquidity following Harford (2005). Lown, Morgan, and Rohatgi (2000) find that this spread is strongly correlated with the tightening of liquidity measured from the Federal Reserve Senior Loan Officer (SLO) survey. When the 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 the one hand, narrowing spreads 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 comparatively cheaper for private firms to obtain loans. This second effect would increase the rate of private acquisitions relative to public acquisitions.

We use several 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 proxies for industry and aggregate investment opportunities, respectively, and examine their impact on merger activities. Tobin's $Q$

[7] For more detailed information on the survey, please refer to http://www.census.gov/econ/overview/mu0700.html. Evidence on the quality of ownership change reporting in the LRD is provided by Davis et al. (2010), who examine transaction dates reported in the Capital IQ database for a series of leverage buyout (LBO) transactions. While they do discover limited discrepancies in the reporting of some LBO transactions, they find that their results are qualitatively the same as the results with SDC Platinum transaction dates, with similar signs and significance levels.

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 the credit spread and the S&P industrial return is 47%. For robustness, 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 Herfindahl index in the specifications to control for the incentive to buy competitors and increase the firm's market power or the ease of finding a trading partner. This index is calculated as the sum of squared firm-industry market shares using sales based on both public and private firms in the industry.

## III. Participation in Merger Waves: Public and Private Firms

### A. Decisions to Buy and Sell Assets

In this section we compare decisions to buy or sell assets for both public and private firms, focusing on the effect of firm characteristics, industry conditions, and conditions in the financial market. We test whether public and private firms respond to fundamentals and financial conditions differently as we hope to understand how fundamentals and financial conditions influence merger activity and the sources of differences in such activity.

Table II examines the probability of buying and selling assets for both public and private firms using firm productivity and industry variables, and indicators for credit market conditions. In Panel A, our dependent variable, *D_Buy*, takes the value of one if a firm buys a plant in the next period and zero otherwise. In Panel B, our dependent variable, *D_Sell*, takes the value of one if a firm sells a plant. In each panel, we run two specifications, one with the aggregate wave indicator (columns 1 and 2), and the other with macro variables such as the credit spread and the S&P return (columns 4 and 5).[8] We estimate each specification separately for public and private firms to allow different coefficients on all variables. Columns 3 and 6 report the $p$-value for testing the difference in coefficients between the two groups. Note that Table II reports the estimated marginal effects using a logit specification. In Table III, we present similar results using a linear probability model. The results are qualitatively unchanged and actually slightly stronger for the linear probability model.

We control for firm size using the total value of shipments across all industries in which the firm operates, as large firms may have higher financing capacity when it comes to acquiring assets. We also include firm productivity (*TFP*) to control for operating efficiency. On the industry level, we include the industry Tobin's $Q$ to control for demand for assets and the Herfindahl index (based on sales) to control for industry structure. We also include a proxy

[8] This variable is equal to one for the six wave years identified in Section I (1986, 1987, 1996, 1998, 1999, and 2000), and zero otherwise.

**Table II**

## Decision to Buy or Sell Assets (Logit)

This table reports the estimated marginal effects (in %) from logit models. In Panel A, the dependent variable, *D_Buy*, equals one if a firm buys at least one plant and zero otherwise. In Panel B, the dependent variable, *D_Sell*, equals one if a firm sells at least one plant and zero otherwise. *Size* is the log of the 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. *Ind_UV* is the average unexplained valuation (*UV*) based on all public firms in that industry. We calculate *UV* using the procedure of Rhodes-Kropf, Robinson, and Viswanathan (2005) as updated by Hoberg and Phillips (2010). Credit Spread is the spread between the C&I loan rate and the Fed Funds rate. S&P is the return of S&P Industrial index. *D_Wave* is an indicator variable that equals one for wave years and zero for nonwave years. Columns 1 and 4 are estimated using public firms and Columns 2 and 5 are estimated using private firms. Columns 3 and 6 report 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. We control for firm random effects. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | Public (1) | Private (2) | *p*-value for Difference (3) | Public (4) | Private (5) | *p*-value for Difference (6) |
|---|---|---|---|---|---|---|
| Panel A: Decision to Buy Assets (Dependent Variable = *D_Buy*) | | | | | | |
| *Size* | 0.425*** | 0.338*** | <0.001 | 0.436*** | 0.335*** | <0.001 |
| | (0.040) | (0.010) | | (0.040) | (0.010) | |
| *TFP* | 0.300*** | 0.023** | 0.294 | 0.307*** | 0.024** | 0.308 |
| | (0.080) | (0.010) | | (0.080) | (0.010) | |
| *I_Tobinq* | –0.361*** | –0.096*** | 0.037 | –0.177 | –0.072*** | 0.039 |
| | (0.130) | (0.020) | | (0.130) | (0.020) | |
| *Ind_UV* | 0.022 | 0.049** | 0.223 | –0.520** | 0.003 | 0.079 |
| | (0.210) | (0.020) | | (0.220) | (0.020) | |
| *HERF* | 1.083 | 0.612*** | 0.143 | 2.131 | 0.701*** | 0.185 |
| | (1.790) | (0.210) | | (1.800) | (0.210) | |
| *D_Wave* | 2.454*** | 0.182*** | <0.001 | | | |
| | (0.18) | (0.020) | | | | |
| Credit spread | | | | –1.941*** | –0.020 | <0.001 |
| | | | | (0.220) | (0.030) | |
| S&P | | | | 3.096*** | 0.383*** | 0.978 |
| | | | | (0.510) | (0.060) | |
| Pr(*D_Buy*) | 7.36% | 1.75% | | 7.36% | 1.75% | |
| Chi Square | 385 | 6,716 | | 291 | 6,600 | |
| Number of obs. | 99,121 | 420,944 | 520,065 | 99,121 | 420,944 | 520,065 |
| Panel B: Decision to Sell Assets (Dependent Variable = *D_Sell*) | | | | | | |
| *Size* | 0.969*** | 1.091*** | <0.001 | 0.963*** | 1.101*** | <0.001 |
| | (0.050) | (0.020) | | (0.050) | (0.020) | |
| *TFP* | –0.813*** | –0.169*** | <0.001 | –0.810*** | –0.169*** | <0.001 |
| | (0.090) | (0.020) | | (0.090) | (0.020) | |
| *I_Tobinq* | –0.602*** | –0.105*** | 0.185 | –0.445*** | –0.083** | 0.478 |
| | (0.130) | (0.030) | | (0.130) | (0.030) | |

(*Continued*)

**Table II**—*Continued*

| | Public (1) | Private (2) | $p$-value for Difference (3) | Public (4) | Private (5) | $p$-value for Difference (6) |
|---|---|---|---|---|---|---|
| Panel B: Decision to Sell Assets (Dependent Variable = *D_Sell*) | | | | | | |
| *Ind_UV* | 1.688*** | 0.330*** | <0.001 | 1.349*** | 0.221*** | 0.001 |
| | (0.230) | (0.050) | | (0.240) | (0.050) | |
| *HERF* | –6.150*** | 1.973*** | <0.001 | –5.656*** | 2.005*** | <0.001 |
| | (2.050) | (0.470) | | (2.050) | (0.470) | |
| *D_Wave* | 3.641*** | 0.441*** | <0.001 | | | |
| | (0.20) | (0.040) | | | | |
| Credit spread | | | | –3.905*** | –0.350*** | <0.001 |
| | | | | (0.250) | (0.050) | |
| S&P | | | | 0.294 | 0.834*** | <0.001 |
| | | | | (0.560) | (0.120) | |
| Pr(*D_Sell*) | 7.91% | 4.08% | | 7.91% | 4.08% | |
| Chi Square | 821 | 5,191 | | 663 | 5,279 | |
| Number of obs. | 107,645 | 557,470 | 665,115 | 107,645 | 557,470 | 665,115 |

for industry-level misvaluation based on public firms following Rhodes-Kropf, Robinson, and Viswanathan (2005) and Hoberg and Phillips (2010). First, for each industry, we regress the log market value of equity on the log book value of equity, net income, an indicator for negative net income, and a leverage ratio using a historical 10-year rolling window. Then, the "misvaluation" measure is computed as the difference between the actual and predicted market values of equity using the estimated coefficients. Following Hoberg and Phillips, we use only lagged data in the calculation of coefficients to avoid any look-ahead bias.[9] Since this measure captures the component of valuation that cannot be explained by a model using firms' financial data, we will refer to it as unexplained valuation (or *UV*) henceforth. To capture conditions in the financial market, we include two macro variables—the credit spread for C&I loans and the return on the S&P industrial index.

Inspection of Tables II and III shows that public firms participate more in acquisitions, in terms of both purchases and sales. On average, 7.36% (7.91%) of all public firms buy (sell) assets every year, compared to 1.75% (4.08%) of all private firms. For both groups, size is positively related with participation—larger firms are more likely to buy and sell assets. Productivity has a positive effect on purchases, but a negative effect on sales, as more productive firms tend to buy assets and less productive firms choose to sell assets. The sensitivity of purchase or sales to productivity is much higher for public firms. The estimated marginal effect of *TFP* is 10 times larger in purchase decisions, and five times larger in sales decisions for public firms than for private firms.

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

**Table III**

## Decision to Buy or Sell Assets (OLS)

This table reports the estimated coefficients from OLS (multiplied by 100). Variables are as defined in Table II. Columns 1 and 4 are estimated using public firms and columns 2 and 5 are estimated using private firms. Columns 3 and 6 report 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. We control for firm random effects. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent the significance at 10%, 5%, and 1% level, respectively.

| | Public (1) | Private (2) | *p*-value for Difference (3) | Public (4) | Private (5) | *p*-value for Difference (6) |
|---|---|---|---|---|---|---|
| Panel A: Decision to Buy Assets (Dependent Variable = *D_Buy*) | | | | | | |
| *Size* | 0.050 | 1.080*** | <0.001 | 0.070 | 1.090*** | <0.001 |
| | (0.100) | (0.000) | | (0.100) | (0.000) | |
| *TFP* | 0.420*** | –0.010 | <0.001 | 0.430*** | –0.010 | <0.001 |
| | (0.100) | (0.000) | | (0.100) | (0.000) | |
| *I_Tobinq* | –0.790*** | –0.310*** | 0.163 | –0.470** | –0.250*** | 0.985 |
| | (0.200) | (0.000) | | (0.200) | (0.000) | |
| *Ind_UV* | 0.050 | 0.050 | 0.806 | –0.740*** | –0.070 | 0.017 |
| | (0.300) | (0.100) | | (0.300) | (0.100) | |
| *HERF* | 7.500** | 3.070*** | 0.891 | 9.570*** | 3.170*** | 0.669 |
| | (3.200) | (0.700) | | (3.200) | (0.700) | |
| *D_Wave* | 2.730*** | 0.390*** | <0.001 | | | |
| | (0.20) | (0.100) | | | | |
| Credit spread | | | | –1.520*** | 0.060 | <0.001 |
| | | | | (0.200) | (0.100) | |
| S&P | | | | 5.180*** | 1.120*** | <0.001 |
| | | | | (0.600) | (0.100) | |
| Pr(*D_Buy*) | 7.36% | 1.75% | | 7.36% | 1.75% | |
| *R*-Square | 0.3% | 2.9% | | 0.2% | 2.9% | |
| Number of obs. | 99,121 | 420,944 | 520,065 | 99,121 | 420,944 | 520,065 |
| Panel B: Decision to Sell Assets (Dependent Variable = *D_Sell*) | | | | | | |
| *Size* | 1.230*** | 2.440*** | <0.001 | 1.210*** | 2.440*** | <0.001 |
| | (0.100) | (0.000) | | (0.100) | (0.000) | |
| *TFP* | –0.900*** | –0.510*** | <0.001 | –0.890*** | –0.510*** | <0.001 |
| | (0.100) | (0.000) | | (0.100) | (0.000) | |
| *I_Tobinq* | 0.110 | 0.340*** | 0.441 | 0.400** | 0.450*** | 0.079 |
| | (0.200) | (0.100) | | (0.200) | (0.100) | |
| *Ind_UV* | 2.010*** | 0.980*** | 0.002 | 1.630*** | 0.890*** | 0.022 |
| | (0.300) | (0.100) | | (0.300) | (0.100) | |
| *HERF* | –2.520 | 6.630*** | 0.327 | –1.550 | 6.720*** | 0.466 |
| | (2.700) | (1.200) | | (2.700) | (1.200) | |
| *D_Wave* | 4.280*** | 1.230*** | <0.001 | | | |
| | (0.20) | (0.100) | | | | |
| Credit spread | | | | –4.750*** | –1.130*** | <0.001 |
| | | | | (0.200) | (0.100) | |

(*Continued*)

**Table III**—*Continued*

| | Public (1) | Private (2) | $p$-value for Difference (3) | Public (4) | Private (5) | $p$-value for Difference (6) |
|---|---|---|---|---|---|---|
| Panel B: Decision to Sell Assets (Dependent Variable = *D_Sell*) | | | | | | |
| S&P | | | | –1.560*** | –0.620*** | 0.003 |
| | | | | (0.600) | (0.200) | |
| Pr(*D_Sell*) | 7.91% | 4.08% | | 7.91% | 4.08% | |
| $R$-Square | 0.8% | 1.3% | | 0.6% | 1.3% | |
| Number of obs. | 107,645 | 557,470 | 665,115 | 107,645 | 557,470 | 665,115 |

Public firms are also much more sensitive to credit spreads and to the aggregate wave indicator. In both panels, the difference between the two groups is significant at the 1% level and economically significant. For both groups, higher levels of the S&P index are associated with a higher transaction rate (for both purchases and sales). Private firms are slightly more likely to sell assets when aggregate stock prices are high, while the difference is not statistically significant for purchase decisions. We also see that higher industry *UV* increases the probability of asset sales for both public and private firms although the marginal effect is much stronger for public firms. On the purchase side, when we include the S&P index the findings show that public firms are less likely to purchase assets when industry *UV* is high, as the S&P index and the credit spread are picking up the general procyclical stock market and business cycle effects.

To better understand factors that are driving the observed differences between public and private firms in their acquisition decisions, in Table IV we calculate the economic effects based on the estimated model in Table II. We predict rates of purchases and sales by varying the credit spread variable from the 10th to the 90th percentile and also our wave indicator variable from zero to one while holding all other variables at their sample median. The results for public and private firms are presented in rows 1 and 2, respectively, of Table IV. In row 3 of Table IV, we also use the estimated coefficients from the private firm regressions and apply them on the median data of public firms and compute the predicted rates of purchases of public firms using the estimated sensitivities of private firms. This way, we can decompose the differences in the outcome variable (in this case, the rate of purchases or sales) between the two groups into the part that is due to differences in the explanatory variables and the 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 larger firms are better equipped to absorb the fixed transaction costs.

**Table IV**

**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 (1) the 10th, 25th, 50th, 75th, and 90th percentiles of the credit spread and (2) on and off the wave. We compute the estimated probabilities using coefficients from the logit regression reported in Table II. Throughout, all other variables are held at the sample median for the respective sample (public and private firms).

| | Credit Spread | | | | | *D_Wave* | |
|---|---|---|---|---|---|---|---|
| | p10 | p25 | p50 | p75 | p90 | 0 | 1 |
| Panel A: Probability of Purchases | | | | | | | |
| (1) Public firms | 6.23% | 5.80% | 5.42% | 5.22% | 4.84% | 4.81% | 7.29% |
| (2) Private firms | 0.50% | 0.49% | 0.49% | 0.49% | 0.48% | 0.45% | 0.59% |
| (3) Private firms using medians of data from public firms | 4.05% | 4.02% | 4.00% | 3.99% | 3.96% | 3.68% | 4.74% |
| Ratio (unadjusted): (2)/(1) | 0.08 | 0.08 | 0.09 | 0.09 | 0.10 | 0.09 | 0.08 |
| Ratio (adjusted for size): (3)/(1) | 0.65 | 0.69 | 0.74 | 0.76 | 0.82 | 0.77 | 0.65 |
| Panel B: Probability of Sales | | | | | | | |
| (1) Public firms | 8.34% | 7.40% | 6.62% | 6.23% | 5.49% | 5.80% | 9.48% |
| (2) Private firms | 2.34% | 2.27% | 2.20% | 2.17% | 2.10% | 2.04% | 2.45% |
| (3) Private firms using medians of data from public firms | 5.26% | 5.11% | 4.97% | 4.90% | 4.75% | 4.63% | 5.52% |
| Ratio (unadjusted): (2)/(1) | 0.28 | 0.31 | 0.33 | 0.35 | 0.38 | 0.35 | 0.26 |
| Ratio (adjusted for size): (3)/(1) | 0.63 | 0.69 | 0.75 | 0.79 | 0.87 | 0.80 | 0.58 |

Table IV shows that the purchase decision is vastly different between public and private firms at every percentile of the credit spread data. For example, when the credit spread is at its median, the rate of purchases is 5.42% for public firms, but only 0.49% for private firms. Public firms are also more sensitive to credit spreads. For public firms, the purchase rate increases from 4.84% to 6.23% when the credit spread moves from its 90th to 10th percentile. In comparison, for private firms, the change is much flatter, from 0.48% to 0.50%.[10]

[10] For this exercise, we estimate the predicted probability using the sample median for the respective sample (public and private firms). Since large firms are far more likely to participate in purchases and sales in both samples, the resulting predicted probability is lower than the reported sample mean.

The difference in the transaction rate between public and private firms shrinks significantly when we apply the estimated coefficients from the private firm regressions to public firm data. For the median credit spread, the predicted rate of purchases by private firms is 9% of the rate for public firms (0.49% vs. 5.42%). However, when we apply the estimated coefficients from the private regression (column 2) using the medians of the data from the public firms, we find that differences in firm characteristics explain about 74% of the observed difference between public and private firms (4% vs. 5.42%). Thus, differences between public firms and private firms in their acquisition behavior are due in part to differences in their fundamentals. Public firms are larger and more productive, and large and more productive firms are more likely to buy assets. Nevertheless, a sizable gap (26%) still remains even after we control for firm characteristics. This gap is attributable to the differences in sensitivities to firm characteristics between these two groups. More interestingly, the gap is bigger when credit spreads are low and during wave years, suggesting that public and private firms also have a different sensitivity to macro conditions.

We find similar patterns in decisions to sell assets. When the credit spread moves from the 90th to the 10th percentile, the sales rate increases from 2.10% to 2.34% for private firms, compared to 5.49% to 8.34% for public firms. When we apply the estimated coefficients from the private firm regression (column 2) to public firm data, we find that differences in firm characteristics explain about 75% of the observed differences between public and private firms. Controlling for firm characteristics, the differences between public and private firms becomes bigger when credit spreads are low and 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 using only firms 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 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 the capital market and aggregate merger activity than private firms in their decisions to buy and sell assets. Thus, a substantial portion of the differences in the level of transactions between public and private firms is driven by differences in fundamentals, while the responsiveness to credit market conditions is affected by public status.

### *B. The Effect of Market Valuation and Liquidity*

We have shown so far that public firms are more sensitive than private firms to financial market conditions such as industry valuation, stock market return, and credit spreads. In this section, we extend our analysis to include firm-level valuation (in addition to the industry-level measures) and stock market liquidity. Our goal is to understand how differences in relative valuation within an industry affect merger and acquisition activities. Since market valuations for private firms are not observable, we use the subsample of public firms in our sample for this analysis.

For public firms, the valuation and liquidity of their own equity play important roles in acquisition decisions because equity can be used as a medium of exchange to finance acquisitions. Rhodes-Kropf, Robinson, and Viswanathan (2005) point out that, while economic shocks might be fundamental determinants of merger activity, misvaluation in the stock market may determine who buys whom and explain why mergers cluster over time. They also emphasize that managers of public firms themselves may suffer from asymmetric information about potential synergies and thus will be more likely to buy with positive signals from the stock market. In our context, overvaluation in the stock market may be associated with more transactions but does not necessarily lead to productivity decreases as firms may use their highly valued equity to facilitate productivity-increasing transactions.

In order to test these ideas, in Table V we add to our earlier specifications from Table II variables that capture firm-level valuation and liquidity such as unexplained valuation (*UV*), annualized stock return (*Ret*), and the Amihud illiquidity index (*Illiq*).[11] For all three variables (*UV*, *Ret,* and *Illiq*), we also include industry averages based on all public firms within the industry. [12,13] Panels A and B present our results for decisions to buy and sell assets, respectively. In each panel, columns 1 and 3 contain the baseline results—one with the wave indicator and the other with the macro variables. Columns 2 and 4 further control for stock market return and stock illiquidity.

Panel A reveals that our baseline results for the decision to buy in Table II are largely unaffected by adding the valuation, return, and liquidity measures. However, the firm-level stock-related variables are significant in explaining decisions to buy for public firms. In all the specifications, firm *UV* is significant and positive, while industry *UV* is only significant for the specification with the global wave dummy variable, and becomes insignificant when illiquidity is added. Stock illiquidity is significant and negative for all specifications, at both the firm level and the industry level. Stock return is positively related to purchase decisions at the firm level, although it is only significant without the wave indicator.

These results indicate that stock market valuation and liquidity have significant independent effects on the decision to buy assets for public firms. Firms that are valued beyond the predicted level based on their fundamental variables are more likely to engage in acquisitions. Stock liquidity also has an important role in facilitating acquisitions for public firms. Firms that have less

[11] We download the Amihud illiquidity measure directly from Joel Hasbrouk's website at NYU. All firm-level measures have been de-meaned by industry.

[12] To calculate industry-level measures, we aggregate firms based on their main industry reported in Compustat.

[13] We also adjust the industry return by the S&P return to filter out the aggregate effect. In the regression, the industry return is the industry raw return adjusted for the S&P return, and the firm return is the firm raw return adjusted for the industry return.

**Table V**

## Public Firms' Decisions to Buy or Sell Assets

This table reports the estimated marginal effects (in %) from logit models using public firms only. *Ret* measures the annualized equity return and *Illiq* measures the Amihud liquidity. For all three variables (*UV*, *Ret*, and *Illiq*), we compute the industry average (based on three-digit SIC codes) and the firm-level de-meaned variable. We control for firm random effects. All other variables are defined as in Table II. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | Panel A: *D_Buy* | | | | Panel B: *D_Sell* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| *Size* | 0.422*** | 0.131** | 0.435*** | 0.128** | 0.872*** | 0.703*** | 0.867*** | 0.690*** |
| | (0.050) | (0.060) | (0.050) | (0.060) | (0.060) | (0.070) | (0.060) | (0.070) |
| *TFP* | 0.255** | 0.208** | 0.275*** | 0.220** | −0.844*** | −0.854*** | −0.829*** | −0.842*** |
| | (0.100) | (0.100) | (0.100) | (0.100) | (0.110) | (0.110) | (0.110) | (0.110) |
| *I_Tobinq* | −0.276* | −0.346** | −0.091 | −0.197 | −0.592*** | −0.619*** | −0.492*** | −0.548*** |
| | (0.160) | (0.160) | (0.160) | (0.160) | (0.160) | (0.160) | (0.160) | (0.160) |
| *HERF* | 3.668 | 3.243 | 4.350* | 3.599 | −6.926*** | −6.273** | −6.485** | −6.195** |
| | (2.300) | (2.290) | (2.300) | (2.290) | (2.570) | (2.550) | (2.570) | (2.560) |
| *D_Wave* | 2.316*** | 2.107*** | | | 3.060*** | 2.787*** | | |
| | (0.220) | (0.230) | | | (0.240) | (0.250) | | |
| Credit spread | | | −1.619*** | −1.580*** | | | −3.575*** | −3.251*** |
| | | | (0.280) | (0.290) | | | (0.310) | (0.330) |
| S&P | | | 2.805*** | 3.335*** | | | 1.431** | 1.337* |
| | | | (0.630) | (0.650) | | | (0.690) | (0.750) |
| Firm *UV* | 1.251*** | 0.659*** | 1.091*** | 2.699*** | 0.481*** | 0.276 | 0.264 | 0.150 |
| | (0.170) | (0.210) | (0.170) | (0.970) | (0.160) | (0.200) | (0.160) | (1.000) |
| *Ind_UV* | 0.602** | 0.315 | −0.009 | −0.336 | 1.528*** | 1.540*** | 0.997*** | 1.067*** |
| | (0.280) | (0.280) | (0.290) | (0.300) | (0.290) | (0.290) | (0.300) | (0.300) |
| Firm *Ret* | | 0.212 | | 0.459** | | −0.988*** | | −0.804*** |
| | | (0.210) | | (0.210) | | (0.240) | | (0.240) |
| Ind. *Ret* | | 0.195 | | 0.191 | | −1.282*** | | −1.223*** |
| | | (0.370) | | (0.370) | | (0.400) | | (0.420) |
| Firm *Illiq* | | −2.133*** | | −2.201*** | | −2.300*** | | −2.320*** |
| | | (0.280) | | (0.280) | | (0.240) | | (0.240) |
| Ind *Illiq* | | −2.615*** | | −2.867*** | | −2.358*** | | −2.556*** |
| | | (0.340) | | (0.340) | | (0.320) | | (0.320) |
| Chi Square | 291 | 333 | 220 | 295 | 425 | 515 | 373 | 470 |
| Number of obs. | 61,252 | 61,252 | 61,252 | 61,252 | 66,501 | 66,501 | 66,501 | 66,501 |

liquid stock (or a high Amihud illiquidity index) are less likely to be acquirers, perhaps reflecting their target's hesitation to hold illiquid stock.

Examining the results for the decision to sell in Panel B of Table V, we notice one important difference relative to the decision to buy. Firms are more likely to sell assets when industry *UV* is high (significant at the 1% level in all specifications) while firm-level *UV* is mostly insignificant. This suggests that, when industries become highly valued, less productive firms are more likely to sell to their highly valued counterparts (as evident from Panel A). Sellers, on the other hand, do not seem to be over- or undervalued. The coefficient on the Amihud illiquidity index is negative, as in Panel A.

It is worth noting that the unexplained valuation measures used here can capture either deviations from the true value (or misvaluation) or market expectations of unmeasured future productivity. One way to shed light on this question is to examine whether and how stock valuation affects firms' decisions to engage in different types of transactions. We perform two additional tests. First, since most of the partial-firm acquisitions are financed with cash, if acquisitions are driven by overvalued equity, we should observe lower valuation–acquisition sensitivity in partial-firm acquisitions, as compared to whole-firm mergers that are more often paid by stock. Second, because diversifying mergers are often viewed as signs of agency problems or a waste of resources (e.g., Morck, Shleifer, and Vishny (1990), Servaes (1997)), if acquisitions on the wave are pursued to use overvalued equity rather than to improve efficiency, then we would expect to see higher valuation–acquisition sensitivity in diversifying acquisitions as compared to horizontal acquisitions.

We present these results in our Internet Appendix.[14] We show that the estimated odds ratio (from a multinomial logit model) for *UV* is greater than one for all types of transactions. More interestingly, *UV* has almost the same effect on partial-firm acquisitions as it has on mergers, and the same effect on horizontal acquisitions as on diversifying acquisitions. These results, while consistent with a model of efficient mergers, are at odds with models that attribute overvaluation as the main driver for merger waves.

To the extent that partial-firm purchases are easier to finance than whole-firm purchases, and financing constraints are more likely to be binding for private firms, we expect that private firms make relatively more partial-firm purchases than whole-firm acquisitions.[15] We do not find that to be the case. The incidence of public purchases is higher (3.53% for partial-firm and 3.83% for whole-firm purchases) than the incidence of private purchases (0.84% for partial-firm and 0.92% for whole-firm purchases). However, the ratios of whole and partial purchases for the two types of sales are very close. The coefficients in the regressions predicting partial- and whole-firm purchase are qualitatively similar. These findings suggest that the lower overall rate of private transactions is determined in part by differences in skill and the ability to exploit investment opportunities as well differences in financing constraints.

### *C. Credit Ratings and Stock Liquidity*

In this section, we examine how public firms with different levels of financial constraints respond differently in terms of their acquisition decisions to changes in economic fundamentals and financial conditions. If the difference

[14] The Internet Appendix may be found in the online version of this article.

[15] Whole and partial purchases by private firms are normally cash transactions, so there is little countervailing tendency for private firms to make whole-firm purchases using stock to avoid using cash in partial sales.

in acquisition activities between public and private firms is partly attributable to differences in access to the financial market, then we would expect public firms with the least access to financial markets to behave similarly to private firms.

We consider both bond market and stock market liquidity. Faulkender and Petersen (2006) show that firms with higher bond ratings have better access to public bond markets. Finding that unrated or low-rated firms' merger activity is the most sensitive to credit spreads and the overall economy would be consistent with the notion that increased liquidity in the market has a bigger impact on firms that are more financially constrained. In contrast, a lower sensitivity of unrated or low-rated firms would indicate that financial constraints are binding for those firms and cannot be relaxed even at times of high liquidity. Stock market liquidity is relevant because firms with low stock liquidity may find it harder to issue equity or use existing equity as a means for payment in acquisitions. These firms are also likely to be financially constrained.

First, we split our sample of public firms into three groups based on S&P long-term debt ratings (Compustat data item 280): firms with an investment grade credit rating (above BBB), firms with a below investment grade rating (BBB and below), and unrated firms. Within our sample, 28% of public firms have an investment grade rating (HR), 14% have a below investment grade rating (LR), and the rest are unrated (NR). We then run regressions to predict decisions to buy and sell assets for each rating group.

Next, we separate public firms into three equal-sized groups based on their stock liquidity using the Amihud illiquidity measure. We then apply a similar specification as used in Table V, column 1, to each group. Table VI reports our results.

For all credit rating groups, credit spreads have a significant negative effect on acquisition decisions, and they affect LR firms the most. The estimated marginal effect of credit spread on acquisitions for LR firms 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. Therefore, credit spreads appear to have a double effect on LR firms: on the one hand, more liquidity in the market helps relax the constraints faced by LR firms and enables them to borrow more or at a lower rate to finance acquisitions; on the other hand, liquidity may also affect LR firms by lifting covenants on previous bank loans that prevent them from selling assets. We find that the effect of credit spreads is the smallest for unrated firms. We also find that acquisition activity by nonrated firms and firms with low stock market liquidity are more sensitive to size. These results parallel the results in Hovakimian, Kayhan, and Titman (2009), who show that, controlling for whether firms have debt ratings, size can have a differential effect on firm decisions, with larger effects for size among smaller nonrated firms.

Our results also show that the effect of productivity (*TFP*) on acquisition decisions is strongest for the high credit rating group. Together with our earlier

**Table VI**

## Decisions by Credit Rating and Liquidity Groups

This table reports the estimated marginal effects (in %) from logit models on the decision to buy (Panel A) or sell (Panel B) assets by credit rating status and liquidity groups. "No Rating" refers to public firms that are not rated, "Low Rating" refers to public firms rated BBB or below, and "High Rating" refers to public firms rated above BBB. For illiquidity, we separate firms into three equal-sized groups based on the Amihud illiquidity measure. All other variables are defined as in Table II. All explanatory variables are lagged. We control for firm random effects. Robust standard errors are computed allowing for clustering at the industry-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. a, b, and c represent significance at the 1%, 5%, and 10% level, respectively, for testing the difference between the Low or High Rating group and the No Rating group or between the Medium or High Liquidity group and Low Liquidity group.

| | Credit Rating Groups | | | Liquidity Groups | | |
|---|---|---|---|---|---|---|
| | No Rating | Low Rating | High Rating | Low Liquidity | Medium Liquidity | High Liquidity |
| | Panel A: Decisions to Buy Assets (*D_Buy*) | | | | | |
| *Size* | 0.460*** | –0.538***,a | –0.405**,a | 0.558*** | –0.374***,a | –0.310**,a |
| | (0.06) | (0.16) | (0.16) | (0.09) | (0.12) | (0.15) |
| *TFP* | 0.072 | 0.251 | 0.482** | 0.069 | –0.035 | 0.352* |
| | (0.11) | (0.27) | (0.21) | (0.13) | (0.18) | (0.20) |
| Firm *UV* | 0.843*** | 1.259*** | 0.115b | 0.898*** | 0.040a | 0.365b |
| | (0.16) | (0.38) | (0.42) | (0.20) | (0.30) | (0.37) |
| *I_Tobinq* | –0.692*** | –0.121b | 0.545*,a | –0.702*** | –0.901*** | 0.132b |
| | (0.17) | (0.37) | (0.29) | (0.23) | (0.28) | (0.25) |
| *HERF* | –2.982 | 17.264***,a | 8.229*,b | –1.583 | –0.950 | 12.978***,b |
| | (2.36) | (5.36) | (4.91) | (2.79) | (3.78) | (4.55) |
| Credit spread | –1.218*** | –4.213***,a | –1.742*** | –0.847** | –2.619***,c | –1.063** |
| | (0.28) | (0.76) | (0.52) | (0.35) | (0.48) | (0.57) |
| S&P | 2.499*** | 1.962 | 1.990* | 1.483 | 2.039* | 4.655*** |
| | (0.75) | (1.49) | (1.19) | (0.95) | (1.11) | (1.12) |
| Pr (*D_Buy*) | 6.10% | 8.89% | 9.37% | 5.07% | 7.75% | 9.30% |
| Chi Square | 152 | 79 | 40 | 82 | 55 | 46 |
| Number of obs. | 43,230 | 12,240 | 22,424 | 19,796 | 21,220 | 22,257 |
| | Panel B: Decisions to Sell Assets (*D_Sell*) | | | | | |
| *Size* | 0.936*** | 0.723***,b | 0.686***,a | 0.443*** | 0.453*** | 0.722*** |
| | (0.07) | (0.14) | (0.12) | (0.09) | (0.10) | (0.12) |
| *TFP* | –0.638*** | –0.899*** | –1.160***,b | –0.381*** | –1.046*** | –1.199*** |
| | (0.11) | (0.25) | (0.21) | (0.13) | (0.17) | (0.22) |
| Firm *UV* | 0.647*** | 0.948*** | 0.383 | –0.142 | –0.444 | 0.510 |
| | (0.16) | (0.36) | (0.42) | (0.18) | (0.29) | (0.43) |
| *I_Tobinq* | –0.139 | –0.082 | 0.194 | –0.001 | –0.307 | –0.791*** |
| | (0.16) | (0.35) | (0.28) | (0.18) | (0.25) | (0.30) |
| *HERF* | –5.989** | –4.197 | –2.174 | –1.480 | –5.554 | –8.307 |
| | (2.59) | (5.45) | (5.06) | (2.67) | (3.73) | (5.73) |
| Credit spread | –2.837*** | –5.016***,b | –4.021*** | –1.426*** | –2.607*** | –4.865*** |
| | (0.30) | (0.72) | (0.58) | (0.35) | (0.46) | (0.72) |
| S&P | 0.463 | –0.393 | 2.899** | 0.401 | 1.308 | 6.050***,b |
| | (0.77) | (1.44) | (1.25) | (0.85) | (1.11) | (1.34) |

(*Continued*)

**Table VI**—*Continued*

| | Credit Rating Groups | | | Liquidity Groups | | |
|---|---|---|---|---|---|---|
| | No Rating | Low Rating | High Rating | Low Liquidity | Medium Liquidity | High Liquidity |
| Panel B: Decisions to Sell Assets (*D_Sell*) | | | | | | |
| Pr (*D_Sell*) | 7.47% | 8.05% | 8.87% | 4.63% | 7.08% | 10.35% |
| Chi Square | 284 | 92 | 128 | 49 | 84 | 133 |
| Number of obs. | 50,337 | 13,606 | 24,139 | 23,058 | 23,552 | 23,375 |

findings, this finding indicates that the constrained low-rated firms are more affected by market liquidity, while the less constrained high-rated firms are more affected by productivity. Public firms with no rating are most similar to private firms with low sensitivity to productivity and credit spreads.

Examining the results for stock liquidity groups, we observe similar patterns as those described for the credit rating groups. Although credit spreads have a negative effect for all liquidity groups, the effect on acquisitions is largest for the midlevel liquidity group. Productivity (*TFP*) has the largest effect for the high-liquidity group. In addition, size has the largest effect in the low-liquidity group, suggesting that size can compensate for the lack of liquidity. On the sales side, credit spreads affect the high-liquidity group the most.

We also compute the economic significance of these results. For low-rated firms, the probability of buying and selling assets increases 62% when the credit spread moves from the 90th to the 10th percentile. In comparison, the increases are 19% and 23%, respectively, for highly rated firms and for nonrated firms, respectively. Similarly, for firms with medium stock liquidity, the rate of asset purchases increases 42% when the credit spread moves from the 90th to the 10th percentile. In comparison, the increases are 18% and 12% for firms in the low- and high-liquidity groups, respectively.

In sum, although public firms with better access to credit or the equity market (the highly rated group and the high liquidity group) do more acquisitions in general, firms with intermediate access (the low-rated group and the medium liquidity group) have the highest sensitivity to changes in credit spreads and are most affected by changes in market liquidity in their acquisition decisions. Among all groups, the acquisitions and sales of public firms with no credit rating and low stock liquidity most resemble private firms. As such, our finding suggests that the observed difference between public and private firms is due in part to the differences in their access to financial markets.

## IV. Endogenizing Public Status

### A. *Predicting the Decision to Be Public*

The preceding sections establish that public firms participate more in acquisitions, especially during merger waves. But the decision to acquire public status is itself a choice variable. If public status confers advantages in financing acquisitions, then firms with superior growth opportunities can self-select into public status to take advantage of the easier financing. Thus, the greater merger activity of public firms could be primarily due to inherent characteristics, such as superior corporate culture or technology, rather than to the advantages of public status in acquisitions. To distinguish between these two effects, we next analyze the decision to be public, and compare the subsequent merger activity of public and private firms with the same productivity and size at birth. Our hypothesis is that the quality of a firm is evident very early in its life, and that firms with greater growth potential select to be public to better engage in mergers and acquisitions later. As such, the decision to be public can be predicted using the initial quality of the firm (model (2)).

We use the LBD from the Census Bureau to confirm the birth year for firms in our sample. LBD is a data set constructed using information from the Business Registry that covers firms with any paid employees in the United States (>10 million establishments per year).[16] The LBD starts in 1976, and thus, to correctly identify the birth year, we only include a subsample of firms that first appeared in the LBD after 1976. As in the overall sample, both public and private firms are included when their segment sales are one million dollars or larger in their initial year. Since we want to examine the decision to be public based on initial conditions, in these tests we also exclude firms that were already public the first time they appear in the database.

For the firms born after 1975 we create an exclusion window to remove the first 5 (or in some specifications 10) years after birth from our sample. We then run probit models to predict firms' public status after this exclusion window as a function of the firm's initial characteristics at birth and, in some specifications, industry conditions. The exclusion window mitigates concerns that contemporaneous shocks affect the incentives both to go public and to trade assets. Thus, 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.

We find that initial conditions are very persistent. For example, 10 years after birth, 44% of the firms that start in the smallest size quintile remain in the same quintile, and 90% of the firms that start in the largest size quintile remain in the same quintile. Similar patterns also exist for productivity, although they are not as strong. Ten years after the birth, 36% (40%) of firms that start in the least (most) productive quintile remain in the same productivity quintile.

Table VII presents our results for predicting public status—columns 1 to 3 use a 5-year window and columns 4 to 6 use a 10-year window.

In column 1, we include initial size and productivity ($Size_0$, $TFP_0$) and their square terms ($Size_0^2$, $TFP_0^2$) to measure the initial quality of a firm, and use the change in aggregate industry shipments in the next 25 years ($CDTVS_{25}$) to measure the long-term growth in industry demand. Both linear and square

[16] See Jarmin and Miranda (2002) for a detailed description of the LBD (http://ideas.repec.org/p/cen/wpaper/02-17.html).

**Table VII**

## Predicting Public Status

This table reports the estimated marginal effects (in %) of probit models predicting public status. The dependent variable, *D_Pub*, equals one for public firms and zero for private firms. $TFP_0$ and $TFP_0^2$ represent the linear and square terms of initial *TFP*, respectively, and $Size_0$ and $Size_0^2$ 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* represents the industry capital expenditures. *S50* measures the percentage of small firms (with less than 50 employees) in the industry. *Persistence* measures the persistence of *TFP* within the industry based on rank correlation. *Ln(N_IPO)* is the log number of annual IPOs. Q2($Size_0$) to Q5($Size_0$) are indicators for the second to fifth quintiles based on $Size_0$, respectively. For columns 1 to 3, we only include firms that are at least 5 years old, and for columns 4 to 6, we only include firms that are 10 years old. All other variables are as defined in Table II. All time-varying variables are lagged. Robust standard errors are computed allowing for clustering at the industry level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | 5 Years after Birth | | | 10 Years after Birth | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $TFP_0$ | 0.29 | 1.98*** | –0.89 | 0.52 | 2.90*** | 1.00 |
| | (0.20) | (0.30) | (0.90) | (0.40) | (0.50) | (1.50) |
| $TFP_0^2$ | 11.48*** | 10.04*** | | 17.16*** | 15.58*** | |
| | (0.60) | (0.60) | | (1.00) | (1.00) | |
| $Size_0$ | 1.80*** | 1.25*** | | 1.90** | 1.46* | |
| | (0.50) | (0.50) | | (0.80) | (0.80) | |
| $Size_0^2$ | 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) |
| *S50* | | –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($Size_0$) | | | 1.43*** | | | 1.42*** |
| | | | (0.30) | | | (0.50) |
| Q3($Size_0$) | | | 5.70*** | | | 6.72*** |
| | | | (0.40) | | | (0.60) |
| Q4($Size_0$) | | | 10.86*** | | | 11.95*** |
| | | | (0.40) | | | (0.60) |
| Q5($Size_0$) | | | 30.05*** | | | 30.51*** |
| | | | (0.60) | | | (0.80) |
| Q2($Size_0$) × *TFP* | | | –2.99** | | | –6.12*** |
| | | | (1.20) | | | (2.00) |
| Q3($Size_0$) × *TFP* | | | –0.75 | | | –3.24* |
| | | | (1.10) | | | (1.80) |

(*Continued*)

**Table VII**—*Continued*

| | 5 Years after Birth | | | 10 Years after Birth | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Q4($Size_0$) × *TFP* | | | 1.45 | | | 0.21 |
| | | | (1.00) | | | (1.70) |
| Q5($Size_0$) × *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 |

terms of productivity and size are positive, suggesting that firms that were larger and more productive at birth are more likely to be public later in their life cycles. In our sample, 5 years after birth, firms that begin in the highest quintile in both size and productivity have a 27% probability of being public, while less than 1% of the firms that begin in the lowest quintile in both size and productivity become public. Industry long-term demand also plays an important role. Firms in industries with increasing long-term demand are more likely to be public. The initial conditions, together with the industry long-term demand, explain about 18% of the total variation in firms' public status 5 years after birth.

In column 2, we add lagged industry and macro variables to account for cases in which firms change their public status over time. Firms in industries with high capital expenditures and more growth opportunities may have higher demand for capital. We capture these effects by including the industry capital expenditure rate (*I_CapEx*) and the industry Tobin's *Q* (*I_Tobinq*). We include the Herfindahl index (*HERF*) to capture the industry concentration ratio. This measure is calculated based on sales from both public and private firms.

Some industries may be more suitable for small private firms than others due to the characteristics of the industry. We use the percentage of firms with less than 50 employees (*S50)* as a proxy for industry business conditions.[17] Initially productive firms might be more likely to go public if productivity is persistent over time. We therefore include a measure for productivity persistence (*Persistence*) calculated as the mean rank correlation between the lagged and current *TFP* for all firms in the industry-year. Lastly, we include the log of the number of IPOs in a year to control for economic conditions for IPOs.[18] All variables have the predicted signs. Firms in industries with higher capital expenditures, better growth prospects, a higher concentration ratio, a lower proportion of small firms, and higher persistence in *TFP* are more likely to go public. Firms are also more likely to go public during an IPO wave. In this expanded specification the initial firm conditions (size, productivity, and their squared terms) remain positive and significant at the 1% level.

[17] We use the employment numbers provided in LBD to compute this percentage.

[18] The series is calculated based on data provided on Jay Ritter's website: http://bear.cba.ufl.edu/ritter/ipoisr.htm.

In column 3, we use initial size quintiles and interact them with initial productivity. The marginal effect on public status is monotonically increasing in size quintiles. Moreover, *TFP* matters for large size quintiles. 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 those for the specification with initial quality and size from 5 years prior.

### *B. Endogenous Selection: Reexamining the Decisions to Buy and Sell Assets*

Firms with higher productivity and greater anticipation of future growth may choose to become public to participate more in acquisitions when opportunities emerge. We show above that initial conditions at birth are good signals for firm quality—firms that are larger and more productive at birth are more likely to be public later in their lives. If the same quality also affects later decisions in participating acquisitions, then we should observe a positive relationship between initial conditions (or the probability of being public) and the probability of engaging in acquisitions. In this section, we control for the endogeneity of public status using first a selection model and then a matching model to reexamine the decision to buy and sell assets.

First, we examine how the selection into public status affects purchase and sale decisions. We estimate the probability of being public using the specification in Table VII, column 1. In predicting the probability of being public we use as independent variables firm characteristics at birth and remove observations in a 5-year exclusion window following the firm's birth. Since all the explanatory variables are time-invariant, the predicted probability captures the firm's initial condition. Because the predicted probability of being public is only available for firms born after 1976, the first year that the LBD is available, our sample of firms with predicted public status is more representative of younger firms.[19]

In Table VIII, we perform a matching exercise based on the predicted probability of being public as a propensity score. We then compare decisions to buy and sell assets between the treated group (public firms) and the control group (private firms) using stratification matching. The estimated average treatment effect on the treated group (ATT) then captures the effect that public status has on acquisition decisions controlling for initial public quality. We also enforce the computation of the ATT only in the region of common support. We report the estimated ATT over the whole sample period and also on and off the wave.

On the purchase side, matching based on the probability of being public predicted by initial conditions explains about 27% of the difference between public and private firms. When we separate our sample period into wave and nonwave years, we find that predicted public status matters more during merger

[19] The predicted probability is available for 15% of public firms and 29% of private firms in our data set.

**Table VIII**

**Decision to Buy or Sell Assets: Propensity Score Matching**

This table shows the difference in estimated probabilities in purchases (Panel 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 VII, column 1. The treatment group includes all firm-year observations for public firms and the control group includes all firm-year observations for private firms.

Panel A: Probability of Purchases

| | All | Off-the-Wave ($D\_Wave = 0$) | On-the-Wave ($D\_Wave = 1$) |
|---|---|---|---|
| Public firms | 5.37% | 4.83% | 6.47% |
| Private firms | 1.11% | 1.03% | 1.28% |
| Difference (w/o matching) | 4.27% | 3.80% | 5.19% |
| Difference (w/ 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% |
| Difference (w/o matching) | 3.22% | 2.68% | 4.26% |
| Difference (w/ 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) |

waves—initial conditions explain 23% of the difference on the wave while 33% of the difference off the wave. On the sales side, most of the differences between public and private firms can be explained by initial selection. Controlling for initial public quality, public firms are no longer more likely to sell assets than private firms. Initial quality selection explains almost all of the difference for off-the-wave sales and 80% of the difference for on-the-wave sales.

Two factors may explain our findings. First, through initial quality (such as size and productivity), we are able to capture the capacity to be public, but not the willingness. Some entrepreneurial firms may have the same initial quality to become public but choose to stay private to maintain a quiet life (Bertrand and Mullainathan (2003)) or to maintain control by insiders for other reasons. In that case, public status is a signal of both quality and preference.

Alternatively, our results can suggest that being public does make a difference when it comes to access to financing. Public firms have better access to capital markets in general, and benefit even more when credit becomes more readily available. Therefore, they are more likely to engage in acquisitions in the presence of good opportunities. The asymmetry in our findings between sales and purchases suggests that, as expected, the advantage of being public through better access to capital is more prominent for acquisitions, while asset sales are driven more by firm fundamentals and initial conditions.

In addition to this matching exercise, we further examine endogenous selection into public status, by running the regression model of Table II by quartiles of firms based on their predicted probability of being public. We first separate firms in quartiles (Q1 to Q4) based on the predicted probability of being public, with Q1 firms having the lowest probability and Q4 having the highest probability. Not surprisingly, the percentage of public firms increases over the quartiles. For example, less than 2% of the firms in Q1 are public, compared to 27% of the firms in Q4. The transaction rate (both purchases and sales) is monotonically increasing from Q1 to Q4.

We use these quartiles of predicted public status to reestimate the decision to buy and sell assets based on firm, industry, and macro factors for each group separately using the same specification as in Table II. These results allow us to assess whether firms based on their predicted probability of being public (and not actual public status) have differential sensitivity to credit spreads and the S&P stock market index. These results, presented in the Internet Appendix, show that the Q4 group has a much higher sensitivity to credit spreads as compared to the Q1 group in terms of both the purchase and the sale of assets. These results parallel our earlier findings using samples of firms that are actually public and private, suggesting that a large portion of the difference in observed acquisition behavior between public and private firms is indeed driven by differences in fundamentals early in a firm's life. Larger and more productive firms self-select to become public, and later these firms participate more in asset purchases and sales when opportunities arise.

We further control for selection effects when we focus on the subsample of Q4 firms with a high probability of being public and divide them based on their actual public status. Private Q4 firms are those firms that we predict, based on initial fundamentals, to be public in future years but are in fact private when observed 5 or more years later. For acquisition decisions, they have a higher sensitivity to macro conditions, such as credit spreads or the aggregate wave indicator, than private firms, but a lower sensitivity than public Q4 firms that are in fact public. However, this difference between public and private firms in the Q4 subsample is smaller than the difference between public and private firms overall. These results thus show that actual public status affects acquisition decisions but to a smaller degree after accounting for selection.

We find even smaller differences between public and private Q4 firms for decisions to sell assets. Private Q4 firms have a much higher sensitivity to credit spreads and to the aggregate wave indicator than do the full sample of private firms. The marginal effect of credit spreads on sales decisions for private Q4 firms is much closer to that of public firms. Our results remain qualitatively the same when we use an exclusion window of 10 years.

## V. Postsale Performance on Merger Waves: Private and Public Firms

### *A. Public Status and Changes in Productivity*

To further pinpoint the effect of fundamentals and financial markets in driving merger waves, we now examine changes in productivity for the transacted plants on and off the wave. If the higher participation of public firms on the wave is driven by differences in their productivity and growth opportunities, then acquisitions of public firms should perform at least as well as or better than acquisitions by private firms. Alternatively, if public firms acquire more on the wave to take advantage of their more favorable access to financial markets rather than to realize synergies, then we should observe worse performance from public acquirers than private acquirers on the wave.

Table IX examines changes in productivity for transacted plants around acquisitions for both off- and on-the-wave mergers. We measure changes in productivity at the plant level using three windows, (−1, 1), (−1, 2), and (−1, 3), with year 0 being the transaction year. Since firms may choose to sell a certain type of plant, we correct for selection bias following Heckman (1979) in all of our regressions. We first use a similar specification as in Table III, columns 1 and 2, to predict the outcome of being sold at the plant level. As in Table III, we also estimate the model separately for public and private firms to allow for differences in sensitivity to firm, industry, and macro factors between the two groups. We then include the inverse Mills ratio or Heckman's lambda in our second-stage regressions when we examine changes in productivity for transacted plants. In all of our specifications, Heckman's lambda is negative and significant, suggesting that it is necessary to correct for selection bias.

Panel A shows that on average transacted plants have bigger improvements in productivity than nontransacted plants. The coefficient on *D_Sale* , the indicator for whether the plant is sold, is significantly positive at the 1% level in all of our specifications, consistent with acquisitions being on average value enhancing. Moreover, the interaction between *D_Sale* and *D_Wave*, the indicator for aggregate wave years, is positive and significant, suggesting that on-the-wave acquisitions experience even greater improvements in productivity. For example, 2 years after acquisition, plants that are sold have a 3.4% increase in productivity compared to nontransacted plants, and on-the-wave transactions realize a 2% additional productivity increase compared to off-the-wave transactions.

Rhodes-Kropf and Robinson (2008) provide evidence that synergies from mergers are greatest when high productivity firms take over other high productivity firms. We find that public firms are more productive than private firms in general and their sensitivity to productivity is higher. Yan (2006) and Duchin and Schmidt (2008) find that on-the-wave horizontal mergers are followed by poor stock and operating performance. By contrast, we find that on-the-wave transactions create bigger efficiency gains. There are several notable differences between our study and theirs. First, we examine efficiency gains rather than stock returns. The two findings are not necessarily inconsistent, in that acquiring firms may overpay for real synergies. Second, due to the unique

**Table IX**

## Changes in Productivity

This table reports regression estimates on changes in *TFP* on the plant level. *D_Sale* is an indicator variable that equals one if the plant is sold and zero otherwise. *D_Wave* is an indicator variable that equals one for aggregate merger wave years and zero 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. *Lambda* is estimated as the inverse Mills ratio based on a first-stage selection model in which we predict the probability of being sold (based on Table II, Panel B). *TFP* and *Ln(output)* measure total factor productivity and the log of output level for the plant, respectively. *TFP*(–1, 1) is the change in *TFP* from $t-1$ to $t+1$ with $t$ being the current year. Similarly, *TFP*(–1, 2) and *TFP*(–1, 3) measure the change in *TFP* from $t-1$ to $t+2$ and $t+3$, respectively. Industry (based on three-digit SIC) fixed effects are included. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively

| | *TFP* (–1, 1) | | *TFP* (–1, 2) | | *TFP* (–1, 3) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Regression 1 | | | | | | |
| *D_Sale* | 0.020*** | 0.014*** | 0.034*** | 0.028*** | 0.028*** | 0.021*** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.00) | (0.01) |
| *D_Wave* | | –0.005* | | –0.009*** | | –0.003 |
| | | (0.00) | | (0.00) | | (0.00) |
| *D_Sale* × *D_Wave* | | 0.021*** | | 0.020** | | 0.024** |
| | | (0.01) | | (0.01) | | (0.01) |
| *Lamda* | –0.065*** | –0.066*** | –0.074*** | –0.078*** | –0.056** | –0.057* |
| | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) |
| *TFP* | –0.019*** | –0.019*** | –0.032*** | –0.032*** | –0.036*** | –0.036*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Ln(Output)* | 0.054*** | 0.054*** | 0.064*** | 0.064*** | 0.066*** | 0.066*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Constant* | –0.389*** | –0.384*** | –0.475*** | –0.467*** | –0.543*** | –0.541*** |
| | (0.05) | (0.05) | (0.06) | (0.06) | (0.07) | (0.07) |
| *R*-Square | 1.46% | 1.46% | 1.70% | 1.70% | 1.61% | 1.61% |
| Number of obs. | 745,940 | 745,940 | 624,899 | 624,899 | 513,743 | 513,743 |
| Panel B: Regression 2 | | | | | | |
| *PrvtoPrv* | 0.004 | 0.002 | 0.013** | 0.006 | 0.003 | –0.001 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *PrvtoPub* | 0.020** | 0.010 | 0.023** | 0.020* | 0.028*** | 0.026** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *PubtoPrv* | 0.046*** | 0.043*** | 0.067*** | 0.072*** | 0.043*** | 0.037** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| *PubtoPub* | 0.034*** | 0.023 | 0.066*** | 0.058*** | 0.071*** | 0.055*** |
| | (0.01) | (0.02) | (0.01) | (0.02) | (0.01) | (0.02) |
| *D_Wave* | | –0.005* | | –0.009*** | | –0.003 |
| | | (0.00) | | (0.00) | | (0.00) |
| *PrvtoPrv* × *D_Wave* | | 0.008 | | 0.029 | | 0.014 |
| | | (0.02) | | (0.02) | | (0.01) |
| *PrvtoPub* × *D_Wave* | | 0.032* | | 0.009 | | 0.007 |
| | | (0.02) | | (0.02) | | (0.02) |

(*Continued*)

**Table IX**—*Continued*

| | *TFP* (–1, 1) | | *TFP* (–1, 2) | | *TFP* (–1, 3) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel B: Regression 2 | | | | | | |
| *PubtoPrv* × *D_Wave* | | 0.009 | | –0.012 | | 0.017 |
| | | (0.02) | | (0.02) | | (0.02) |
| *PubtoPub* × *D_Wave* | | 0.028* | | 0.024 | | 0.039* |
| | | (0.02) | | (0.02) | | (0.02) |
| *Lambda* | –0.064*** | –0.066*** | –0.075*** | –0.078*** | –0.056** | –0.057* |
| | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) |
| *TFP* | –0.019*** | –0.019*** | –0.032*** | –0.032*** | –0.036*** | –0.036*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Ln(Output)* | 0.054*** | 0.054*** | 0.064*** | 0.064*** | 0.066*** | 0.066*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Constant* | –0.389*** | –0.384*** | –0.474*** | –0.465*** | –0.542*** | –0.540*** |
| | (0.05) | (0.05) | (0.06) | (0.06) | (0.07) | (0.07) |
| *R*-Square | 1.46% | 1.46% | 1.70% | 1.71% | 1.62% | 1.62% |
| Number of obs. | 745,940 | 745,940 | 624,899 | 624,899 | 513,743 | 513,743 |

feature of the Census data set, we are able to track transacted plants before and after the acquisition whereas the other studies examine changes in operating performance for all of the assets managed by the acquirer. In additional tests, we find that acquirers' existing plants do not perform worse compared to other plants within the industry.

Panel B 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 types of transactions have positive post-transaction productivity gains significant at the 5% level. Across the four groups, changes in productivity for on-the-wave acquisitions are positive and either significantly higher than or statistically indistinguishable from changes in productivity for off-the-wave acquisitions. In particular, on-the-wave transactions between public firms are associated with post-transaction productivity gains—plants sold between public firms increase productivity 5% to 10% in the next 3 years. Both of these results, namely, on-the-wave mergers generating more efficiency gains and public-to-public transactions generating bigger improvements in productivity, suggest that the higher incidence of such mergers may be the consequence of higher expected synergies. In addition, our findings have implications for corporate governance in public and private firms. Acquisition decisions made in public firms may result in productivity gains from more efficient or skilled management.

### *B. Valuation and Changes in Productivity*

Our results in Table V show that public firms are more likely to make acquisitions when their unexplained valuation (*UV*) is high. If highly valued

**Table X**

**Change in Productivity and Market Valuation**

This table reports changes in productivity for transacted plants based on the buyer's valuation. *Prv Buyer* and *Pub Buyer* are indicator variables for private and public acquirer, respectively. *D_UV* is an indicator variable that equals one if the acquirer has higher than average unexplained valuation (based on all public firms in that year) and zero otherwise. All other variables are as defined in Table II and Table IX. Industry (based on three-digit SIC) fixed effects are included. Robust standard errors allow for clustering at the industry-year level and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | *TFP* (–1, 1) | | *TFP* (–1, 2) | | *TFP* (–1, 3) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *D_Sale* × *Prv Buyer* | 0.020*** | 0.016*** | 0.031*** | 0.027*** | 0.021*** | 0.014** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *D_Sale* × *Pub Buyer* × (*D_UV* = *0*) | 0.015 | 0.004 | 0.036*** | 0.035** | 0.041*** | 0.039** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| *D_Sale* × *Pub Buyer* × (*D_UV* = *1*) | 0.028*** | 0.013 | 0.048*** | 0.029** | 0.050*** | 0.038** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| *D_Wave* | | –0.005*** | | –0.009*** | | –0.003 |
| | | (0.00) | | (0.00) | | (0.00) |
| *D_Sale* × *Prv Buyer* × *D_Wave* | | 0.013 | | 0.015 | | 0.023* |
| | | (0.01) | | (0.01) | | (0.01) |
| *D_Sale* × *Pub Buyer* × (*D_UV* = *0*) × *D_Wave* | | 0.035 | | 0.005 | | 0.008 |
| | | (0.02) | | (0.03) | | (0.03) |
| *D_Sale* × *Pub Buyer* × (*D_UV* = *1*) × *D_Wave* | | 0.038** | | 0.048** | | 0.029 |
| | | (0.02) | | (0.02) | | (0.03) |
| *Lambda* | –0.065*** | –0.066*** | –0.074*** | –0.078*** | –0.056*** | –0.056*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *TFP* | –0.019*** | –0.019*** | –0.032*** | –0.032*** | –0.036*** | –0.036*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| *Ln(Output)* | 0.054*** | 0.054*** | 0.064*** | 0.064*** | 0.066*** | 0.066*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | –0.389*** | –0.384*** | –0.475*** | –0.467*** | –0.544*** | –0.542*** |
| | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) |
| *R*-Square | 1.46% | 1.46% | 1.70% | 1.70% | 1.61% | 1.61% |
| Number of obs. | 745,940 | 745,940 | 624,899 | 624,899 | 513,743 | 513,743 |
| Number of clusterings | 1,915 | 1,915 | 1,872 | 1,872 | 1,799 | 1,799 |

firms make inefficient acquisitions using their overvalued stock, then they are likely to realize lower subsequent productivity gain in purchased plants. On the other hand, if higher *UV* reflects higher expected future productivity, then acquisitions by highly valued firms should do better.

We test the relation between *UV* and subsequent merger productivity gains in Table X. We separate all purchased plants into three groups by their acquirer type—private acquirers (*Prv Buyer*), public acquirers with low *UV* ($Pub\ Buyer \times (D\_UV = 0)$), and public acquirers with high *UV* ($Pub\ Buyer \times (D\_UV = 1)$) and estimate the same specification as in Table X, Panel A using three event windows. The low and high *UV* groups are defined based on the median of the *UV* measure calculated using all public firms in Compustat following the method described in Section III(A). For robustness, we repeat our analysis using alternative grouping methods such as (1) using industry-adjusted *UV* and (2) defining the high *UV* group based on the 75th percentile rather than the median. The results are qualitatively the same.

Table X shows that transacted plants in all three groups experience gains in productivity following the acquisition, with the gains largest for public buyers with high *UV*. Three years following the transaction, plants purchased by public acquirers with high *UV* realize a 5% gain in productivity, compared to 2.1% and 4.1% when acquirers are private firms and public firms with low *UV*, respectively. Moreover, when we interact the acquirer group indicator and the indicator for aggregate wave years, we see an additional large incremental effect for public buyers on the wave when they have high *UV*. This effect persists for up to 2 years after the transaction.

For robustness, in our Internet Appendix we use the annualized stock return as an alternative valuation measure. Similar to Table X, we separate all purchased plants into three groups by their acquirer type—private acquires, public acquirers with low returns, and public acquirers with high returns. We find that, for public firms, the efficiency gains are bigger for acquirers with high recent stock returns. For example, 3 years following the transaction, plants purchased by public acquirers with high returns realize a 7.4% gain in productivity, compared to 2.6% for acquirers with low past returns. There is an additional productivity gain in aggregate wave years but this additional gain is concentrated in low-return acquirers, suggesting that high-return acquirers consistently do better while low-return acquirers have additional gains on the wave.[20]

In sum, adding *UV* and stock returns to our specifications provides new insights, but does not change any of our previous results. *UV* predicts higher participation in acquisition activity for public firms. Changes in productivity for transacted plants remain positive, both on and off the wave, and are particularly high for public buyers with high stock market valuation in aggregate wave years. This evidence is consistent with public buyers paying for synergies as they are more likely to buy with highly valued stock but still make productivity improvements ex post. This result is consistent with high valuations facilitating productive mergers, even if potentially at the wrong price.

## VI. Conclusions

We examine the participation of public and private firms in merger waves. We find that public firms participate in the market for assets more than private firms, in terms of both purchases and sales, and especially so during merger waves. Acquisitions by public firms are more likely to lead to increases in the

[20] For robustness, we repeat this analysis using alternative grouping methods such as (1) using industry-adjusted unexplained valuation and (2) defining the high *UV* group based on the 75th percentile rather than the median. The results are qualitatively the same.

productivity of acquired assets, especially in transactions between public firms and when public acquirers have higher valuations and stock market liquidity.

Our paper enhances our understanding of mergers and acquisitions across different organization forms and over the business cycle. First, we find that both efficiency and financial access affect acquisition decisions. Firms with higher productivity are more likely to buy assets and firms with lower productivity are more likely to sell assets, and transacted plants improve in productivity. Further, the higher participation of public firms is due in part to their better access to financial markets. Among all public firms, those with a better credit rating and more liquid stock are more likely to buy and sell assets. We show that acquisition decisions of public firms with intermediate access to the capital market (low-rated and medium-liquidity firms) are most sensitive to credit spreads. Public firms that do not have a credit rating, on the other hand, behave like private firms.

Second, differences in participation between public and private firms are not driven just by contemporaneous efficiency and valuation. Firms with higher productivity and greater anticipation of future growth choose to become public and later participate more in acquisitions when opportunities rise. Using initial conditions at birth, we show that initial quality explains a significant portion of variation in public status 5 or 10 years later as well as subsequent acquisition behavior. Productive firms self-select to become public and later participate more in the market for corporate assets as both buyers and sellers in ways that increase the productivity of the acquired assets. Hence, a firm's later financial policies are predictable based on its early characteristics before going public. There are thus differences between firms that persist over many years and that affect their behavior and value creation. Purchases and sales of assets are driven in part by firm characteristics that are set when a firm is created by its entrepreneur.

Third, consistent with neoclassical theories, Maksimovic and Phillips (2001, 2002) and Yang (2008), we find that mergers that occur on the wave are associated with greater efficiency improvements. In particular, acquisitions by public firms during wave years realize bigger productivity gains. We find little evidence that merger waves are causing economic inefficiency. We do find that public firms with high *UV* and high stock market liquidity are more likely to engage in acquisitions. However, those transactions also result in greater productivity gains, although we do not know whether the efficiency gains from these reallocations create sufficient value to the acquiring firms' shareholders to cover the premiums usually paid. The finding that highly valued acquirers do better in terms of productivity improvements suggests that there might be some economic rationale for high *UV* with the high valuations resulting from the capitalized value of future synergies or productivity gains.

Our results also have implications for corporate governance. We find that public firms make better acquisition decisions than private firms as judged by efficiency gains despite potential conflicts due to separation of ownership and control in public firms. This finding suggests that gains from access to capital for productive firms may outweigh the potential costs from the separation of ownership and control.

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