Geographic Overlap, Agglomeration Externalities and Post-Merger Restructuring*

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Abstract

We study how agglomeration forces influence post-merger restructuring. We hypothesize and find that geographic overlap of acquirer and target establishments creates the potential for (co)agglomeration benefits that will differ for horizontal and vertical mergers. In vertical mergers, the target establishments are more likely to be kept when the acquirer establishment is located in the same city, indicating that firms benefit from geographically proximate inputs for production. In horizontal mergers, local redundancy increases the likelihood of target establishment closure rather than being kept or sold, consistent with the hypothesis that the acquirer aims to contain local competition through closure rather than sale. Using proxies to capture three dimensions of (co)agglomeration: input sharing, knowledge spillover, and labor pooling, we find that both horizontal and vertical acquirers are more likely to keep target establishments in proximate cities when (co)agglomeration benefits are high. Retained target establishments benefiting the most from agglomeration externalities in horizontal mergers show a significant increase in productivity. In addition to explaining how acquirers restructure the firm post-acquisition, our findings show how agglomeration externalities are reinforced and expanded by establishment-level decisions made following mergers.

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1 Introduction

Despite decades of research on mergers and acquisitions, we know relatively little about how firms make post-merger restructuring decisions (i.e., which bidder and target establishments to keep, sell, or close after the merger is completed). One notable exception is Maksimovic et al. (2011), which provides important evidence that such establishment-level activity is extensive following a merger, and that a bias toward focus (keeping core, disposing of peripheral establishments) helps explain what stays and what goes. In this paper, we study how agglomeration forces acting through the geographic distribution of bidder and target establishments can explain their post-merger disposition. We hypothesize that agglomeration benefits are a driver of the decision, and that disposition decisions will vary depending on whether the merger is horizontal or vertical. In doing so, we not only add to the nascent literature studying post-acquisition establishment level decisions, but also provide important evidence on how agglomeration considerations influence and are reinforced by post-acquisition location decisions.

We start with a sample of horizontal and vertical mergers from 1997 through 2016, allowing for several years post-acquisition to study the establishment disposition decision. We track the establishments of both the target and acquirer three years after the acquisition and assign each to the status of kept, closed, or sold. Horizontal deals are those where the target and acquirer have at least one overlapping main industry (using the 2007 BEA Input-Output Table industries). Vertical deals are those that are not horizontal and also have a 1% or more supply chain connection between the target and acquirer, meaning that one buys at least 1% of its input from the other or sells at least 1% output to the other.[1] As a starting point for agglomeration considerations, we code each target establishment as overlapping or not with acquirer establishments at the zip code, city, county, commuter zone and state.

For horizontal deals, the baseline results confirm Maksimovic, et al.'s (2011) findings that, all else equal, target establishments in the horizontally overlapping (core) industry

[1] Ahern and Harford (2014) note that accounting for labor input makes intermediate goods a relatively small part of the total input. They show that over 95% of the inputs in an average industry individually account for less than 1% of total inputs. Further, almost half of those industries supplying more than 1%, supply less than 2%.

and/or in the target's main industry are more likely to be retained. Additionally, we find that the geographic overlap matters; target establishments in the same city as existing acquirer establishments are more likely to be closed (and less likely to be sold). This latter result is likely driven by not wanting to bolster a competitor by selling them an establishment. The city-level findings are on average for all establishments, so we study whether the decision varies with theoretically-motivated agglomeration benefits.

Specifically, we use the establishment's industry's reliance on manufactured inputs as a proxy for goods transport agglomeration benefits, measures of its patenting and R&D activity for knowledge-spillover agglomeration benefits, and its use of non-routine labor as a measure of labor market agglomeration benefits. We find that establishments in industries requiring a low percentage of manufactured inputs (i.e., low transport agglomeration benefits) are more likely to be closed and less likely to be kept when they share a city with acquirer establishments. Further, we find that establishments in industries with low knowledge spillovers, measured by patent breadth, citation attraction, or R&D spending, are more likely to be closed and less likely to be kept. Finally, we find evidence that establishments with a high share of routine labor (low labor pooling agglomeration benefits) are more likely to be closed and less likely to be kept, different from those with non-routine labor. Overall, with respect to target establishments, we find the strongest evidence for agglomeration benefits of goods transport and knowledge spillovers. Notably, the evidence for acquirer establishments is consistent with that for target establishments, but generally weaker—rather it appears that there is a bias toward keeping acquirer establishments, and their disposition three years following the merger is governed more by standard performance characteristics and core vs. peripheral considerations than overlap with target establishments, per se.

For vertical mergers, the baseline results show that target establishment geographic proximity to acquirer establishments predicts that the target establishment is more likely to be retained. We further assess the degree to which the theoretical concept of coagglomeration externalities influence the disposition of establishments after a merger. Coagglomeration applies the concept of agglomeration benefits within an industry to pairs of industries instead. The extension from within industry to across industry is straightforward in the sense that vertically related industries can benefit from physical proximity to minimize physical transport costs, increase knowledge spillovers along the supply chain, and potentially benefit from related labor markets as well.

We start by identifying target establishments belonging to industries with high vertical relatedness to acquirer establishments, where high relatedness is defined as above the median across industry pairs. The degree of vertical relatedness does not alter the effect of geographical proximity on the decision to retain the target establishment. However, we find that target establishments in industries with high technological proximity (based on Jaffe's (1986) approach to measuring technological overlap of two industries) with acquirer establishment industries are also more likely to be kept when they are located in a city with an existing acquirer establishment. Finally, we measure the occupational similarity between target and acquirer establishments to test for the benefits of labor market pooling. Again, the results show that, conditional on being in the same city as an acquirer establishment, a target establishment is more likely to be retained when it shares high occupational similarity with the acquirer establishment. Each of these results is consistent with the theoretically predicted benefits of agglomeration economies and pro- vides further evidence of how these benefits shape the boundaries of the firm post-merger.

In our final set of tests, we study changes in productivity for the establishments that are retained by the merged firm. Again, we focus on three years after the merger and compare it to one year prior to the merger. For horizontal mergers, we find evidence that establishment level productivity increases when establishments are retained in cities where they have substantial agglomeration benefits, especially for goods transport and knowledge spillover. For vertical mergers, we find similar increases in productivity for high knowledge spillover benefits, as well as in mergers with high occupational similarity between the acquirer and target.

Our study makes two main contributions. First, despite a large literature dedicated to understanding merger activity, relatively few papers provide evidence on the reshuffling of assets that follows the consummation of a merger. Maksimovic and Phillips (2001) highlights the importance of viewing merger and acquisition activity at the establishment level. Maksimovic et al. (2011) provides early evidence that there is substantial selling and closing of establishments post-acquisition and that the outcome is consistent with a goal of increasing focus and shedding peripheral establishments. Levine et al. (2020) study how overlapping branch networks impact which banks merge and the resulting post-merger network. Hsu et al. (2022) show that acquirers discontinue product lines and consolidate product offerings post-merger. Ma et al. (2022) document labor reallocation as technology is diffused across the merged entity. Gehrke et al. (2022) study labor force restructuring in Germany after mergers. Li and Wang (2023) track the benefits of acquirer-target inventor collaboration post-merger. Our paper adds to this strand of the literature by confirming Maksimovic, et al.'s findings and showing that capturing potential positive agglomeration externalities is integral to explaining the keep vs. sell/close decision. We further show supporting evidence that these benefits manifest in higher productivity of the retained establishments.

Second, we contribute to the literature attempting to understand the economic externalities that drive agglomeration, increasingly the focus of study in economics and finance.[2] For example, Rosenthal and Strange (2001) study the foundations of agglomeration economies within the manufacturing sector. Ellison et al. (2010) use the colocation of vertically-related industries to understand the causes of agglomeration. Almazan et al. (2010) study how local acquisition opportunities in agglomeration economies can influence firm financial policies. By using mergers to study the question, we not only apply a different approach to providing evidence on the theoretically predicted forces explaining agglomeration, but also show that such forces shape the resulting boundaries of the firm once the merger is completed. After a merger, the managers of the combined firm must actively choose whether to keep, sell or close each establishment. Our study is the first to show that agglomeration externalities help explain the disposition of each establishment. This finding bolsters the evidence for the existence of these externalities while simultaneously showing how they are reinforced and expanded by establishment-level decisions made following mergers.

[2] See Carlino and Kerr (2015) and Duranton and Kerr (2015) for reviews of the literature.

2 Economic Framework and Hypothesis Development

The idea that agglomeration has potential economic benefits is at least 100 years old. Marshall (1920) emphasized that the costs of moving goods, people and ideas each provided potential gains from industrial agglomeration. While there has been success in establishing evidence in support of theoretically proposed drivers of agglomeration, extant work typically takes the existing agglomeration as given and tries to explain it. Here, we focus on the active decisions that firms make in locating establishments that react to and enhance potential agglomeration benefits. Specifically, we study the drivers of which establishments are kept, sold or closed following horizontal and vertical mergers.

We focus on three types of agglomeration benefits: input sharing, knowledge spillovers, and labor market pooling, and two types of mergers: horizontal and vertical. Horizontal mergers naturally have more potential redundancies, and have alternative incentives to close some collocated establishments to reduce local competition.

Agglomeration benefits from input sharing is based on the idea that when more geographically proximate firms share an input, there will be certain scale economies in shipping, distribution and even localized production of that input. To measure the potential input sharing benefits, we use each industry's percent of manufactured inputs, because manufactured inputs most closely match the 'cost of moving goods' motivation in Marshall (1920)'s characterization of these benefits. One can view labor market pooling as a subcase of input sharing since similar forces are at work—more firms demanding a particular skill will lead to greater migration of those with that skill to the area and more investment by local labor in acquiring that skill. Finally, knowledge spillover agglomerations flow from complementarities in knowledge production. We measure the potential for these complementarities through input (R&D), output (patents and citations), and industry characteristics (high-tech or not).

While never stated publicly, horizontal mergers can be motivated at least partly by the desire to reduce competition. Closing proximate establishments can reduce competition in addition to eliminating redundancies. Whereas these forces potentially are at work in any horizontal merger, the degree to which they are opposed by agglomeration benefits will vary across industries. We hypothesize that these forces will interact in such a way that the typical redundancy and competition effects will be most prominent in situations where there are low agglomeration externalities.

For vertical mergers, there is a lower tendency to dispose of geographically proximate establishments than there is for horizontal mergers. Further, the potential for agglomeration externalities depends on the interaction between the vertically-related industries. Agglomeration benefits among vertically related industries have been termed coagglomeration in the literature. In the context of vertical mergers, the input-sharing externality depends on the value of reduced shipping between the two industries and so is a function of how strong the supply-chain relationship is—how much the two industries buy/sell from each other. The knowledge spillover externality is a function of how related the two industries' technology spaces are, measured by the degree to which they overlap in patent technology classifications. Finally, the labor market externality depends on the similarity of the job-types in the two industries being great enough that the larger local labor pool benefits the co-located establishments.

3 Data and Sample

3.1 Data Sources

We obtain data from a number of sources. The key database we use to identify firms' establishments is the Your-economy Time Series (YTS) database from the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin. The YTS database is composed of annual snapshots from the Infogroup Historic Datafiles and provides establishment-year level information on location, industry, employment, and sales for both public and private firms.[3] Within the YTS database each establishment is linked to a firm headquarters location creating a network of establishments for each firm. This network of establishments is crucial for analyzing the post-merger restructuring decision following a merger.

We use the Securities Data Company's (SDC) U.S. Mergers and Acquisition Database to identify mergers and acquisitions. We obtain financial and accounting data from Compustat and stock price and return data from the Center for Research in Security Prices (CRSP). To control for state-level economic conditions we collect the State Coincident Index from the Federal Reserve Bank of Philadelphia. To measure asset redeployability at the industry level following Kim and Kung (2017), we download the data from Kim's website.[4]

We use a variety of data sources to construct the various proxies for agglomeration externalities. These data sources include the Bureau of Economic Analysis (BEA) data on input and output flows between industries, patent citation data from the USPTO, Kogan et al. (2017) data repository for patent data linked to publicly traded companies, industry-level labor-technology substitutability data from the Zhang (2019) data repository, and industry employee occupation data from the Bureau of Labor Statistics (BLS). We discuss the specific databases used from each source, as well as the variables calculated below in the respective section.

3.2 Sample Construction

Our sample of mergers and acquisitions (M&As) begins with all M&A transactions in the SDC database that become effective between January 1, 1998 and December 31, 2016. We choose this sample period because the YTS data covers a period of 1997 and 2019. This way we are able to observe the merging firms' establishments from the year before to the three

[3] For additional information on the validity of the YTS database and how the YTS database is constructed see Kunkle (2018) Specifically, Kunkle (2018) describe how Infogroup collect data underlying YTS as follows, "To develop its data sets, Infogroup operates a 225-seat call center that makes contact with over 55,000 businesses each and every day in order to record and qualify company information. During a typical month, 15% of the entire Infogroup business data set is re-verified. On average, 150,000 new businesses are added while 100,000 businesses are removed each month, capturing the dynamic business churn happening in the economy. Infogroup's team also identifies new companies through the U.S. Yellow Pages, county-level public sources on new business registrations, industry directories, and press releases." Flynn and Ghent (2022) state that they can match two-thirds of Compustat firms to YTS firms. YTS data therefore cover most public firms.

[4] We obtain the data from the web link: `https://sites.google.com/view/hyunseobkim/asset-redeployability`.

years after the merger. We require both the target firm and acquiring firm to be U.S. based firms and the acquirer owns less than 50% of the target prior to the acquisition and owns 100% at completion of the deal. Additionally, we require the deal value to be greater than $1 million, both target and acquirer have nonmissing industry information from SDC, and the effective date to be less than 365 days away from the announcement date. The target can be either a public or private firm, but we require the acquirer to be a public firm and to have data from the CRSP database.

Our final requirement is the existence of both the target and acquirer in the YTS database for the year prior to the merger. To match SDC and YTS firms, we first rely on their tickers, provided that ticker is available in YTS.[5] If the ticker information is not available (for all private firms and for some public firms), we use a fuzzy-name-matching algorithm and require that a firm has the same headquarters city and industry in both the YTS database and SDC. During each step of the process we hand check a random sample of matched M&A transactions to ensure our method correctly identifies the headquarters location. After applying all these filters, we are left with 4,284 M&A transactions that are completed during 1998-2016.

3.3 Merger Type Classification

We classify each merger transaction as horizontal, vertical, or conglomerate based on the two merging firms' industry information. We rely on the Input-Output (IO) Make and Use tables from the BEA to determine the vertical relationships between industries (Fan and Lang (2000); Fan and Goyal (2006); Ahern (2012); Ahern and Harford (2014)). We hence use IO industry codes for industry classification. We map the North American Industry Classification System (NAICS) code for each establishment in the YTS database and the primary NAICS industry code for each firm in the SDC to the respective IO code.[6]

[5]YTS provides the latest ticker for public firms. If a firm was public and is no longer public by 2019, then the ticker information is missing. To account for changing ticker over time, we first match YTS and SDC to CRSP/Compustat respectively, and then match between them.

[6]The YTS database provides the 2012 6-digit NAICS industry code and the 1987 4-digit SIC industry code for each establishment. If the NAICS industry code is missing in the YTS database, the 4-digit SIC code is converted to the 2012 NAICS industry code. Approximately 10% of establishments rely on the 1987 SIC industry code to identify the appropriate 2012 NAICS industry code. We then map the 2012 6-digit NAICS codes to 2007 6-digit IO codes based on a crosswalk provided by the BEA. For a more detailed breakdown on the various industry codes and how they relate to one another see Ahern and Harford (2014).

We identify a firm's main industry or industries as follows. First, the primary industry identified by SDC is considered a main industry. Second, we calculate the percentage of employees at establishments that operate in each IO industry in the year prior to the merger completion. An IO industry is identified as a main industry of the firm if at least 25% of the firm's total employees are from the respective IO industry.

We classify merger types based on the relationships between the two merging firm's main industries. An M&A transaction is a horizontal merger if any of the acquirer's main industries overlaps with any of the target's main industries. This definition ensures that at least 25% of the target's and the acquirer's operations fall into the same IO industry. In our sample 2,839 M&A transactions match this definition and are classified as horizontal mergers.

For the remaining mergers, we calculate the vertical relations among all combinations of the target's main industries and the acquirer's main industries, following the process outlined in Becker and Thomas (2010) and Ahern and Harford (2014). We create two matrices, a customer matrix and a supplier matrix, from the Make and Use tables. For our analysis we implement the IO Make and Use tables from 2007, the midpoint of our sample, for all M&A transactions in our sample. This method has been shown to be qualitatively similar to using the table from the year closest to the merger announcement date (Ahern (2012)).

The customer matrix and the supplier matrix measure the percentage of industry *i*'s sales purchased by industry *j* and the percentage of industry *j*'s inputs purchased from industry *i*, respectively. Between two industries *i* and *j* there then exists four measures of the vertical relatedness between the two industries: i) industry *i* sells to industry *j*; ii) industry *i* purchases from industry *j*; iii) industry *j* sells to industry *i*; and iv) industry *j* purchases from industry *i*. If the maximum of the four vertical relations between any pair of the acquirer and the target's main industries exceeds the 1% threshold, the M&A transaction is classified as a vertical merger. In our sample, 1,134 MA transactions are defined to be vertical mergers. The remaining 311 MA transactions are considered to be conglomerate mergers and are dropped from our final sample.

The breakdown of the horizontal and vertical mergers by announcement year is presented in Table 1. Our final sample consists of 3,973 M&A transactions that are completed between 1998 and 2016. Approximately 31% of the MA transactions in our final sample are vertical mergers and the remaining 69% are horizontal mergers. The percentage of vertical mergers in our sample is consistent with the prior literature examining the differences between horizontal mergers and vertical mergers (e.g., see Ahern (2012) and Frésard et al. (2020)).

3.4 Variables and Summary Statistics

The focus of this paper is to study firms' post-merger restructuring decisions. For each target establishment that existed in the year prior to the merger, we determine its status three years after the merger and define three indicator variables: *Keep*, *Sell*, and *Close*. *Keep* equals one if the establishment is linked to the merging firm's headquarters three years and zero otherwise. *Sell* equals one if the establishment is linked to another firm's headquarters and zero otherwise. *Close* equals one if the establishment no longer exists.

The main variable of interest measures the geographic overlap between the two merging firms. Specifically, for each target establishment, we define *Overlapcity* equal to one if there is an existing establishment of the acquirer in the same city in the year prior to the merger, and zero otherwise. Thus, we measure overlap at the city level. Alternatively, we measure overlap at the zip code, county, commuter zone, and state level as well. Our main results are robust at the zip code and the county levels, but, as expected, become weaker at the commuter zone and state levels.

We use a set of control variables following Maksimovic et al. (2011). *TarMainBus* equals to one if the establishment is in a main segment of the target firm, and zero otherwise. Several variables measure the industry characteristics of the establishment: *IndRD* is the aggregate R&D spending scaled by the aggregate total assets of all public firms in the industry in the year prior to the merger. *IndOpMargin* is the aggregate operating income before depreciation scaled by the aggregate sales of all public firms in the industry. *IndReturn* is the industry return in the two years after the merger. *Redeployability* is asset redeployability for the industry (Kim and Kung (2017)). *OverlapHor* equals 1 if the establishment is in the same industry as one of the acquirer's main industries. *OverlapVer* equals one if the establishment is vertically related with one of the acquirer's main industries at the 1% level. Two variables measure the local conditions of where the establishment is located. *LocQuotient* measures the county-level employment concentration in the industry (Boasson et al. (2005)). *StateCoinIndex* is the State Coincident Index provided by the Federal Reserve Bank of Philadelphia that captures the state economic conditions for the establishment's location using four economic indicators. Finally, *Public* is equal to one if the target is a public firm. *AcqTotalLoc* is the number of establishments the acquirer has. *SameStateHQ* equals one if the two merging firms are headquartered in the same state, and zero otherwise. The detailed definition for each variable is in the appendix.

Table 2 presents the summary statistics of the status of target establishments three years after the merger completion. In our final sample of 3,973 MA transactions, 110,423 target firm establishments are acquired. Only around 54% of these establishment are kept by the acquirer three years after the merger becomes effective. For the remaining establishments, around 31% are closed and the remaining 15% are sold to another firm. The keep rate of target establishments by the acquirer is similar to the keep establishment rate reported in Maksimovic et al. (2011). Nonetheless, the rate that establishments are closed in our sample is higher, 31% compared to 18% in their sample. The two samples differ in both the time period (1998-2016 vs. theirs 1981-2000) and the industries covered (we include mergers in all industries whereas they consider only mergers in the manufacturing industries).

Dividing the sample based on the number of target establishments in each merger deal, we note that the keep rate is the highest for the deals that include the smallest number of target establishments (1-5), with over 62% of the target establishments being kept. The rate steadily declines for target firms with 6-10, 11-25, 26-50 locations, being 49%, 45%, and 42%, respectively. The rate however reverts upward when the target gets big enough, i.e., with more than 51 locations: 56% of locations are kept for these firms. The disposal rates also differ between horizontal mergers and vertical mergers. For horizontal mergers, over 56% of the target establishments are kept by the acquirer while the keep rate for the vertical mergers is a much lower, approximately 39%. As will be discussed below, however, horizontal acquirers are less likely to keep target establishments in areas the acquirer is already present. There is notable time variation in disposal rates. We therefore include time-period dummies in our regressions.

Table 3 presents the summary statistics for our main variable *OverlapCity* and control variables at the establishment level. In our sample, around 42% of the target establishments are located in a city where the acquiring firm also has at least one establishment. Nearly 80% of the target establishments operate in its main industries.

4 Empirical Results

The focus of this paper is to identify the role that geographic overlap between the target and the acquirer plays in the post-merger restructuring decision and how this differs for horizontal mergers and vertical mergers and depends on agglomeration externalities. In this section, we first describe the empirical model used to analyze the establishment disposal decision. We then present the empirical results, first on how the role of geographic overlap differs between horizontal mergers and vertical mergers, and then on the contribution of (co)agglomeration externalities in the establishment disposal decision. Finally, we examine the impact of geographic overlap and (co)agglomeration on the productivity change of kept establishments.

4.1 Establishment Disposal Decisions: Horizontal and Vertical Mergers

We use a multinomial logit model following Maksimovic et al. (2011) to examine the decision to keep, sell, or close an acquired target establishment within three years of the merger becoming effective. We estimate the following regression:

$$\text{Pr(disposal decision = j | OverlapCity, X)} = \frac{\exp(\beta_j \text{OverlapCity} + \gamma_j \mathbb{X})}{\sum_{k=0}^{2} \exp(\beta_k \text{OverlapCity} + \gamma_k \mathbb{X})} \quad (1)$$

Where *j* is the disposal decision of establishment *i* and is equal to 0 if the establishment is kept, 1 if the establishment is sold, and 2 if the establishment is closed, within three years of the effective year of the merger. *OverlapCity* is the key variable of interest, and $\mathbb{X}$ is a vector of control variables including *TarMainBus*, *LocQuotient*, *IndRD*, *IndOpMargin*, *IndReturn*, *AcqTotalLoc*, *StateCoinIndex*, *Public*, *Redeployability*, *SameStateHQ*, *OverlapHor* (for horizontal deals) or *OverlapVer* (for vertical mergers), *1990s*, and *2000s*. Standard errors are clustered at the deal level and all variables are defined in the appendix.

We hypothesize that horizontal and vertical acquirers have different predispositions toward target establishments in geographic proximity with the firms' existing establishments. We thus estimate the model for horizontal mergers and vertical mergers separately. Firms may seek to acquire a competitor in a horizontal merger to reduce their competition (Stigler (1964) and Perry and Porter (1985)). Closing the target company's establishments, especially in areas where the acquirer already has a presence, is an effective way to reduce supply and increase power vis-à-vis consumers. We thus expect that the target establishments in a horizontal merger would be less likely to be kept or sold, and more likely to be closed if they are located where the acquiring firm already has an establishment. Vertical mergers, on the other hand, are often motivated by the need to reduce transaction costs, input price risk, and to integrate the supply chain under a single firm (Grossman and Hart (1986); Hart and Moore (1990); Williamson (1971); Alchian and Demsetz (1972); Klein et al. (1978); Garfinkel and Hankins (2011)). A customer or supplier establishment nearby can facilitate the acquiring firm's production. Thus, we expect that the target establishments in a vertical merger would be more likely to be kept, and less likely to be sold or closed if the establishments are located where the acquiring firm already has an establishment.

Table 4 presents the results of the multinomial logit regressions. Columns (1)-(5) are results for horizontal mergers. Columns (1) and (2) present the regression coefficients where the baseline decision is to keep the target establishment. Columns (3)-(5) present the marginal effects for each disposal possibility, including the implied marginal effects for the decision to keep an establishment.

The main variable of interest is *OverlapCity* which is an indicator variable equal to 1 if the target's establishment is located in the same city as at least one of the acquirer's establishments. The coefficient on *OverlapCity* is negative and significant for the likelihood of being sold (Column 1), and positive and significant for the likelihood of being closed (Column 2). We turn to marginal effects in Columns (3)-(5) to interpret the magnitude of the effects. The results suggest that for horizontal mergers, holding all else equal, a target establishment that is located in a city where the acquiring firm also has at least one establishment is 5.4% more likely to be closed than an establishment located in a city where the acquirer does not have any locations. These locations in the same city as an acquirer's existing establishment are also 2.5% less likely to be kept and 2.9% less likely to be sold. These effects are substantial compared to the unconditional probability for an establishment to be closed (29%), kept (47%) or sold (14%) for horizontal mergers. The results support the prediction that some firms complete horizontal mergers to reduce their local competition.

Columns (6)-(10) report results for vertical mergers. Columns (6) and (7) present the regression coefficients where the baseline decision is to keep the target establishment. Columns (8)-(10) present the marginal effects for each disposal possibility. Focusing on the marginal effects, when the target establishment is located in the same city as an acquirer's existing establishment, the location is 6.6% more likely to kept by the acquirer and 7.6% less likely to be sold to another firm. These effects are substantial compared to the unconditional probability for an establishment to be kept (39%) or sold (19%) for horizontal mergers. The estimates for the decision to close is statistically insignificant. The results suggest that vertical acquirer's treatment of geographically proximate target establishments is different from the horizontal acquirers: they do not have a predisposition to close them and rather prefer to keep them.

For control variables, we find that establishments are more likely to be kept if they are in the target firm's main business, for both horizontal and vertical mergers. Establishments in industries with high R&D expenditures are less likely to be kept for horizontal mergers, and establishments in industries with high operating margins are less likely to be kept for vertical deals. These results are all consistent with Maksimovic et al. (2011), although their tests do not distinguish between horizontal and vertical mergers. Other control variables are largely insignificant.

4.2 Agglomeration Externalities and Disposal Decisions in Horizontal Mergers

We have shown that in horizontal mergers, acquirers are more likely to close target establishments that are in proximity to their existing locations, consistent with a motive of eliminating redundancies or of reducing local competition. The degree to which these incentives drive outcomes, however, should vary with agglomeration externalities. We hypothesize that the positive effect of *OverlapCity* on the closing likelihood, and its negative effect on the keeping likelihood will be stronger if the merging firms are in low agglomeration industries. We test this hypothesis in this section. To do this, we divide the sample into establishments in high and low agglomeration industries and re-estimate Equation (1).

We use three sets of measures for industry agglomeration. Marshall (1920) argues that by locating near each other, firms can reduce costs along three dimensions: (i) input sharing, (ii) knowledge spillovers, and (iii) labor market pooling. Following the literature (e.g., Rosenthal and Strange (2001); Greenstone et al. (2010)), we measure agglomeration externalities within an industry along these three dimensions. All measures are constructed based on an establishment's industry information.

The first agglomeration externality is based on input sharing. We follow the literature and use the manufactured inputs per dollar of shipments to measure the potential for an establishment to benefit from input sharing. If manufactured inputs are important for an industry, then the gains from sharing inputs are likely to be large because of two reasons: manufactured inputs are likely to be more industry specific compared to service or utility inputs, and they are more likely to have economies of scale. We calculate this measure using the 2007 IO Make and Use tables from the BEA. The manufactured inputs per $ of shipments is calculated as the ratio of the cost of inputs purchased from manufacturing industries (6-digit IO codes between 300000 and 399999 with some exclusions[7]) to the total value of shipments for the entire IO industry. An establishment is considered to have high reliance on

[7] Several IO codes in the range are excluded from the manufacturing group as they are classified into the natural resource industry instead. These include 327999 (Miscellaneous nonmetallic mineral products), 331313 (Alumina refining and primary aluminum production), 331410 (Nonferrous Metal (except Aluminum) smelting and refining), and 331490 (Nonferrous metal (except copper and aluminum) rolling, drawing, extruding and alloying).

manufactured inputs if it has an above-median value (across the sample of target establishments in horizontal mergers) for this measure.

The knowledge spillover externality posits that firms benefit from idea sharing with their local industry peers. This benefit should be larger if knowledge and innovation are important for the industry. To capture this benefit, we implement four proxies based on an industry's patenting and other innovation characteristics. Our first measure of an establishment's reliance on knowledge spillovers is the number of patenting classes its industry overlaps with. Specifically, we count the number of Cooperative Patent Classification (CPC) codes that the establishment's 6-digit NAICS code overlaps with. The idea is that if an industry overlaps with many patenting classes, it benefits from a wider variety of technological advances compared to an industry that overlaps with a few CPC codes.

Specifically, we download the full USPTO CPC-NAICS concordance table, which provides the co- sine similarity between the text of the CPC code description and the text of the NAICS code description between each CPC-NAICS pair.[8] We count the number of CPC codes that each NAICS industry has greater than or equal to 10% similarity with.

The second measure of knowledge spillovers is the cumulative number of citations for patents granted to public firms in an IO industry scaled by the total aggregate assets of the public firms in that industry in the deal effective year. We obtain the number of patents, patent value, and patent citations for each public company from the data repository supplied by Kogan et al. (2017). We calculate the total of all the forward patent citations for patents granted to firms in the industry from 1987 to the year in question[9] For example, in 2005 the total citations for an industry is the sum of all forward patent citations for patents granted in the industry from 1987 through 2005. We then scale the number of patent citations by the aggregate industry assets to account for the size of the industry. In addition to patent citations, we also use two alternative patent-based measures: the number of patents and the value of patents, each scaled by the aggregate industry assets. The value of a patent is measured as the change in firm value around the announcement of a granted patent (Ko-

[8]The full USPTO CPC-NAICS concordance table can be found at `https://commercedataservice.github.io/cpc-naics/`.

[9]The starting year of 1987 is chosen arbitrarily to provide a sufficient amount of time before the beginning of our sample.

gan et al. (2017)).[10] Our main results are robust to these alternative measures (untabulated).

The third measure of knowledge spillovers is the level of R&D activity in the establishment's IO industry, i.e., the aggregate R&D expenses scaled by the aggregate total assets for all public firms in the industry. The fourth measure of knowledge spillover is based on whether the establishment operates in a high-tech industry or not. High-tech industries are classified at the 4-digit NAICS code level following Appel et al. (2019).[11]

The labor market pooling agglomeration externality posits that when firms locate their operations in an industry cluster, they will benefit from access to a larger pool of labor with industry-specific skills. Due to difficulty identifying the specialization of an industry's labor force, the labor market pooling agglomeration externality is the most difficult externality to proxy for (Rosenthal and Strange (2001)). We measure this externality based on the extent the industry employs non-routine labor in its operations (Zhang (2019)). An occupation is considered routine if the tasks performed in that occupation can be easily substituted with technology or the process can be easily automated with machines, removing the need for an employee to perform the tasks. If an industry's share of routine job employment is small, then the labor force cannot be easily substituted and the industry will benefit from labor market pooling.

Data on the intensity of routine labor in an industry is collected from the data repository maintained by Zhang (2019).[12] The industry level share of routine labor is measured at the establishment's industry level using the Occupational Employment Statis- tics (OES) database from the Bureau of Labor Statistics (BLS). Zhang (2019) first classifies all occupations as either routine-task or nonroutine-task following Autor and Dorn (2013). The percentage of wages paid to the routine-task occupations relative to the industry's total wage bill is calculated each year and this value is used to measure the level of routine labor in the industry.

Table 5 presents estimates of Equation (1) for subsamples based on the input sharing ex-

[10]Specifically, the economic value of a patent is measured as the product of the estimate of the stock return due to the value of the patent times the firm's market cap on the day prior to the patent grant, divided by a surprising factor (i.e., one minus the unconditional probability of a successful patent application).

[11]The 4-digit NAICS codes that correspond to high-tech industries include 2211, 3341, 3342, 3344, 3353, 4234, 5112, 5161, 5171, 5172, 5173, 5174, 5179, 5181, 5182, 5415, and 5416.

[12]Data is downloaded from `https://www.miaobenzhang.com/`.

ternality. We divide the sample into two based on whether an establishment is in an industry with above- or below-median manufactured inputs per $ shipments. The subsample with higher manufactured inputs is considered to have higher input sharing externality. Columns (1)-(3) present the marginal effects of the estimation for the subsample with high agglomeration, and Columns (4)-(6) present those for the subsample with low agglomeration. For brevity, we only present the marginal effects for our main variable of interest, *OverlapCity*, and suppress those for control variables.

Consistent with our hypothesis, Table 5 shows that the positive effect of *OverlapCity* for an establishment to be closed and its negative effect for an establishment to be kept are statistically significant only in the low agglomeration subsample. The effects in the low agglomeration subsample are stronger than those in the whole sample: an establishment is 7.8% more likely to be closed and 6.5% less likely to be kept if the acquirer already has a presence in the establishment's city. In contrast, both effects are statistically insignificant in the high agglomeration subsample. This suggests that the agglomeration benefits counter the incentive to reduce competition.

Table 6 presents estimates of Equation (1) for subsamples based on the knowledge spillover externality. We measure this externality as the number of patenting classes in Panel A, as the number of patent citations in Panel B, R&D expenditures in Panel C, and whether the establishment is in a high-tech industry in Panel D. In each panel, we find that an establishment is more likely to be closed and less likely to be kept if it is located in a city the acquirer already had a presence, but only when agglomeration externalities are low. These effects do not hold when agglomeration externalities are high.

Table 7 presents estimates of Equation (1) for subsamples based on the labor pooling externality. An establishment is considered to have high labor pooling externality if its industry has below-median share of routine labor. Again, we find that the effect of *OverlapCity* on *Keep* is significantly negative and that on *Close* is significantly positive only in the low agglomeration subsample, and these effects become insignificant in the high agglomeration subsample.

In untabulated tests, we re-estimate our specifications collapsing the close and sell outcomes to one no-keep outcome so that we can examine the keep vs. dispose decision. The results are consistent with the richer set we present in Tables 5-7 and allow us to test for differences in the impact of *Overlapcity* on the keep vs. dispose decision across the high and low agglomeration benefit subsamples in Tables 5-7. In all cases, the differences are significant.

As a robustness check, we employ a linear probability model to estimate the likelihood of keeping an establishment. Specifically, we regress *Keep* on *Overlapcity*, *High Agglomeration*, and *Overlapcity*$\times$ *High Agglomeration*, where *High Agglomeration* is equal to one if the observation belongs to the high agglomeration subsample. This linear probability specification allows us to use the interaction term to test the difference in the impact of *Overlapcity* between high and low agglomeration deals. It also enables us to include deal fixed effects (in contrast, including many fixed effects in logit or multi-logit regressions will result in inconsistent estimates). Appendix IA.1 presents the results. Consistent with Tables 5-7, for most measures of agglomeration, we find a significantly positive coefficient on *Overlapcity*$\times$ *High Agglomeration* on *Keep*, suggesting that overlapped establishments are less likely to be kept if agglomeration is low.

Overall, the evidence shows that when agglomeration externalities are low, the incentive to reduce redundancy or contain local competition dominates and horizontal acquirers are more likely to close and less likely to keep target establishments that are in proximity to their existing locations; but when agglomeration is high, the agglomeration benefits countervails the competition concerns and on average geographic proximity does not have a significant role on closing or keeping decisions.[13]

4.3 Coagglomeration Externalities and Disposal Decisions in Vertical Mergers

Unlike horizontal acquirers, vertical acquirers have a predisposition to keep target establishments in proximity to their existing locations. We hypothesize that this effect will be

[13]As noted in the introduction, we also estimate analogous specifications for the acquirer establishments, and find consistent, but weaker results. There appears to be a bias toward keeping acquirer establishments, and disposition decisions are primarily driven by core vs. peripheral considerations.

even stronger if the coagglomeration between the establishment and the acquiring firm is higher. Cross-industry coagglomeration externalities can also arise due to input sharing, knowledge spillover, and labor market pooling (Ellison et al. (2010); Faggio et al. (2017)). Along each dimension, we measure coagglomeration externality between the target establishment's industry and each of the acquiring firm's main industries, using the maximum value if there are multiple industry pairs.

The input sharing externality, in the context of vertical mergers, posits that firms will benefit from reduced transportation costs by locating their operations near their customers and suppliers. The more they buy from or sell to each other, the higher this externality. We use the maximum value of vertical relatedness (the %input from and %output to each other) between the establishment's IO industry and each of the acquiring firm's main industries to proxy for an establishment's reliance on the input sharing coagglomeration externality with the acquiring firm.

The knowledge spillover externality is more valuable if the two industries use each other's technology or innovations to a larger extent. We measure this externality based on the technological proximity between two industries following JAFFE (1986). Specifically, technological proximity measures the uncentered correlation between the vector of the number of patents in different technology classes (based on CPC codes) for industry i and industry j.

The labor market pooling coagglomeration externality posits that firms operating in industry i will benefit from locating operations near firms in other industries that employ the same type of labor force, due to access to a larger labor pool. To capture this externality, we measure the similarity of labor types between two industries. Specifically, we calculate the cosine similarity between the vector of the share of employees in different occupations for industry i and industry j.

We divide the sample into subsamples based on each of the coagglomeration measures and re-estimate Equation (1). Table 8 divides the sample based on the input sharing externality. An establishment is considered to have high input sharing externality with the acquiring firm if it has above-median vertical relatedness with one of the acquirer's main businesses. When there is high coagglomeration, an establishment is 4.2% less likely to be sold and 5.2% more likely to be kept if it is located in a city where the acquirer already has a presence. We find similar results if coagglomeration is low, suggesting the input sharing coagglomeration externalities may not play as significant of a role as in the horizontal mergers.

Table 9 divides the sample based on the knowledge spillover externality. An establishment is considered to have high knowledge spillover externality with the acquiring firm if it has above-median technological proximity with one of the acquirer's main businesses. The results show that in the high coagglomeration subsample, an establishment is more likely to be kept if it is in the same city as an acquirer's existing establishment. This does not hold in the low coagglomeration subsample where the effect of *Overlapcity* is insignificant for the decision to keep an establishment. This difference is statistically significant. Thus, acquirers are more likely to keep an overlapped establishment when coagglomeration is high than when coagglomeration is low, consistent with our hypothesis.

Table 10 divides the sample based on the labor pooling externality. An establishment is considered to have high labor pooling externality with the acquiring firm if it has above-median occupational similarity with one of the acquirer's main businesses. Like the previous table for the knowledge spillover externality, we find that when coagglomeration is high, an establishment is more likely to be kept if it is in the same city as an acquirer's existing establishment. When agglomeration is low, such an establishment is no more likely to be kept. The difference, however, is not statistically significant.

In summary, Tables 8-10 present some evidence that coagglomeration externalities play a role in vertical acquirers' disposal decisions with target establishments in proximity to their existing locations, although the evidence is weaker than that in horizontal mergers. They are more likely to keep a proximate establishment when coagglomeration externalities are high. Table IA.2 in the Internet Appendix presents linear probability regression models. Results are overall consistent with those in Tables 8-10.

The results presented for both horizontal and vertical deals not only establish (co)agglomeration considerations as an important determinant of post-merger establishment-level disposition decision, but also provide important evidence on how agglomeration economies arise and are reinforced by merger-related establishment location decisions.

4.4 Kept Establishment Productivity and (Co)Agglomeration Externalities

In this section we examine the post-merger change in productivity of the kept target establishments, conditional on the agglomeration or coagglomeration externality enjoyed by the establishment. We hypothesize that firms benefit more from keeping a geographically proximate establishment when (co)agglomeration externality is high. Specifically, we estimate the following regression.

$$\begin{aligned}\Delta Productivity_{i,t+3} = \beta_0 &+ \beta_1 * OverlapCity_{i,t-1} \\ &+ \beta_2 * HighAgglomeration_{i,t-1} \\ &+ \beta_3 * OverlapCity_{i,t-1} \times HighAgglomeration_{i,t-1} \\ &+ \beta_4 * Controls + \epsilon_{i,t+3}\end{aligned} \tag{2}$$

The dependent variable, $\Delta Productivity_{i,t+3}$, is the percentage change in productivity for establishment *i* from year *t-1* to year *t+3*, year *t* being the deal effective year. Productivity is calculated as the establishment's total sales divided by its total number of employees. $HighAgglomeration_{i,t-1}$ equals one if the establishment has above-median agglomeration (or coagglomeration) externality with the acquiring firm. If firms truly benefit from agglomeration by keeping establishments in overlapping locations, then we expect those establishments to have higher productivity increases, i.e., $\beta_3 > 0$. We include the same control variables as before. In addition, we include deal fixed effects as well as industry-year fixed effects.[14] Standard errors are clustered at the deal level.

Table 11 presents the regression results for horizontal merger, with Columns (1)-(5) each based on a different measure of agglomeration benefits discussed in Section 3.2, i.e., manufactured inputs, industry RD expenditures, patent citations, patenting classes, and %non-routine labor, respectively. Consistent with our hypothesis, the coefficient on *Overlapc-*

[14]Deal fixed effects do not supersede industry-year fixed effects because each target firm often have establishments in multiple industries.

ity×*High Agglomeration* is significantly positive in three out of these five columns. The coefficient on *Overlapcity* itself is insignificant in most specifications. The results thus show that when agglomeration externalities are high, kept establishments in overlapping cities experience greater productivity increases than those in non-overlapping cities. This cross-sectional effect does not hold when agglomeration externalities are low.

Table 12 presents regression results for vertical deals. Columns (1)-(3) each measures coagglomeration based on vertical relatedness, technological proximity, occupational similarity, respectively. Similar to Table 11, the coefficient on *Overlapcity*×*High Coagglomeration* is significantly positive in two out of three columns. Also similar to Table 11, the coefficient on *Overlapcity* itself is insignificant. This result suggests that greater productivity increases in overlapping cities are concentrated in places where coagglomeration externalities are high, again consistent with our hypothesis.

Maksimovic et al. (2011) shows that kept establishments increase productivity whereas sold establishments do not, suggesting that acquirers choose to keep establishments on a path to increased productivity. We conduct cross-sectional tests among kept establishments and document the incremental effect of geographic overlap. This effect is consistent with the previous result that the acquiring firm is more likely to keep such an establishment when (co)agglomeration benefits are high.

5 Conclusion

This study addresses two important questions: how are post-merger firms shaped through establishment-level disposition decisions, and how are agglomeration economies established and reinforced. By empirically studying the decision to keep, sell or close individual establishments after a merger, we are able to establish the importance of geographic overlap. We further show that the importance of this overlap expresses itself through attempts to capture agglomeration benefits.

Our consistently strong results for agglomeration considerations have important implications for the study of agglomeration economies. First, by demonstrating the sensitivity of the establishment disposition decision to potential agglomeration externalities, we establish that managers are aware of such benefits and actively seek to exploit them. Second, these establishment location decisions reinforce existing agglomeration economies, providing novel evidence on how such economies are established and grow.

Appendix A: Variable Definitions

Variable	Definition
Establishment Level Variables:	
$Sell$	Indicator variable equal to 1 if the establishment is sold by the acquirer by year $t+3$ relative to the effective date.
$Close$	Indicator variable equal to 1 if the establishment is closed by the acquirer by year $t+3$ relative to the effective date.
$Keep$	Indicator variable equal to 1 if the establishment is still owned by the acquirer in year $t+3$.
$OverlapZip$	Indicator variable equal to 1 if the Target's is located in the same zip code as at least one of the Acquirer's establishments.
$OverlapCity$	Indicator variable equal to 1 if the Target's is located in the same city as at least one of the Acquirer's establishments.
$OverlapCounty$	Indicator variable equal to 1 if the Target's is located in the same county as at least one of the Acquirer's establishments.
$OverlapCZ$	Indicator variable equal to 1 if the Target's is located in the same Commuter Zone (CZ) as at least one of the Acquirer's establishments.
$OverlapState$	Indicator variable equal to 1 if the Target's is located in the same state as at least one of the Acquirer's establishments.
$OverlapHor$	Indicator variable equal to 1 if the Target's establishment is in the same IO Industry as one of the Acquirer's main IO industries.
$OverlapVer$	Indicator variable equal to 1 if the Target's establishment is not in any of the Acquirer's main IO industries and is vertically related at the 1% level to at least one of the Acquirer's main IO industries.

(*continued*)

$TarMainBus$	Indicator variable equal to 1 if the establishment in one of the Target's main IO industries. An IO industry is considered one of the target's main IO industries if at least 25% of the target's employees are located at establishments linked to that IO industry in year $t-1$ relative to the effective year.
$LocQuotient$	The establishment's county level IO industry employment concentration calculated following Boasson et al. (2005) in year $t-1$. The location quotient determines if there is industry clustering in the county based on local employment share of an industry relative to the total employment share of the industry nationally.
$IndR\&D$	The aggregate R&D expenditure scaled by the aggregate total assets of all public firms in the Compustat database in the establishment's IO industry in year $t-1$.
$IndOpMargin$	The aggregate Operating Margin of all public firms in the establishment's IO industry in year $t-1$. The aggregate operating margin is calculated as the total operating income before depreciation in the establishment's IO industry divided by the aggregate total sales in the establishment's IO industry from Compustat.
$IndReturn$	The $(t,t+2)$ equally-weighted buy-and-hold portfolio return for the establishment's IO industry.
$AcqTotalLoc$	The total number of establishments linked to the acquirer in the YTS database in year $t-1$.

(*continued*)

$StateCoinIndex$	The State Coincident Index summarizes the local economic conditions within the respective state and is provided by The Federal Reserve Bank of Philadelphia for the establishment's state in year $t-1$. The index is calculated using four state-level variables which include non-farm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements adjusted for inflation.
$Public$	Indicator variable equal to 1 if the establishment is owned by a public target and zero otherwise.
$Redeployability$	The establishment's IO industry measure of asset redeployability provided by Kim and Kung (2017). The linking table provided by Kim and Kung (2017) is used to assign the establishment's NAICS code to corresponding BEA industry.
$1990s$	Indicator variable equal to 1 if year $t-1$ is between 1997 and 1999.
$2000s$	Indicator variable equal to 1 if year $t-1$ is between 2000 and 2009.
$2010s$	Indicator variable equal to 1 if year $t-1$ is between 2010 and 2015.
$SameStateHQ$	Indicator variable equal to 1 if the headquarter location of the target and acquirer is in the same state based on the SDC Platinum database.

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Table 1: Sample Breakdown.
This table presents the number of mergers and acquisitions included in the sample by completion year and type of merger. A merger is considered horizontal if any acquirer main segment IO industry overlaps with at least one target main segment IO industry code. A merger is considered vertical if the vertical relatedness between any combination of an acquirer main segment IO industry code and a target main segment IO industry code is greater than or equal to 1% and there are no overlapping acquirer main segment IO industry code and target main segment IO industry codes.

	Horizontal Mergers		Vertical Mergers		Total	
Year	%	Deals	%	Deals	%	Deals
1998	7.43	295	2.34	93	9.77	388
1999	5.69	226	2.06	82	7.75	308
2000	4.43	176	2.32	92	6.75	268
2001	4.20	167	1.28	51	5.49	218
2002	2.67	106	1.18	47	3.85	153
2003	2.74	109	1.06	42	3.80	151
2004	4.56	181	1.54	61	6.09	242
2005	4.10	163	1.49	59	5.59	222
2006	4.56	181	1.96	78	6.52	259
2007	4.76	189	1.86	74	6.62	263
2008	3.90	155	1.36	54	5.26	209
2009	1.86	74	1.01	40	2.87	114
2010	2.54	101	1.38	55	3.93	156
2011	2.49	99	1.36	54	3.85	153
2012	3.30	131	1.56	62	4.86	193
2013	2.57	102	1.33	53	3.90	155
2014	3.42	136	1.23	49	4.66	185
2015	3.73	148	1.08	43	4.81	191
2016	2.52	100	1.13	45	3.65	145
Total	71.46	2839	28.54	1134	100.00	3973

Table 2: Target establishment post merger disposal decision.
This table presents the disposal decision at time $t+3$ relative to merger effective date of the target establishments owned prior to acquisition. The disposal decision for the target firm is broken down by the number of plants owned by the target pre-merger, deal type, and time period of the deal effective date. Establishments are considered sold if they are linked to a firm other than the target at time $t+3$. Establishments are considered closed if the last year in YTS is less than or equal to year $t+3$. All remaining establishments are considered kept and remain linked to the target firm at time $t+3$.

	# Deals	# Locations	Keep (%)	Sell (%)	Close (%)	Total (%)
By Number of Plants Owned by Target						
Tar Loc 1-5	2,806	3,964	62.06	5.50	32.44	100
Tar Loc 6-10	345	2,536	49.29	14.31	36.40	100
Tar Loc 11-25	360	5,669	44.58	19.23	36.20	100
Tar Loc 26-50	199	6,699	40.93	19.70	39.36	100
Tar Loc $\geqslant 51$	263	91,555	55.58	14.65	29.77	100
By Deal Type						
Horizontal	2,839	94,224	56.86	14.12	29.02	100
Vertical	1,134	16,199	38.82	19.17	42.01	100
By Time Period						
1990s	765	25,135	52.55	17.52	29.93	100
2000s	2,060	52,796	48.45	18.45	33.10	100
2010s	1,148	32,492	64.87	6.95	28.18	100
Total	3,973	110,423	54.22	14.86	30.93	100

Table 3: Target Summary Statistics.
This table presents the summary statistics for the target establishments included in the final sample. All variables are defined in Appendix A.

	Count	Mean	Std	Min	25%	50%	75%	Max
OverlapZip	110364	0.272	0.445	0.000	0.000	0.000	1.000	1.000
OverlapCity	110364	0.423	0.494	0.000	0.000	0.000	1.000	1.000
OverlapCounty	110364	0.587	0.492	0.000	0.000	1.000	1.000	1.000
OverlapCZ	110364	0.724	0.447	0.000	0.000	1.000	1.000	1.000
OverlapState	110364	0.869	0.338	0.000	1.000	1.000	1.000	1.000
TarMainBus	110364	0.793	0.405	0.000	1.000	1.000	1.000	1.000
LocQuotient	110364	1.316	1.540	0.188	0.759	0.986	1.306	12.392
IndR&D	110364	0.171	0.628	0.000	0.000	0.000	0.018	4.503
IndOpMargin	110364	0.204	0.154	0.029	0.074	0.124	0.331	0.645
IndReturn	110364	0.396	0.460	-0.491	0.171	0.319	0.664	1.850
AcqTotalLoc	110364	25.347	34.365	0.010	1.770	8.840	43.870	139.100
StateCoinIndex	110364	95.348	12.744	72.064	85.945	94.914	102.511	125.411
Public	110364	0.842	0.365	0.000	1.000	1.000	1.000	1.000
Redeployability	110364	0.527	0.129	0.032	0.477	0.501	0.650	0.913
SameStateHQ	110364	0.143	0.350	0.000	0.000	0.000	0.000	1.000
OverlapHor	110364	0.670	0.470	0.000	0.000	1.000	1.000	1.000
OverlapVer	110364	0.120	0.325	0.000	0.000	0.000	0.000	1.000
1990s	110364	0.228	0.419	0.000	0.000	0.000	0.000	1.000
2000s	110364	0.478	0.500	0.000	0.000	0.000	1.000	1.000
2010s	110364	0.294	0.456	0.000	0.000	0.000	1.000	1.000

Table 4: Multinomial logit for target establishment decision.

This table presents the results for the multinomial logit regressions for the target's establishments. Columns (1)-(2) and (6)-(7) present the logit coefficient estimates. Columns (3)-(5) and (8)-(10) present the marginal effects of the logit estimates for the respective sample. All variables are defined in Appendix A. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Horizontal Deals					Vertical Deals				
	Sell	Close	Keep	Sell	Close	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Multi-Logit		Marginal Effects			Multi-Logit		Marginal Effects		
OverlapCity	-0.179*	0.232***	-0.025*	-0.029***	0.055***	-0.742***	-0.168**	0.066***	-0.076***	0.009
	(-1.75)	(3.54)	(-1.74)	(-2.61)	(4.12)	(-3.26)	(-2.06)	(3.22)	(-3.74)	(0.60)
TarMainBus	-0.851***	-0.458**	0.129***	-0.073***	-0.056*	-1.420***	-0.440***	0.146***	-0.138***	-0.008
	(-3.20)	(-2.44)	(2.98)	(-3.07)	(-1.80)	(-4.55)	(-3.16)	(4.75)	(-5.54)	(-0.31)
LocQuotient	-0.018	0.010	-0.000	-0.002	0.003	-0.021	-0.077***	0.013***	0.003	-0.016***
	(-0.67)	(0.67)	(-0.12)	(-0.90)	(1.13)	(-1.01)	(-6.59)	(5.14)	(1.22)	(-6.95)
$IndR\&D_{agg}$	0.009	0.209***	-0.034***	-0.008	0.042***	-0.116	0.048	-0.002	-0.017	0.018**
	(0.12)	(4.30)	(-3.01)	(-1.07)	(5.18)	(-0.95)	(1.11)	(-0.13)	(-1.36)	(2.55)
$IndOpMargin_{agg}$	0.234	1.003*	-0.175	-0.017	0.193*	1.907	1.782***	-0.388**	0.109	0.279**
	(0.28)	(1.66)	(-1.29)	(-0.22)	(1.90)	(1.35)	(2.59)	(-2.30)	(0.82)	(2.48)
IndReturn	0.386	0.019	-0.028	0.041	-0.013	-0.034	0.039	-0.004	-0.006	0.011
	(1.39)	(0.13)	(-0.81)	(1.47)	(-0.49)	(-0.09)	(0.42)	(-0.14)	(-0.16)	(0.63)
AcqTotalLoc	-0.011	-0.009***	0.002***	-0.001	-0.001**	-0.006*	0.006***	-0.001	-0.001***	0.002***
	(-1.63)	(-3.09)	(3.00)	(-1.15)	(-2.46)	(-1.74)	(3.45)	(-1.52)	(-3.21)	(5.62)
StateCoinIndex	-0.029**	-0.008	0.003	-0.003*	-0.000	-0.050**	-0.010*	0.004***	-0.005***	0.001
	(-2.06)	(-0.86)	(1.63)	(-1.83)	(-0.18)	(-2.48)	(-1.75)	(2.67)	(-2.60)	(0.68)
Public	0.476	-0.074	-0.020	0.055*	-0.035	0.984**	0.640***	-0.155***	0.074	0.081**
	(1.41)	(-0.33)	(-0.35)	(1.78)	(-0.98)	(2.09)	(3.35)	(-3.29)	(1.61)	(2.32)
Redeployability	-1.031	-0.536	0.154	-0.089	-0.064	1.545	0.922	-0.230*	0.122	0.108
	(-1.27)	(-0.68)	(0.89)	(-1.38)	(-0.48)	(1.37)	(1.62)	(-1.70)	(1.16)	(1.13)

(continued)

Table 4 continued.

SameStateHQ	0.571	0.153	-0.062	0.055	0.007	-0.170	0.738***	-0.110**	-0.067*	0.176***
	(1.32)	(0.95)	(-1.22)	(1.28)	(0.30)	(-0.47)	(4.22)	(-2.53)	(-1.94)	(6.28)
OverlapHor	-0.846***	-0.251	0.096**	-0.081***	-0.015					
	(-3.38)	(-1.37)	(2.30)	(-3.62)	(-0.49)					
OverlapVer						-0.293	-0.232	0.053	-0.019	-0.033
						(-1.22)	(-1.54)	(1.54)	(-0.87)	(-1.32)
1990s	-0.428	-0.178	0.057	-0.039	-0.018	-0.094	0.314	-0.046	-0.031	0.077
	(-0.99)	(-0.52)	(0.86)	(-0.82)	(-0.26)	(-0.16)	(1.08)	(-0.66)	(-0.53)	(1.48)
2000s	0.368	0.041	-0.031	0.038	-0.007	0.846**	0.175	-0.073	0.088**	-0.015
	(1.49)	(0.16)	(-0.67)	(1.41)	(-0.14)	(2.09)	(0.85)	(-1.49)	(2.24)	(-0.42)
Constant	2.591	0.820				3.301	-0.021			
	(1.63)	(0.71)				(1.52)	(-0.03)			
Observations	94,224	94,224	94,224	94,224	94,224	16,199	16,199	16,199	16,199	16,199
Chi-Square	374.2	374.2				577.4	577.4			
Pseudo R-Squared	0.0675	0.0675				0.134	0.134			

Table 5: Horizontal Target Establishment Based on Input Sharing (Agglomeration Externality One)

This table presents the marginal effects of the logit estimates for the target establishments at time $t+3$. The sample is split based on the first agglomeration externality, input sharing. An establishments reliance on input sharing is measured using the establishment's IO industry's reliance on manufacturing inputs per $ of shipments. All target establishments included in a horizontal merger are included in the regressions. The IO industry's reliance on manufacturing inputs is calculated as the percentage of inputs from the manufacturing industries in relation to the IO industry's total inputs and is calculated using the 2007 BEA IO tables. Each IO industry is classified as manufacturing, non-manufacturing, natural resources, energy, or water following the classification in Rosenthal and Strange (2001). An establishment is considered to have high manufacturing inputs if it is greater than the median percentage of inputs from the manufacturing industries. Each regression includes all control variables included in Table 4. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High Manufacturing Inputs			Low Manufacturing Inputs		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.025	-0.043***	0.018	-0.065***	-0.013	0.078***
	(1.03)	(-3.17)	(0.93)	(-3.95)	(-0.98)	(3.71)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,875	45,875	45,875	48,349	48,349	48,349

Table 6: Horizontal Target Establishment Based on Knowledge Spillovers (Agglomeration Externality Two)

This table presents the marginal effects of the logit estimates for the target establishments at time $t+3$. The sample is split based on the second agglomeration externality, knowledge spillovers. An establishment's reliance on knowledge spillovers is measured at the establishment's IO industry level. All target establishments included in a horizontal merger are included in the regressions. Panel A determines the establishment's reliance on knowledge spillovers based on the number of Cooperative Patent Classification (CPC) codes that the establishment's 6-digit NAICS code overlaps with based on the code descriptions cosine similarity. Codes are determined to overlap if the cosine similarity is greater than 10% and is based off the USPTO CPC-NAICS concordance table (`https://commercedataservice.github.io/cpc-naics/`). Panel B determines the establishment's reliance on knowledge spillovers based on the cumulative number of patent citations for patents granted to the establishment's IO industry scaled by the total aggregate assets of the IO industry in the deal effective year. Panel C determines the establishment's reliance on knowledge spillover using the IO industry's aggregate R&D expenditure as a percentage of the IO industry's aggregate total assets. Panel D determines the establishment's reliance on knowledge spillovers based on whether the establishment is in a high-tech industry or not. High-tech industries are classified at the 4-digit NAICS level following Appel et al. (2019). An establishment is considered to have high knowledge spillovers in Panel A, Panel B and Panel C if it is greater than the median of the respective knowledge spillover measure. Each regression includes all control variables included in Table 4. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Number of Patenting Classes

	High # Patent Classes			Low # Patent Classes		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.038**	-0.059***	0.021	-0.059***	-0.011	0.069***
	(2.13)	(-4.49)	(1.43)	(-3.66)	(-0.91)	(3.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,723	34,723	34,723	59,501	59,501	59,501

Panel B: High Patent Citations vs Low Patent Citations
(Results are robust to using the number of patents and the value of patents)

	High Citation			Low Citation		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.009	-0.026*	0.017	-0.063***	-0.029**	0.092***
	(0.76)	(-1.86)	(1.13)	(-3.03)	(-2.25)	(5.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,072	47,072	47,072	47,152	47,152	47,152

Panel C: High R&D Industries vs Low R&D Industries

	High R&D			Low R&D		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	-0.001	-0.047***	0.049***	-0.049***	-0.012	0.061***
	(-0.08)	(-3.70)	(2.67)	(-2.65)	(-1.04)	(3.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,903	39,903	39,903	54,321	54,321	54,321

Panel D: High Tech Industries vs Non High Tech Industries

	High Tech			Non High Tech		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.038*	-0.035**	-0.003	-0.027*	-0.030***	0.057***
	(1.89)	(-2.21)	(-0.14)	(-1.80)	(-2.58)	(4.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,830	3,830	3,830	90,394	90,394	90,394

Table 7: Horizontal Target Establishment Based on Labor Market Pooling (Agglomeration Externality Three)

This table presents the marginal effects of the logit estimates for the target establishments at time $t+3$. The sample is split based on the third agglomeration externality, labor market pooling. An establishment's reliance on labor market pooling is measured at the establishment's 4-digit NAICS code industry. All target establishments included in a horizontal merger are included in the regressions. An establishment's reliance on labor market pooling is determined by the level of routine labor employed by the establishment's industry from Zhang (2019). The industry level of routine labor is measured at either the establishment's 4-digit NAICS industry (2002-2016) or the establishment's 3-digit SIC industry (1997-2001). An establishment is considered to employ non-routine labor if the establishment's industry routine labor value is less than or equal to the median value of routine labor. Each regression includes all control variables included in Table 4. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low Routine Labor			High Routine Labor		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	-0.001	-0.024*	0.025	-0.054***	-0.039***	0.092***
	(-0.05)	(-1.68)	(1.41)	(-2.83)	(-2.73)	(7.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,259	53,259	53,259	40,965	40,965	40,965

Table 8: Vertical Target Establishment Based on Input Sharing (Coagglomeration Externality One)

This table presents the marginal effects of the logit estimates for the target establishments at time $t+3$. The sample is split on the first coagglomeration externality, input sharing. An establishment's reliance on input sharing for a vertical merger is measured by the maximum vertical relatedness between target establishment's IO industry and the IO industry for each of the acquirer's main businesses. All target establishments included in a vertical merger are included in the regressions. An establishment is considered to have high vertical relation with the acquirer if the establishment's vertical relatedness score is greater than the median vertical relatedness score. Each regression includes all control variables included in Table 4. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High Vertical Relation			Low Vertical Relation		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.052**	-0.042***	-0.009	0.061***	-0.087***	0.026
	(2.15)	(-3.59)	(-0.58)	(2.70)	(-2.69)	(1.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,225	8,225	8,225	7,974	7,974	7,974

Table 9: Vertical Target Establishment Based on Knowledge Spillovers (Coagglomeration Externality Two)

This table presents the marginal effects of the logit estimates for the target establishments at time $t+3$. The sample is split based on the second coagglomeration externality, knowledge spillovers. An establishment's reliance on knowledge spillovers is based on the establishment's 4-digit NAICS code industry's technological proximity with the acquirer's primary 4-digit NAICS code industry. All target establishments included in a vertical merger are included in the regressions. The measure of technological proximity is calculated following JAFFE (1986) and measures the degree to which technology in industry i overlaps with technology in industry j. The patenting activity begins in 1987, 10 years prior to the first year of our sample. For each industry pair i and j, we calculate the uncentered correlation of the cumulative number of patents in each patent class.. An establishment is considered to have high tech proximity with the acquirer if the establishment's tech proximity is greater than the median tech proximity for the sample of vertical mergers. Each regression includes all control variables included in Table 4. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High Tech Proximity			Low Tech Proximity		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.076***	-0.046	-0.030	0.023	-0.073***	0.050***
	(2.81)	(-1.60)	(-1.61)	(1.51)	(-4.27)	(3.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,684	7,684	7,684	8,183	8,183	8,183

Table 10: Vertical Target Establishment Based on Labor Market Pooling (Coagglomeration Externality Three)

This table presents the marginal effects of the logit estimates for the target establishments at time $t+3$. The sample is split based on the third coagglomeration externality, labor market pooling. An establishment's reliance on labor market pooling is measured using the occupational similarity between the establishment's industry and the acquirer's primary industry. All target establishments included in a vertical merger are included in the regressions. Occupational similarity between the target establishment and the acquirer is measured using the cosine similarity between the vector of the share of employees in an occupation within industry i and the vector of the share of employees in an occupation within industry j. Occupational similarity is calculated for all industry combinations. Occupational data is from the Occupational Employment and Wage Statistics (OEWS) database supplied by the U.S. Bureau of Labor Statistics. For 2002-2016 the 4-digit NAICS code is used and for 1997-2001 the 3-digit SIC code is used. An establishment is considered to have high occupational similarity with the acquirer if the establishment's occupational similarity is greater than the median occupational similarity. Each regression includes all control variables included in Table 4. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High Occupational Similarity			Low Occupational Similarity		
	Keep	Sell	Close	Keep	Sell	Close
	(1)	(2)	(3)	(4)	(5)	(6)
OverlapCity	0.076***	-0.046	-0.030	0.023	-0.073***	0.050***
	(2.81)	(-1.60)	(-1.61)	(1.51)	(-4.27)	(3.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,684	7,684	7,684	8,183	8,183	8,183

Table 11: Kept Horizontal Target Establishment Productivity Changes and Agglomeration Externalities

This table presents the OLS estimates for the change in productivity for kept target establishments in horizontal mergers. The dependent variable in each regression is the percent change in productivity from year $t-1$ to year $t+3$ relative to the deal effective year. All target establishments kept in year $t+3$ and that are included in a horizontal merger are included in the regressions. The results for the input sharing agglomeration externality are presented in column (1). This is measured using the establishment's IO industry's reliance on manufacturing inputs per dollar of shipments. Columns (2)-(4) present the results for the different proxies for an establishment's reliance on knowledge spillovers. In column (2) an establishment's reliance on knowledge spillovers is based on the aggregate R&D expenditure as a percentage of the IO industry's aggregate total assets. In column (3) an establishment's reliance on knowledge spillovers is based on the cumulative number of patent citations for patents granted to the establishment's IO industry scaled by the total aggregate assets of the IO industry in the deal effective year. In column (4) an establishment's reliance on knowledge spillovers is based on the number of Cooperative Patent Classification (CPC) codes that the establishment's 6-digit NAICS code overlaps with based on the code descriptions cosine similarity. Column (5) present the results for the labor market pooling agglomeration externality. An establishment's reliance on labor market pooling is determined by the level of routine labor employed by the establishment's industry from Zhang (2019). For each proxy of an establishment's reliance on agglomeration externalities, the indicator variable *High Agglomeration* is equal to one if the respective measure of an establishment's reliance on agglomeration externalities is greater than the median for the respective measure. Each regression includes deal fixed effects and establishment industry-year fixed effects. The control variables included in each regression include *OverlapHor*, *TarMainBus*, $IndR\&D$, $IndOpMargin$, *IndReturn*, *AcqTotalLoc*, *Public*, *Redeployability*, and *SameStateHQ*. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Agglomeration Measure	Manufacturing Shipments	Industry R&D	Patent Citations	# Patent Classes	Non-routine Labor
	(1)	(2)	(3)	(4)	(5)
OverlapCity	0.007	0.010	0.023**	0.014	0.023
	(1.39)	(1.06)	(2.00)	(1.49)	(1.32)
High Agglomeration	0.354	0.152	-0.706*	0.009	0.129
	(0.55)	(0.66)	(-1.73)	(0.20)	(1.25)
OverlapCity × *High Agglomeration*	0.042*	0.043***	0.001	0.031*	-0.000
	(1.81)	(2.69)	(0.10)	(1.76)	(-0.02)
Observations	51,470	51,470	51,470	51,470	51,470
R-squared	0.427	0.427	0.427	0.427	0.427
Controls	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes	Yes

Table 12: Kept Vetical Target Establishment Productivity Changes and Coagglomeration Externalities

This table presents the OLS estimates for the change in productivity for kept target establishments in vertical mergers. The dependent variable in each regression is the percent change in productivity from year $t-1$ to year $t+3$ relative to the deal effective year. All target establishments kept in year $t+3$ and that are included in a vertical merger are included in the regressions.The results for the input sharing coagglomeration externality are presented in column (1). An establishment's reliance on input sharing for a vertical merger is measured by the maximum vertical relatedness between target establishment's IO industry and the IO industry for each of the acquirer's main businesses. Columns (2) presents the results for the establishment's reliance on the knowledge spillovers coagglomeration externality. An establishment's reliance on the knowledge spillovers coagglomeration externality. An establishment's reliance on knowledge spillovers is based on the establishment's 4-digit NAICS code industry's technological proximity with the acquirer's primary 4-digit NAICS code industry. Column (3) presents the results for the labor market pooling coagglomeration externality. An establishment's reliance on labor market pooling is measured using the occupational similarity between the establishment's industry and the acquirer's primary industry. For each proxy of an establishment's reliance on coagglomeration externalities, the indicator variable *High Coagglomeration* is equal to one if the respective measure of an establishment's reliance on coagglomeration externalities is greater than the median for the respective measure. Each regression includes deal fixed effects and establishment industry-year fixed effects. The control variables included in each regression include *OverlapVer*, *TarMainBus*, $IndR\&D$, $IndOpMargin$, *IndReturn*, *AcqTotalLoc*, *Public*, *Redeployability*, and *SameStateHQ*. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Coagglomeration Measure	Vertical Relatedness	Tech Proximity	Occupational Similarity
	(1)	(2)	(3)
OverlapCity	-0.063	-0.069	-0.073
	(-0.99)	(-1.62)	(-1.45)
High Coagglomeration	-0.140	1.187***	0.037
	(-0.75)	(3.35)	(0.04)
OverlapCity ×	0.092	0.150**	0.129*
High Coagglomeration	(1.18)	(2.15)	(1.78)
Observations	5,309	5,286	5,044
R-squared	0.579	0.584	0.586
Controls	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes

Internet Appendix: Geographic Overlap, Agglomeration Externalities and Post-Merger Restructuring

Table IA.1: LPM for horizontal target establishment keep decision with agglomeration externalities.

This table presents the OLS estimates for a linear probability model on the decision to keep an establishment for horizontal mergers. The dependent variable in each regression is an indicator variable *Keep*, which is equal to one if the target establishment is kept by the acquirer and zero otherwise. All target establishments that are included in a horizontal merger are included in the regressions. Column (1) presents the baseline specification. The results for the input sharing agglomeration externality are presented in column (2). This is measured using the establishment's IO industry's reliance on manufacturing inputs per dollar of shipments. Columns (3)-(6) present the results for the different proxies for an establishment's reliance on knowledge spillovers. In column (3) an establishment's reliance on knowledge spillovers is based on the number of Cooperative Patent Classification (CPC) codes that the establishment's 6-digit NAICS code overlaps with based on the code descriptions cosine similarity. In column (4) an establishment's reliance on knowledge spillovers is based on the cumulative number of patent citations for patents granted to the establishment's IO industry scaled by the total aggregate assets of the IO industry in the deal effective year. In column (5) an establishment's reliance on knowledge spillovers is based on the aggregate R&D expenditure as a percentage of the IO industry's aggregate total assets. In column (6) an establishment's reliance on knowledge spillovers is based on whether the establishment is in an industry that is classified as high-tech (*High Tech = 1*). Column (7) present the results for the labor market pooling agglomeration externality. An establishment's reliance on labor market pooling is determined by the level of routine labor employed by the establishment's industry from Zhang (2019). For each proxy of an establishment's reliance on agglomeration externalities (excluding *High Tech*), the indicator variable *High Agglomeration* is equal to one if the respective measure of an establishment's reliance on agglomeration externalities is greater than the median for the respective measure. Each regression includes deal fixed effects. The control variables included in each regression include *OverlapHor*, *TarMainBus*, $IndR\&D$, $IndOpMargin$, *IndReturn*, *StateCoinIndex*, and *Redeployability*. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Agglomeration Measure		Manufacturing Shipments	# Patent Classes	Patent Citations	Industry R&D	High Tech	Non-routine Labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OverlapCity	-0.046***	-0.075***	-0.060***	-0.087***	-0.052**	-0.048***	-0.087***
	(-3.24)	(-3.76)	(-3.47)	(-6.97)	(-2.30)	(-3.27)	(-5.47)
High Agglomeration		-0.018	-0.096***	-0.018	-0.073***	-0.002	-0.102***
		(-0.36)	(-3.05)	(-1.02)	(-2.69)	(-0.06)	(-3.04)
OverlapCity × *High Agglomeration*		0.063**	0.038**	0.082***	0.015	0.061***	0.073***
		(2.12)	(2.19)	(3.69)	(0.59)	(2.72)	(3.50)
OverlapHor	0.017	0.018	0.024	0.020	0.005	0.016	0.007
	(0.40)	(0.43)	(0.58)	(0.48)	(0.12)	(0.39)	(0.18)

TarMainBus	0.157***	0.158***	0.148***	0.154***	0.142***	0.157***	0.148***
	(4.07)	(4.24)	(3.91)	(4.09)	(3.94)	(4.07)	(4.05)
LocQuotient	0.004*	0.004*	0.003	0.004*	0.004*	0.004*	0.003
	(1.80)	(1.78)	(1.57)	(1.81)	(1.89)	(1.78)	(1.59)
$IndR\&D_{agg}$	0.007	0.006	0.006	0.006	0.009	0.005	-0.000
	(0.99)	(0.96)	(1.03)	(0.86)	(1.38)	(0.68)	(-0.02)
$IndOpMargin_{agg}$	-0.258**	-0.253**	-0.291***	-0.259**	-0.153	-0.260**	-0.179*
	(-2.39)	(-2.30)	(-2.60)	(-2.38)	(-1.32)	(-2.38)	(-1.69)
IndReturn	-0.039	-0.038	-0.038	-0.037	-0.035	-0.040	-0.039
	(-1.48)	(-1.58)	(-1.38)	(-1.54)	(-1.52)	(-1.50)	(-1.40)
StateCoinIndex	0.001	0.001*	0.001*	0.001	0.001	0.001	0.001
	(1.60)	(1.67)	(1.66)	(1.48)	(1.60)	(1.58)	(1.34)
Redeployability	0.233***	0.231***	0.225**	0.245***	0.184**	0.235***	0.200**
	(2.77)	(2.73)	(2.45)	(3.06)	(2.15)	(2.78)	(2.36)
Constant	0.257**	0.256***	0.303***	0.266***	0.315***	0.258**	0.357***
	(2.55)	(2.89)	(3.23)	(2.76)	(3.41)	(2.57)	(3.63)
Observations	92,861	92,861	92,861	92,861	92,861	92,861	92,861
R-squared	0.272	0.273	0.274	0.273	0.273	0.272	0.274
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.2: LPM for vertical target establishment keep decision with coagglomeration externalities.

This table presents the OLS estimates for a linear probability model on the decision to keep an establishment for vertical mergers. The dependent variable in each regression is an indicator variable *Keep*, which is equal to one if the target establishment is kept by the acquirer and zero otherwise. All target establishments that are included in a horizontal merger are included in the regressions. Column (1) presents the baseline specification. The results for the input sharing coagglomeration externality are presented in column (2). An establishment's reliance on input sharing for a vertical merger is measured by the maximum vertical relatedness between target establishment's IO industry and the IO industry for each of the acquirer's main businesses. Columns (3) presents the results for the establishment's reliance on the knowledge spillovers coagglomeration externality. An establishment's reliance on knowledge spillovers is based on the establishment's 4-digit NAICS code industry's technological proximity with the acquirer's primary 4-digit NAICS code industry. Column (4) presents the results for the labor market pooling coagglomeration externality. An establishment's reliance on labor market pooling is measured using the occupational similarity between the establishment's industry and the acquirer's primary industry. For each proxy of an establishment's reliance on coagglomeration externalities, the indicator variable *High Coagglomeration* is equal to one if the respective measure of an establishment's reliance on coagglomeration externalities is greater than the median for the respective measure. Each regression includes deal fixed effects. The control variables included in each regression include *OverlapVer*, *TarMainBus*, $IndR\&D$, $IndOpMargin$, *IndReturn*, *StateCoinIndex*, and *Redeployability*. We report t-statistics based on robust standard errors clustered at the deal level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Coagglomeration Measure		Vertical Relatedness	Tech Proximity	Occupational Similarity
	(1)	(2)	(3)	(4)
OverlapCity	0.023**	0.023*	0.012*	0.003
	(2.09)	(1.75)	(1.83)	(0.33)
High Coagglomeration		0.009	-0.132*	-0.003
		(0.37)	(-1.93)	(-0.21)
OverlapCity × *High Coagglomeration*		-0.000	0.020	0.036**
		(-0.03)	(1.03)	(2.40)
OverlapVer	-0.000	-0.000	0.002	-0.002
	(-0.01)	(-0.01)	(0.12)	(-0.12)
TarMainBus	0.058***	0.058***	0.054***	0.063***
	(3.18)	(3.09)	(3.06)	(3.29)
LocQuotient	0.010***	0.010***	0.010***	0.010***
	(3.97)	(3.95)	(3.91)	(3.66)
$IndR\&D_{agg}$	0.011	0.012	0.013*	0.008
	(1.37)	(1.45)	(1.67)	(0.92)
$IndOpMargin_{agg}$	-0.117	-0.118	-0.107	-0.103
	(-1.14)	(-1.16)	(-1.02)	(-0.96)
IndReturn	-0.051***	-0.051***	-0.053***	-0.045***
	(-4.32)	(-4.52)	(-4.77)	(-3.95)
StateCoinIndex	0.000	0.000	0.000	0.000
	(0.37)	(0.37)	(0.44)	(0.20)

Redeployability	-0.205	-0.202	-0.214	-0.205
	(-1.43)	(-1.44)	(-1.47)	(-1.37)
Constant	0.413***	0.407***	0.479***	0.428***
	(3.50)	(3.34)	(3.59)	(3.72)
Observations	15,516	15,516	15,456	15,200
R-squared	0.225	0.225	0.227	0.224
Deal FE	Yes	Yes	Yes	Yes