Varieties of Agglomeration: Disentangling Features of Horizontal and Vertical Agglomeration within the Manufacturing Sector in the United States

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Abstract

We introduce a novel measure of agglomeration that differentiates between horizontal (co-location with the own/peer industries) and vertical (co-location with suppliers) agglomeration. Using employment and establishment data at the US county level and the six-digit industry level, we demonstrate that industries and regions vary in their degree of vertical versus horizontal agglomeration. Industries with a higher contribution of manufactured goods to overall inputs' value are correlated with vertical agglomeration while more R&D intensive industries are correlated with horizontal agglomeration. Using the semiconductor industry as an example, we illustrate how heterogeneity in industry-county rates of vertical and horizontal agglomeration might reflect differences in the products that firms operating in different counties manufacture. These industry-level and within-industry differences are not observable with existing agglomeration measures. We present a new theoretical framework for regional and industrial policy interventions.

Keywords

Agglomeration; Manufacturing; Regional Economics; R&D; Production

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1. Introduction

Industrial activity, and manufacturing activity in particular, is distributed heterogeneously across regions in the United States. While Alfred Marshall's (1890) original concept of agglomeration mechanisms included knowledge sharing, thick labor markets, and supplier economies of scale all as reasons for co-location, measures of agglomeration have largely focused on own-industry agglomeration and pairs of industries co-locating together (Ellison et al., 2010), their knowledge spillovers (Feldman & Audrestch, 1999) and shared skilled labor requirements (Koo, 2005; Glaeser & Kerr, 2009). Co-location with firms in the same industry may be particularly important for sharing of industry-specific knowledge and skills. Similarly, the sharing of knowledge has been argued to be an important factor in co-location with suppliers. However, for suppliers that produce physical inputs, co-location with downstream manufacturers provides further benefits, such as minimizing transportation costs, offering benefits from economies of scale, and increasing the ability to enhance input components (Pisano & Shih, 2012).

In contrast to other sectors that are less dependent on physical inputs, all three Marshallian mechanisms of agglomeration are particularly salient in manufacturing. However, the importance of each mechanism may differ depending on the relative role of skilled labor, knowledge, transportation costs, and economies of scale in particular manufacturing industries. For example, semiconductors have high R&D expenditures and requirements but lower transportation costs. Whereas food production has lower R&D expenditures but higher transportation costs. Certainly, the distribution of contemporary manufacturing clusters in the US reflects the differential impact of these mechanisms. Manufacturing firms operating in certain industries might be more likely to benefit from regional coordination of supplier networks

(Helper & Henderson, 2014), while firms in other industries might be more inclined to co-locate to maximize knowledge spillovers and/or access to skilled labor (Audretsch & Feldman, 1996). The assets and strategies that support the former are likely meaningfully different than those that support the latter. *Marshallian equivalence* (Duranton & Puga, 2004), the argument that establishments in the same industry simultaneously benefit from all three mechanisms, is likely true, but current approaches make characterizing the different contributions of each of these mechanisms in different industries difficult.

We develop a novel and nuanced measure of agglomeration with *two components* that differentiate between horizontal (co-location with the own/peer industries) and vertical (co-location with suppliers) types of agglomeration. The first component accounts for co-locating near own-industry peer/competitor firms that produce similar outputs. Drawing on the literature from industrial organization, we define this as horizontal agglomeration. The second component accounts for co-locating near suppliers or customers in a value chain and is defined as vertical agglomeration. We present evidence that the synergies and unique conditions that bolster these two components of agglomeration are meaningfully different from one another. If we measure agglomeration as a single composite construct, we risk overlooking factors that distinctly contribute to the resilience and dynamism of regional economies.

This paper presents descriptive results of six-digit industry and US county-level heterogeneity in relative and absolute rates of horizontal and vertical agglomeration. Our measure combines employment and establishment data from the US Census County Business Pattern data with Bureau of Economic Analysis Input-Output Accounts National Use and Supply tables. We explore how industry differences in their extent of horizontal versus vertical

agglomeration are correlated with differences in those industries' manufactured share of inputs' value and their R&D intensity.

We find that industries with a higher contribution of manufactured goods to overall inputs' value are correlated with vertical (supplier) agglomeration while more R&D intensive industries are correlated with horizontal (peer) agglomeration. We observe significant heterogeneity in which industries and counties are highly horizontally agglomerated compared to those that are highly vertically agglomerated. At the regional level, we observe significant spatial variation in the level and type of agglomeration that regions appear able to support. Only specific regions support high levels of both horizontal and vertical agglomeration. Our new measure helps untangle the question of Marshallian equivalence, allowing for an investigation of how exposure to individual Marshallian mechanisms of agglomeration might result in meaningfully different varieties of agglomeration.

This paper is organized as follows. Section 2 reviews the literature and provides a conceptual framing for making advancements to the measurement of agglomeration; section 3 motivates the empirical focus on manufacturing; section 4 discusses data, and methods, and construction of agglomeration measures; section 5 reports the results; section 6 discusses the findings, considers policy implications, and concludes.

2. Literature Review and Conceptual Framing

An extensive literature on regional industry agglomerations suggests that their existence is correlated with economic growth and regional performance (e.g., employment growth, wage growth, patenting, and innovation; see Feldman, 1994; Porter, 2003; Boschma & Iammarino, 2009; Delgado et al., 2016, Hausmann et al., 2022). Multiple mechanisms drive agglomeration. To-date, the literature has focused on knowledge spillovers (Feldman & Audrestch, 1999;

Audrestch & Feldman, 2004) and skilled labor (Koo, 2005; Glaeser & Kerr, 2009). The location of suppliers is gaining importance as influencing regional resilience (Ter Wal & Boschma, 2007) and the literature has begun to explore regional input-output linkages among industries (Ellison, Glaeser & Kerr, 2010) and value chain co-location (Diodato, Neffke & O'Clery, 2018).

Foundational papers in industrial agglomeration (summarized in Table 1) have employed a range of approaches to measure and characterize the geographic concentration of economic activity. Ellison and Glaeser (1997) pioneered the use of a co-location metric based on industry shares and the Herfindahl index, capturing the extent to which industries are geographically clustered at the state level. Porter (2003) examined the economic performance of regions and the correlation between regional performance and geographic heterogeneity in industrial activity. He classified US industries into traded, local, and resource dependent based on the geographic distribution of employment (i.e., manufacturing industries are all traded). Subsequent work has refined and extended this approach, incorporating input-output linkages (Feser & Bergman, 2000; Ellison et al., 2010, Delgado et al., 2014), occupational composition (Delgado et al., 2014), and supply chain or business to consumer characterization (Delgado & Mills, 2020) to better understand the drivers and boundaries of industrial clusters. Viewing agglomeration activity from another angle, Boschma and Iammarino (2009) estimated the impact of regional variety and trade linkages on economic growth using regional import and export data to identify the impact of different types of agglomeration on economic growth. Similarly, Hausmann et al. (2022) measured the comparative advantage of specific locations based on employment, exports, and payroll, and estimated the correlation with industry-location heterogeneity and regional growth rates.

Table 1: Varieties of Agglomeration Literature Review

Paper	Core Aim	Metric	Methodology	Data	Sector	Geography
Ellison & Glaeser, 1997	Define a metric to measure industry co-location	Industry concentration is measured as a function of industry shares and the Herfindahl index in a region	Introduce theoretical model; report descriptive statistics of new metric	1987 US Census County Business Patterns (CBP)	459 manufacturing industries; SIC 4-digits	State Level
Feser & Bergman, 2000	Identify how industry relations based on input-output linkages	Define industry relatedness based on principle component analysis of correlations across industry input-output matrices	Define 23 clusters to describe how manufacturing sectors based on industry correlations vary across input-output tables. Present case study applying NC clusters	1987 Input-Output (IO) Accounts, 1992 Census of Manufactures	362 manufacturing industries; SIC 3 & 4-digits	Regions within North Carolina
Porter, 2003	Examine economic performance of regions and its correlation with geographic heterogeneity in industrial activity	Classify US industries into traded, local, and resource dependent based on geographic distribution of employment. Define clusters of traded industries based on statistically significant locational correlations in employment	Report descriptive statistics of regional heterogeneity outcomes; classify industries based on geographic distribution of employment; examine correlations of cluster strength and regional performance	1996 CBP Data, 1997 Economic Census	879 industries; SIC 4-digits	Economic Areas

Paper	Core Aim	Metric	Methodology	Data	Sector	Geography
Boschma & Iammarino, 2009	Estimate the impact of regional variety and trade linkages on economic growth	Define related and unrelated variety based on diversity of export portfolio. Assume three-digit export sectors that share 2-digit class understand each other (more opportunities for learning, knowledge spillovers, etc.)	Use regional export and import data to identify the impact of specific types of agglomeration. (diversified economies, related variety, and unrelated variety) on economic growth	Italian data from 1995-2003	121 industries ATECO-3 level	103 Italian provinces NUTS 3 level
Ellison & Glaeser, 2010	Assess determinants of industry agglomeration (aggl.); test Marshall's theories	Create pairwise coagglomeration (coaggl.) measure for mfg. industries based on plant location data that is a function of the share of employment in an area across industries	Report descriptive statistics for pairwise coaggl. measures for mfg. industries. Present regression of coaggl. index on input-output linkages, labor-correlation, and R&D linkages	1987 US Census of Mfg., 1987 IO Accounts, 1987 Bureau of Labor Statistics (BLS) National Ind. Occupation Emp. Matrix	122 manufacturing industries; SIC 3-digit	250-mile radius around a plant
Delgado, Porter & Stern, 2014	Define boundaries of clusters (i.e., how industries are related); compare clusters across locations	Determine industry relatedness based on pairwise industry co-location patterns using Economic Areas, correlation across IO links between industries (maximum of all unidirectional input and output links) and correlation across	Separates industries into traded and local categories using Porter, 2003. Classify 778 traded industries into 51 clusters based on industry correlations across employment, est., buyer-supplier	2009-2016 US CBP, 2002 IO Accounts, 2009 BLS Occupational Employment Statistics	778 industries; NAICS 6-digit	179 Economic Areas

		occupational composition of any two industries	linkages, and shared labor requirements			
Delgado, Porter & Stern, 2016	Investigate role of regional cluster composition in the performance of industries, clusters, and regions	Use measures of industry relatedness from Porter, 2003 and Delgado et al., 2014.	Estimate economic-area industry growth (in employment, establishment, patents) based on industry and cluster specialization	US Census County Business Pattern Data 1990–2005	778 industries; NAICS 6-digit	179 Economic Areas
Delgado & Mills, 2020	Quantify and characterize suppliers in the economy and examine role in economic growth and innovation	Traded or local industries are classified as supply chain industries if they sell less than 35 percent of the value of their output to personal consumption expenditures	Classify traded and local industries into supply chain or business to consumer (B2C) industries. Examine differences across growth, occupations, and patenting across sectors	1998–2015 US CBP; 2002 IO Accounts	978 industries; NAICS 6-digit	National
Hausmann et al., 2022	Measure comparative advantage of a location	Create industry and location similarity matrices based on employment, exports, and payroll, calculate implied and revealed comparative advantage for industry-locations	Create model to estimate implied comparative advantage; estimate regression on how this measure explains industry-location heterogeneity and correlates with growth	CBP data from 2003-2011	1086 industries; NAICS 6-digit	708 Commuting Zones

Overall, this research measures agglomeration as a *single index* and tends to use geographic heterogeneity in the concentration and composition of industrial activity to draw conclusions about industry agglomeration and relatedness at the national level. Accordingly, these measures are limited in their ability to capture how patterns of agglomeration for a single industry might vary across the regions in which that industry operates.

Generally, these measures focus on own-industry localization in specific areas. While the benefits from such own-industry agglomeration might be easier to measure and model, this focus ignores the presence of other related industries – especially suppliers. Firms within the same, or similar, industries might co-locate for historical reasons such as the presence of a large firm that generates spinoffs (Buenstorf & Klepper, 2010) or acts as an anchor-tenant (Agrawal & Cockburn, 2003). The Ellison and Glaeser co-agglomeration index (1997) focuses on identifying pairs of industries that consistently co-locate across geographies and not the full (and geographically heterogenous) set of industries that surround a focal industry in a specific region. Such a measure might be limited in its ability to capture regional supplier and production networks that span multiple industries (Carvalho & Taha-Salehi, 2019) and the role that such supplier networks play in mediating firm and regional outcomes (Bernard et al., 2019).

Moreover, the treatment of agglomeration as a single index does not account for the tradeoffs that firms face maximizing certain agglomeration benefits over others. As Alcácer and Chung (2007) demonstrate, technologically advanced firms may tend to locate near academic institutions, while less technologically advanced firms may tend to locate in areas of high industrial innovative activity. In other words, co-location to prioritize access to knowledge might require different strategies than co-location to coordinate a supplier network (Audrestch &

Feldman, 1996). Importantly, these preferences likely represent distinct constructs over which agglomeration can be measured.

Hence, we define a novel measure of agglomeration with two components that differentiate between the following: (1) *horizontal agglomeration* accounting for own and peer industry co-location patterns across firms that produce similar outputs; and (2) *vertical agglomeration* accounting for co-location patterns between suppliers and upstream companies (e.g., original equipment manufacturers). Each component directly reflects different Marshallian externalities that, in resource constrained settings, may represent concrete tradeoffs for firms in specific industries, producing specific technologies.

3. Empirical Context

The manufacturing sector serves as an illustrative and theoretically compelling exemplar to assess the distinct features and correlates of both forms of agglomeration. Despite the importance of physical location in manufacturing, existing approaches to study industrial agglomeration do not allow for a granular exploration of how patterns of agglomeration might vary within industries in the manufacturing sector and across geographies. Diodato, Neffke, and O'Clery (2018) find that manufacturing industries agglomerate differently than service industries. While Ellison et al. (2010) focus explicitly on the manufacturing sector, their approach is aggregated at the US state and three-digit SIC industry levels, obscuring more micro-geographic and industry specific effects.

Importantly, there is substantial variation in R&D intensity, reliance on physical inputs, value added, and labor intensity across manufacturing industries (Fuchs et al., 2020). Not only do different manufacturing industries produce distinct underlying products that have different labor, materials, or R&D requirements (Autor et al., 2013), but also, value chain linkages are more

clearly defined in manufacturing than compared to other sectors. For example, in software, firms might both be the customer of, and supplier to, other software firms.

In addition, there is substantial regional variation in manufacturing activity. Research on heterogeneity in manufacturing activity emphasizes the importance (and difficulty) of network formation between manufacturers and their surrounding institutions and highlights cases of network failure (Whitford, 2006; Shrank & Whitford, 2011). This literature specifically highlights the importance of relational contracts in mediating firm outcomes (Helper & Henderson, 2014), as well as regional variation in the strength and quality of these relational contracts (Safford, 2009). Existing research also describes substantial regional variation in innovative activity in manufacturing. Some states have higher rates of innovation than others, and certain regions might exhibit a greater intensity of knowledge spillovers than others (Audretsch & Feldman, 1996). This especially holds when research universities co-locate with large anchor firms (Delgado, 2020; Agarwal & Cockburn, 2003; Audrestch & Feldman, 2004; Acs et al., 1994). Altogether, the manufacturing sector presents a rich and varied empirical context in which to study how different industries and regions agglomerate vertically as opposed to horizontally.

4. Design

4.1 Data

We combine employment and establishment data from the US Census County Business Patterns (CBP) with commodity use and supply data from the Bureau of Economic Analysis (BEA) Input-Output (IO) Accounts. The former reports county-level economic data for establishments with paid employees by industry and employment size. This source serves as a foundation for understanding the distribution of the manufacturing sector across various counties

in the US. The latter reports how industries interact with each other and the economy. This source provides a comprehensive framework that illustrates the interactions among industries and depicts the flow of goods and services through production processes.

These sources have been extensively used in prior scholarship to study how industries are related to one another. Feser and Bergman (2000) used IO Accounts data from 1987 to understand how industries relate to one another based on a principal component analysis of industry correlation in use of similar inputs, production of similar outputs, and similar buying-selling patterns. Delgado et al. (2014; 2016) used IO Accounts data from 2002 to capture which industries share common inputs or produce common outputs. Moreover, they also used CBP data through 2016 to measure which industries co-locate together. Hausmann et al. (2022) used CBP data through 2011 to estimate the implied comparative advantage in a particular sector for a given region.

Linking these two databases together involves connecting manufacturing establishments reported in the CBP data to their corresponding details in the IO Accounts. Usefully, the heterogenous nature of manufacturing activity described in the CBP data provides a way to observe geographic variation in which industries co-locate. This linkage between CBP and IO Account data can be used to examine how a given industry produces similar outputs to the set of industries that are within some geographic radius. This comparison enables us to assess peer effects and, hence, *horizontal* agglomeration. Additionally, this linkage can be further augmented by combining the use and supply tables in the IO Accounts to explore which industries within a geographic radius might supply a focal industry. This augmentation allows us to assess supply-chain effects and, hence, *vertical agglomeration*.

These linkages come with limitations. Namely, IO Accounts data are national and do not detail regional differences in the use and supply of various commodities.[1] Moreover, certain CBP data may be suppressed due to limited sample size by six-digit NAICS and county-level specification. Nevertheless, CBP does provide an estimation of the total size and composition of regional manufacturing activity.

Operationally, we utilize CBP data from 2019 and IO Accounts data from 2017.[2] The latter covers the domestic supply and use of commodities by 405 industries in addition to the dollar value of the output and use of commodities.[3] Together, these data allow for the construction of a more current measure of manufacturing agglomeration in the US, and the data enable us to unpack the distinct features of both horizontal and vertical agglomeration.

4.2 Construction of Measures

For a given industry (i), let X_i be the vector of commodities that industry (i) purchases as intermediate *inputs* (minus imports). Let Y_i be the vector of commodities that industry (i) *outputs* (minus exports). Following Feser and Bergman (2000), we measure the correlation between the vector of outputs across each two-way industry pairing, as well as the correlation between the inputs used and outputs supplied. By focusing on the manufacturing sector, we limit our analysis to the 232 manufacturing industries described in the IO Accounts data. These 232 industries output a total of 255 commodities and use a total of 326 commodities as intermediate inputs. We discuss the construction of each measure in turn.

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[1] For example, the IO Account data detail that semiconductor and related device manufacturing (NAICS 334413) uses a variety of inputs, including commodity code non-ferrous metal (except aluminum) smelting and refining (NAICS 331410). However, these data do not cover any regional variation in how the semiconductor manufacturing sector uses nonferrous metal.

[2] We limit our analysis to the most current data available before 2020 to ensure that our analysis is not skewed by changes in the configuration of US manufacturing activity that occurred during and after the COVID-19 pandemic.

[3] Refer to Appendix B1 for more detail.

We follow Feser and Bergman's (2000) estimation of industry correlation in the production of common outputs to guide the estimation of the horizontal agglomeration measure. Moreover, we create a new measure of the degree to which one industry supplies another to guide the estimation of the vertical agglomeration measure. Regarding the former, we define the horizontal distance between two industries (i) and (j) by the correlation between an industry (i)'s vector of outputs and industry (j)'s vector of outputs, denoted by $R(y_i, y_j)$. As for the latter, we define the vertical distance between two industries by the share of an industry (i)'s vector of inputs that is produced by another industry (j), denoted by $R(x_i, y_j)$.

4.2.1 Construction of Horizontal Distance

Let $\mathbf{Y_{i,\,k}}$ be a matrix with columns representing industries and the rows representing the value of the commodities that these industries output. For the manufacturing sector, the input-output supply table data yields a matrix of 232 manufacturing industries (i) by their output of 255 commodities (k) (232 x 255 matrix). To measure the degree to which two industries produce common outputs, we measure the correlation between the vector of outputs produced by industry (i) and the vector of outputs produced by other industries (j). An individual entry in this vector is defined as the share of the total value of commodity (k) produced by manufacturing industry (i). We focus on the derivation of $R(y_i, y_j)$, or the correlation between the output vector of industry (i) with industry (j).

To contextualize the calculation of this correlation, we illustrate with the case of the semiconductor and related devices manufacturing industry (NAICS 334413). This industry produces 23 outputs, the majority of which are semiconductor and related devices followed by scientific R&D.[4] We measure the correlation between the industry in question (NAICS 334413)

[4] Refer to Appendix B2 for list of outputs.

and the set of industries that account for at least 20 percent of the total value of their production of outputs;[5] we assume all other industries are uncorrelated. In this case, the leading correlated industries include: (1) printed circuit assembly electronic assembly manufacturing (NAICS 334418); (2) electricity and signal testing instruments manufacturing (NAICS 334515); (3) search detection and navigation instrument manufacturing (NAICS 334511); (4) other electronic component manufacturing (NAICS 334410); and (5) telephone apparatus manufacturing (334210). We repeat this procedure for each industry code accordingly.

4.2.2 Construction of Vertical Distance

Let $\mathbf{X_{i,\,k}}$ be a matrix with columns representing industries and the rows representing the value of the commodities that these industries use. For the manufacturing sector, the input-output supply table results in a matrix of 232 manufacturing industries (i) by their use of 326 commodities (k) (232 x 326 matrix). To measure the production of outputs used as inputs by another industry, we measure the correlation between the vector of inputs used by industry (i) and the vector of outputs produced by industry (j). We focus on the derivation of $R(x_i, y_j)$, or the correlation between the input vector of industry (i) and the output vector of industry (j). Again, we illustrate with the case of the semiconductor and related devices manufacturing industry (NAICS 334413). This industry uses 109 different inputs, the majority of which come from semiconductor and related devices sector, followed by nonferrous metal manufacturing sector. Of these, 67 percent are produced by the manufacturing sector. To account for the fact that some products are used more as intermediate inputs, we adjust the vector with a weight to account for the total share of the value of each commodity that is used as an intermediate input

[5] We base the total value of their production of outputs from the set of commodities produced by this industry. Most industries do not produce the same set of outputs as this industry. We determined the value of 20 percent through random sampling of industry distributions and the persistence of a clear cut-off across industries.

(the next section offers more detail). For each other industry (j), we calculate the share of the vector of manufactured inputs used by the focal industry that industry (j) produces. We focus on industries that supply at least one percent of the total value of the vector of commodities used by the focal industry.[6] We assume other industries are uncorrelated. In this case, the top correlated industries include: (1) semiconductor and related device manufacturing (NAICS 334413); (2) search, detection, and navigation instruments manufacturing (NAICS 334511); (3) printed circuit assembly electronic assembly manufacturing (NAICS 334418); (4) nonferrous metal except aluminum smelting and refining (NAICS 331410); and (5) electronic component manufacturing (NAICS 334111). Again, we repeat this procedure for each industry code accordingly.

4.2.3 Geographic Weighting

Let the construct $E_{i,c}$ represent the employment or establishments of industry (i) in county (c). Let $E_{i,n}$ represent the employment or establishments of industry (i) across the nation (n). The geographic weight, $S_{i,c}$, is the share of a given industry in a specific county as a percent of total industry activity, as specified in equation 1.

$$S_{i,c} = \frac{E_{i,c}}{E_{i,n}} \qquad \text{(Eq. 1)}$$

We do not include county-level normalizations to account for the fact that economic activity varies across geography. Of note, we are interested in the extent to which each industry, in each county, is surrounded by firms that either produce common outputs (horizontal agglomeration) or supply needed inputs (vertical agglomeration).[7]

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[6] The cutoff of one percent of the total value of commodities used (for our measure of vertical agglomeration) and of twenty of the value of set of output commodities supplied (for our measure of horizontal agglomeration) are both designed to capture at least 90% of non-zero observations.

[7] The Ellison, Glaeser, and Kerr (2010) measure of co-agglomeration between two industries is not appropriate in this context for several reasons. First, we are not concerned about the relationship between any two industries. Second, we are not concerned if industries locate near each other randomly.

4.2.4 Measures of Agglomeration

Formally, we define *agglomeration* as the co-location of a given industry (*i*) with *all other industries* within a specific geographic radius of industry (*i*). The horizontal and vertical dimensions of agglomeration report the average horizontal and vertical geographical weighting of all industries within the geographic radius of the focal industry (*i*), respectively.

$$\tau_{i,c} = \frac{1}{|\theta_{i,c}|}\sum_{j}^{\theta}(S_{j,c} * R(x_i, y_j)), \qquad \text{(Eq. 2)}$$

$$\phi_{i,c} = = \frac{1}{|\theta_{i,c}|}\sum_{j}^{\theta}(S_{j,c} * R(y_i, y_j)), \quad \text{(Eq. 3)}$$

$(\theta_{i,c})$ represents the set of industries within some set geographical radius of the focal industry (*i*) in the focal county (*c*). Accordingly, $(\tau_{i,c})$ represents the vertical agglomeration of industry (*i*) in county (*c*); and $(\phi_{i,c})$ represents the horizontal agglomeration of industry (*i*) in county (*c*).

5. Results

Here, we unpack county and industry heterogeneity in the rates of horizontal and vertical agglomeration across the US. Consistent with prior research, certain counties with large populations are more agglomerated overall than others (Feldman, 1994; Glaeser et al., 2016). Though, while highly correlated with one another (0.83), horizontal and vertical agglomeration are not the same. While some counties have high rates of both, counties and industries that have high rates of horizontal agglomeration do not necessarily have high rates of vertical agglomeration.[8] Second, we find that industries vary in their relative and absolute rates of horizontal and vertical agglomeration across the counties in which they operate. Third, we

[8] Out of the total 1,899 counties in our data, 47 percent have relatively high rates of both vertical and horizontal agglomeration compared to the national average; 38 percent have relatively low rates of both horizontal and vertical agglomeration; while just over 5 percent of counties have relatively high rates of horizontal agglomeration but low rates of vertical agglomeration; and just under 10 percent of counties have relatively high rates of vertical agglomeration but low rates of horizontal agglomeration.

explore how both relative and absolute rates of horizontal and vertical agglomeration correlate with industrial characteristics, specifically the manufactured share of inputs' value and the R&D intensity.

5.1 Geographic Trends of Agglomeration

Figure 1 shows county-normalized values for horizontal and vertical agglomeration. Using a four-color schematic, we illustrate how county-level average rates of horizontal versus vertical agglomeration vary across geographies. Blue denotes counties correlated with high horizontal *and* vertical agglomeration; green denotes counties correlated with relatively high vertical agglomeration (and relatively low horizontal agglomeration); pink denotes counties correlated with relatively high horizontal agglomeration (and relatively low vertical agglomeration); and gold depicts counties with relatively low levels of both horizontal and vertical agglomeration.[9] There is a substantial skew in rates of horizontal and vertical agglomeration with the largest counties and surrounding regions having 20 to 30 times greater average rates of both horizontal and vertical agglomeration than the corresponding mean rate of agglomeration across the country. This underlying skew towards large population centers with many industries reflects heightened levels of employment generally and industrial employment specifically (as can be seen by the distribution of blue areas). For example, agglomeration rates (both horizontal and vertical) in San Diego, California and Los Angeles, California are over 500x

[9] To divide counties into these four categories, we take the county-mean level of horizontal and vertical agglomeration across all the industries that operate in that county. We then log-normalize these variables to create a measure of the "elasticity" of agglomeration for the county (e.g., a higher elasticity means county-returns to agglomeration might be higher than the cost of such agglomeration). We then standardize these variables to center them around the mean-county-level horizontal and vertical agglomeration across the data. Counties that have equal to or greater than average horizontal and vertical agglomeration are considered *generally* agglomerated. Counties that have lower than average horizontal and vertical agglomeration are *low* agglomerated. Counties that have equal or greater than average vertical agglomeration but less than average horizontal agglomeration are *supplier* agglomerated, and counties that have equal or greater than average horizontal but less than average vertical agglomeration are considered *peer* agglomerated.

times greater than agglomeration rates in smaller counties, such as Mesa County, Colorado.[10] The set of counties that appear to differentially support horizontal or vertical agglomeration likely warrant their own attention. These types of counties appear to be near generally high agglomerated counties, but only in specific regions (e.g., low horizontal and high vertical agglomeration in Louisiana; high horizontal and low vertical agglomeration around Portland, Oregon and Seattle, Washington). Areas with only high vertical agglomeration or only high horizontal agglomeration are not as geographically contiguous to one another compared against counties that have both.

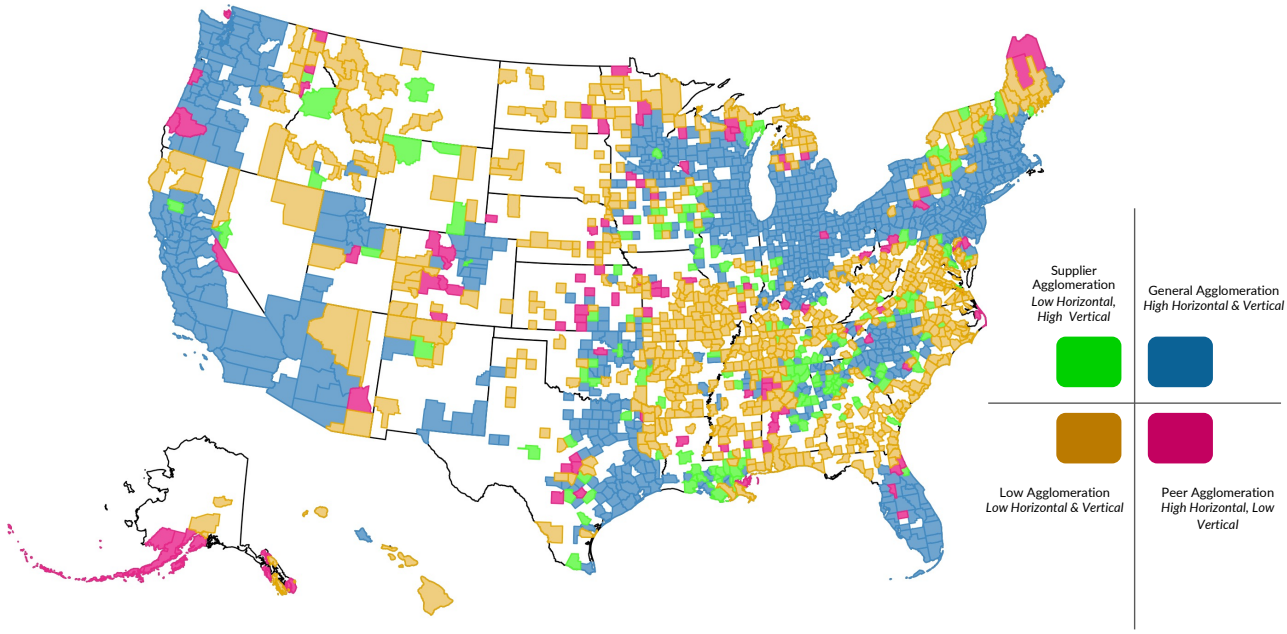


Figure 1: Geographic Patterns of Horizontal and Vertical Agglomeration: Counties are grouped into one of four groups based on their mean levels of horizontal and vertical agglomeration relative to the national average. Green denotes relatively low horizontal but relatively high vertical agglomeration (supplier agglomeration), blue denotes relatively high levels of both horizontal and vertical agglomeration, gold denotes relatively low levels of both horizontal and vertical agglomeration, and pink denotes relatively high levels of horizontal

[10] Appendix Table A1 reports the leading and lagging horizontally and vertically agglomerated counties. While the leading counties of both types of agglomeration are the same, we see that different sets of counties are at the lowest end of the distribution of county-level horizontal and vertical agglomeration. Large counties with high rates of economic activity have higher rates of agglomeration than other counties. In addition, more remote locations with lower rates of economic activity and smaller populations have lower rates of agglomeration than others.

agglomeration and low levels of vertical agglomeration. Areas in white are areas without manufacturing activity.

Previous literature has primarily focused on industry trends, aggregating over counties that industries are present in to draw industry-level conclusions (Delgado et al., 2016; Ellison et al., 2010). Our novel measure with two components differentiating horizontal and vertical agglomeration at the county and six-digit NAICS level enables us to assess geographic heterogeneity in absolute and relative rates of horizontal and/or vertical agglomeration. Moreover, we can account for variation both across industries, as well as within a single industry across different counties.

5.2 Considerations of the Skew

We next unpack industry-level heterogeneity in rates of horizontal and vertical agglomeration. To account for the skew, we benchmark measures of horizontal and vertical agglomeration at the industry and county level against the mean-level of horizontal and vertical agglomeration in that county, respectively. These county-level means are the same values visualized in Figure 1. In this way, large and small counties are benchmarked separately, and this county-normalization technique allows for a meaningful comparison of rates of horizontal and vertical agglomeration across counties of different sizes with different levels of baseline economic activity.

In doing so, a clear trend emerges. Different county-industry pairings have higher rates of vertical agglomeration relative to the county average than the county-industry pairings that have higher rates of horizontal agglomeration relative to the county average. We report exemplars of these trends in Table 2. For example, guided missile and space vehicle manufacturing in Pima County, Arizona is one of the highest vertically and horizontally agglomerated industries. Ready-mix concrete manufacturing, on the other hand, is a low vertically and horizontally agglomerated

industry. However, within this industry, different *counties* are the lowest vertically agglomerated compared to those that are the lowest horizontally agglomerated. Notably, at the middle of the distribution, there is almost no overlap across both geographies and industries between the county industry pairings at the average level of horizontal agglomeration and those at the average level of vertical agglomeration. These findings provide further evidence of differential county-level and industry-level effects of horizontal and vertical agglomeration that warrant further investigation.

Table 2: Exemplars of agglomerated county-industry pairings

	Vertical Agglomeration	Horizontal Agglomeration
County Industry Pairings with High Values of Agglomeration	**Motor Vehicle Engine & Engine Parts:** Jackson County, Missouri **Guided Missile & Space Vehicle Manufacturing**, Pima County, Arizona; **Laminated Plastics Plate & Sheet Manufacturing**, Clark County, Nevada; **Ophthalmic Goods Manufacturing**, Salt Lake County, Utah; **Ice Cream & Frozen Desert Manufacturing**, Montgomery County, Pennsylvania	**Aircraft Manufacturing**, King County, Washington; **Broadcast & Wireless Communications**, Maricopa, Arizona; **Carbon & Graphite,** Salt Lake County, Utah; **Guided Missile & Space Vehicle Manufacturing**, Pima County, Arizona; **Textile & Fabric Finishing**, Mecklenburg County, North Carolina
County-Industry Pairings with Average Values of Agglomeration	**Machine Shops**, Peoria County, Illinois; **All Other Wood Product Manufacturing**, Deschutes County, Oregon; **Coatings, Engraving, Heat Treating**, Marion County, Indiana; **Bread and Bakery Product Manufacturing**, Hillsborough County, Florida;	**Other Fabricated Metal Manufacturing**; San Mateo County, California; **Sign Manufacturing,** Ottawa County, Michigan; **Plate Work and Fabricated Structure Manufacturing**, Broome County, New York; **Plastics Packaging Materials and Unlaminated Film/Sheet**

	Showcase Partition, Shelving, and Locker Manufacturing, Kings County, New York	**Manufacturing**, Hartford County, California; **Nonferrous Metal Foundries**, Wayne County, Michigan
County-Industry pairings with Low Values of Agglomeration	**Ready Mix Concrete Manufacturing**, Kankakee County Illinois; Lebanon County Pennsylvania; Rockland County, New York; **Sawmills & Wood Preservation**, Franklin County, Pennsylvania; Cattaraugus County, New York	**Dental laboratories**, Washington County MN; Thurstan County WA; **Ready Mix Concrete Manufacturing**, Dodge County Wisconsin; Sherburne County Minnesota; **Veneer Plywood and Engineered Wood Products**, Dekalb County, Illinois

5.3 Local Industry Level Heterogeneity

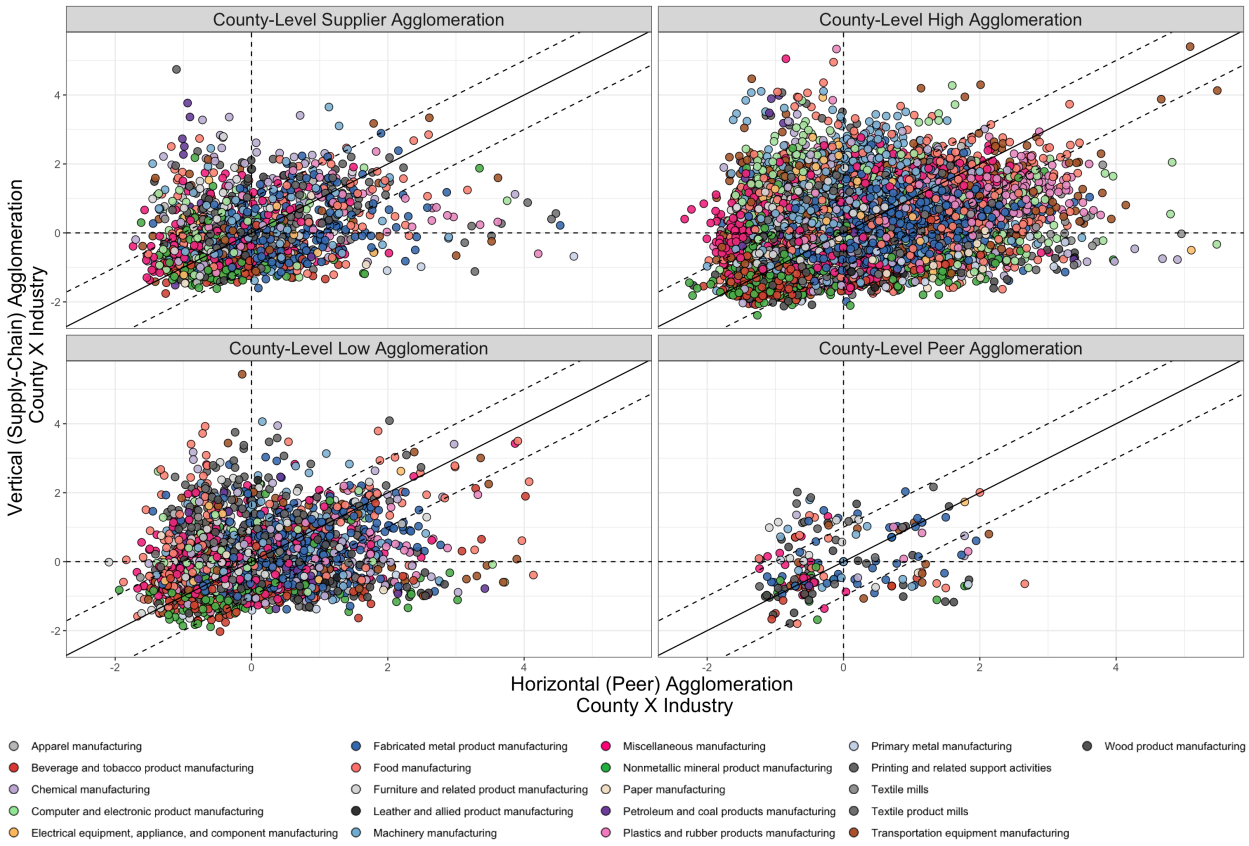
Following the four categories of county-level horizontal and vertical agglomeration as reported in Figure 1, we explore industry and county level heterogeneity in the distribution of horizontal and vertical rates of agglomeration. Let us define the county-normalized relative rate of horizontal (vertical) agglomeration for a specific industry in a specific county as the local industry rate of horizontal (vertical) agglomeration. Figure 2plots local industry values of horizontal and vertical agglomeration for each manufacturing industry, across each of the counties in which that industry operates.[11] As discussed above, this county-normalization allows for a more meaningful visualization of the high dimensional[12] heterogeneity in rates of vertical and horizontal agglomeration across industries and counties. We segment the results into four

[11] County normalization centers each industry-county value against the average value of agglomeration for a county, across all industries that operate in that county. In this way, counties with higher average rates of agglomeration (due to a high density of economic activity in general) do not dominate much smaller counties. This county normalization can be thought of as adaptation of an adjustment used by Ellison, Glaeser, and Kerr (2010) in their effort to measure of co-agglomeration, which benchmarks industry share of economic activity against the average county share of manufacturing activity. In this work, we benchmark industry agglomeration against average county agglomeration.

[12] Our data contain more than 20,000 observations about over 200 industries operating across over 1,800 counties. Industry and county level heterogeneity is accordingly high-dimensional.

quadrants based on the county-level average rate of horizontal and vertical agglomeration.[13] Each dot represents a manufacturing industry in a specific county, where values are normalized relative to the county-means. Accordingly, a zero value denotes agglomeration exactly at the county-mean level of agglomeration with units being standard deviations from the mean (i.e., z-score). The solid diagonal line highlights where there exists a one-to-one ratio of horizontal to vertical agglomeration, and the dotted diagonal lines demark one standard deviation above and below that one-to-one ratio.

Figure 2: County and Industry Trends of Horizontal and vertical agglomeration



Notes: County and industry-level rates of horizontal and vertical agglomeration for all industries and counties are reported, segmented into four quadrants. The upper right quadrant corresponds to high agglomeration counties (the blue counties from Figure 1) that have higher rates of vertical and horizontal agglomeration than the national average. The lower left quadrant corresponds with low agglomeration counties (the gold counties from Figure 1) that have lower rates of vertical and horizontal agglomeration than the national average. The upper left quadrant

[13] A version of this figure without segmentation into four quadrants can be found in Appendix Figure A1.

corresponds with counties that have higher rates of vertical agglomeration than the national average, but lower rates of horizontal agglomeration (the green counties from Figure 1); while the lower right quadrant corresponds with counties that have lower rates of vertical agglomeration than the national average, but higher rates of horizontal agglomeration (the pink counties from Figure 1). Each dot represents an individual manufacturing industry, where values are normalized relative to the county-means. Accordingly, a zero value denotes agglomeration exactly at the county-mean level of agglomeration, with units being standard deviations from the mean. The solid diagonal line highlights where there exists a one-to-one ratio of horizontal to vertical agglomeration, and the dotted diagonal lines demark one standard deviation above and below that one-to-one ratio.

We color code each county-industry observation by the NAICS three-digit manufacturing family to which the industry belongs (e.g., apparel manufacturing; electronics equipment manufacturing; and transportation equipment manufacturing). We observe significant variation in the patterns of horizontal and vertical agglomeration across both industries and counties. There appears to be some clustering of observations that belong to the same NAICS three-digit manufacturing family, such as a clump of relatively higher vertically agglomerated machinery manufacturing activity in high agglomerated counties (reported in light blue). Moreover, there appears to be a substantial selection effect, where certain industries are only present in counties with certain levels of agglomeration. High agglomerated areas tend to have a diversity of manufacturing activity (more than 100 active manufacturing industries), and certain industries (i.e., machine shops) are present in all types of counties. However, certain industries, such as petrochemical manufacturing, are exclusively active in counties with generally high levels of agglomeration.[14]

To help conceptualize these county and industry level differences in patterns of agglomeration, we consider three exemplar manufacturing industries known to be significantly different from one another (Fuchs et al., 2020). They include: (1) seafood product preparation

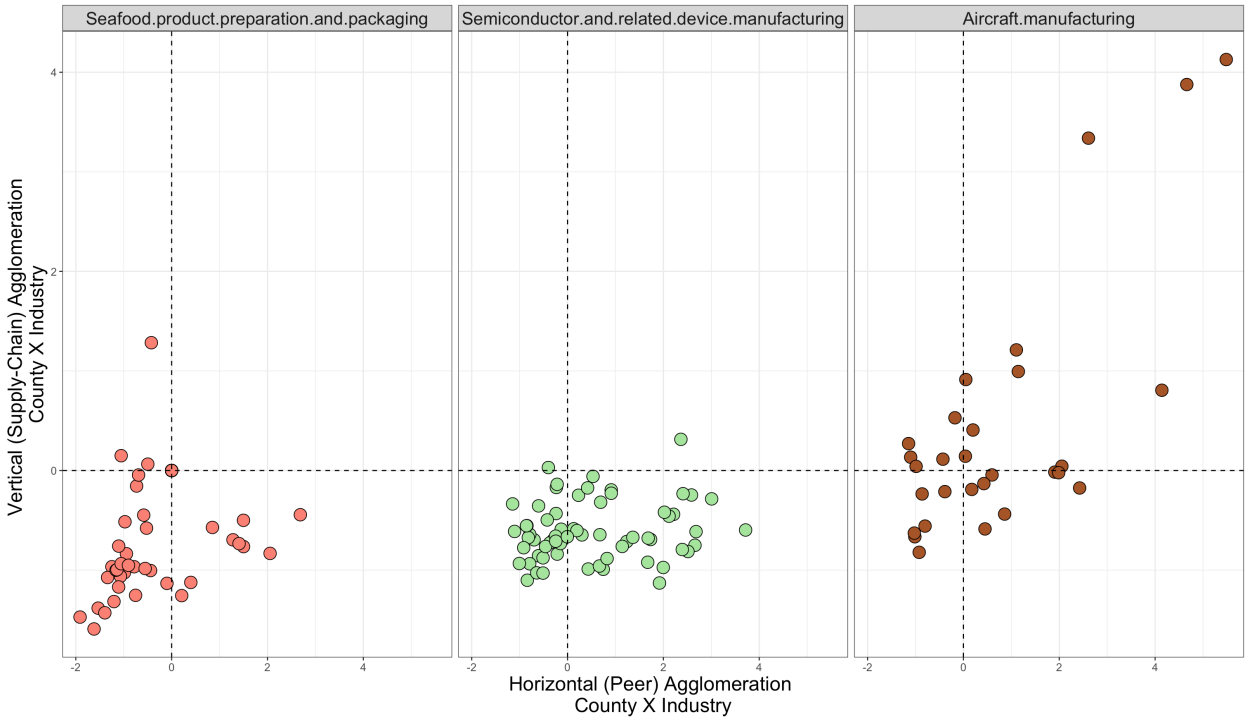
[14] Alumina refining and production is only present in supplier-agglomerated counties, but other industries are distributed over all types of counties.

and packaging (311700), (2) aircraft manufacturing (336411), and (3) semiconductor manufacturing (334413) (Figure 3). These industries have different global supply chains, different R&D requirements, different supplier networks and relationships, and different labor requirements. Seafood product preparation is relatively labor intensive, with lower values of R&D output; semiconductor manufacturing has very high value R&D output and a globalized and segmented supply-chain; and aircraft manufacturing, requiring many manufactured components as inputs, is dominated by large firms and has high value R&D output. The patterns of agglomeration across these industries are substantially different. Moreover, the center and shape of the distribution of horizontal and vertical agglomeration for these three industries varies.

While all three industries are mostly located in high agglomeration counties, aircraft manufacturing appears to be located in higher horizontally and vertically agglomerated counties (e.g., Snohomish County, Washington; King County, Washington; and Sedgwick County, Kansas). In addition, we notice that these counties are home to large aircraft manufacturing companies (e.g., Boeing) that make up for a significant amount of employment and manufacturing activity in these counties. For semiconductor manufacturing, the local rate of vertical agglomeration is consistently lower than the county-average across almost all the counties in which semiconductor manufacturing is active. However, the local rate of horizontal agglomeration in many counties with semiconductor manufacturing activity is higher than the county-average rate of horizontal agglomeration. We also notice that seafood preparation and packaging has a tighter distribution of rates of local horizontal and vertical agglomeration than either aircraft manufacturing or semiconductor manufacturing. Moreover, the counties with seafood preparation and packaging tend to be, on average, on the lower end of the set of high

horizontally and vertically agglomerated counties, especially compared to the counties with semiconductor and aircraft manufacturing.[15] This comparison of local rates of horizontal and vertical agglomeration across three industries serves to demonstrate how our novel measure can be used as a diagnostic to identify and categorize heterogeneity in the economic activity of specific industries operating in specific counties. In the next section, we begin to unpack some of the correlates of the industry-level heterogeneity in our data.

Figure 3: Variation in rates of horizontal and vertical agglomeration across select industries



Notes: County-normalized values of horizontal and vertical agglomeration for the Seafood product preparation and packaging, Semiconductor, and Aircraft manufacturing industries. Observations are colored based on their 3-digit NAICS code. Each dot represents an individual manufacturing industry, where values are normalized relative to the county-means. Accordingly, a zero value denotes agglomeration exactly at the county-mean level of agglomeration, with units being standard deviations from the mean, denoted by the dotted lines

[15]Counties where seafood manufacturing occurs have, on average, 39 percent the rate of horizontal agglomeration of counties where semiconductor manufacturing occurs, and 29 percent the rate of horizontal agglomeration of counties where aircraft manufacturing occurs. Counties where seafood manufacturing occurs have, on average, 29 percent the rate of vertical agglomeration of counties where semiconductor manufacturing occurs, and 13 percent the rate of vertical agglomeration of counties where aircraft manufacturing occurs.

5.4 Correlates of Horizontal and Vertical Agglomeration – Regression Assessment

5.4.1 Empirical Approach

In exploring the underlying correlates between both relative and absolute rates of horizontal and vertical agglomeration, we return to the literature on the heterogeneity in industrial characteristics and Marshallian mechanisms. As previously discussed, manufacturing industries vary in their position along the value chain (Alcácer & Chung, 2007), labor intensity, R&D intensity (Fuchs et al., 2020), the degree to which they depend on suppliers (Audretsch & Feldman, 1996), and the global nature of supply chains (Acemoglu et al., 2016). Existing research on agglomeration reveals that the benefits from co-location that industries seek to maximize (and the costs that these industries face) might vary across these different industrial characteristics. By measuring agglomeration across our two components of agglomeration, we can observe and characterize how industries with specific technological characteristics (e.g., highly R&D intensive industries with globalized supply chains such as semiconductor manufacturing) agglomerate differentially from industries with different technological characteristics (e.g., lower R&D intensive industry focused more on production such as food manufacturing).

To set up this analysis, we differentiate between industries with a higher manufactured share of inputs' value versus R&D intensive industries. Such a differentiation dates back to Pavitt (1984), who created a taxonomy for understanding sectoral rates of technical change, differentiating between supplier dominated, production intensive, and science based industries.[16] Of note, it is not entirely clear how high value-added and R&D intensive manufacturing

[16] Similarly, Hauknes, and Knell (2009) differentiate between technology producing and technology using industries. The latter tend to require specialized supplier relationships and there is heterogeneity in the role that industries play in the production, diffusion, and use of technology. Within manufacturing, the importance of regional supplier relations (Helper & Henderson, 2014) suggests that even with low transportation costs, manufacturing firms that rely on complex assemblies or components might especially benefit from locating near suppliers.

industries might agglomerate. On the one hand, Alcácer and Chung (2007) find that more technologically advanced firms might locate away from industrial centers and closer to academic institutions, while less technological advanced firms locate in areas of high industry activity. As such, we expect that firms operating in R&D intensive industries may be less likely to agglomerate in general. On the other hand, Agarwal and Cockburn (2003) identify how the presence of a large anchor firm in a region contributes to the commercialization of university research and rates of industrial R&D, suggesting that certain areas might become R&D hotspots and attract peer firms seeking to maximize access to R&D and knowledge spillovers. Drawing on this literature, we compile a set of constructs that captures some of the common differences in characteristics between manufacturing sectors (Appendix Table A2).

We continue to use CBP data for the geographic distribution of manufacturing activity and IO Accounts data for variation in how industries use or supply different commodities. However, we also include four measures of industrial characteristics: (1) employment intensity, measuring the industry share of national employment; (2) local economic activity, reporting the county employment location quotient; (3) R&D intensity, reporting the industry share of value of total manufacturing R&D; and (4) manufactured share of inputs' value, reporting the share value of intermediate inputs from the manufacturing sector. Figure 4 illustrates how these constructs capture heterogeneity in industrial characteristics; here, we report R&D intensity along the x-axis and the manufactured share of inputs' value along the y-axis. These measures serve as proxies to capture heterogeneity in the characteristics of technologies produced by each manufacturing sector and represent theoretical opposites along the spectrum of Marshallian benefits that companies might seek to maximize in their choice of location.[17]

[17] We report the distribution of rates of horizontal and vertical agglomeration for the exemplar industries denoted in Figure 4 in Appendix Figure A2.

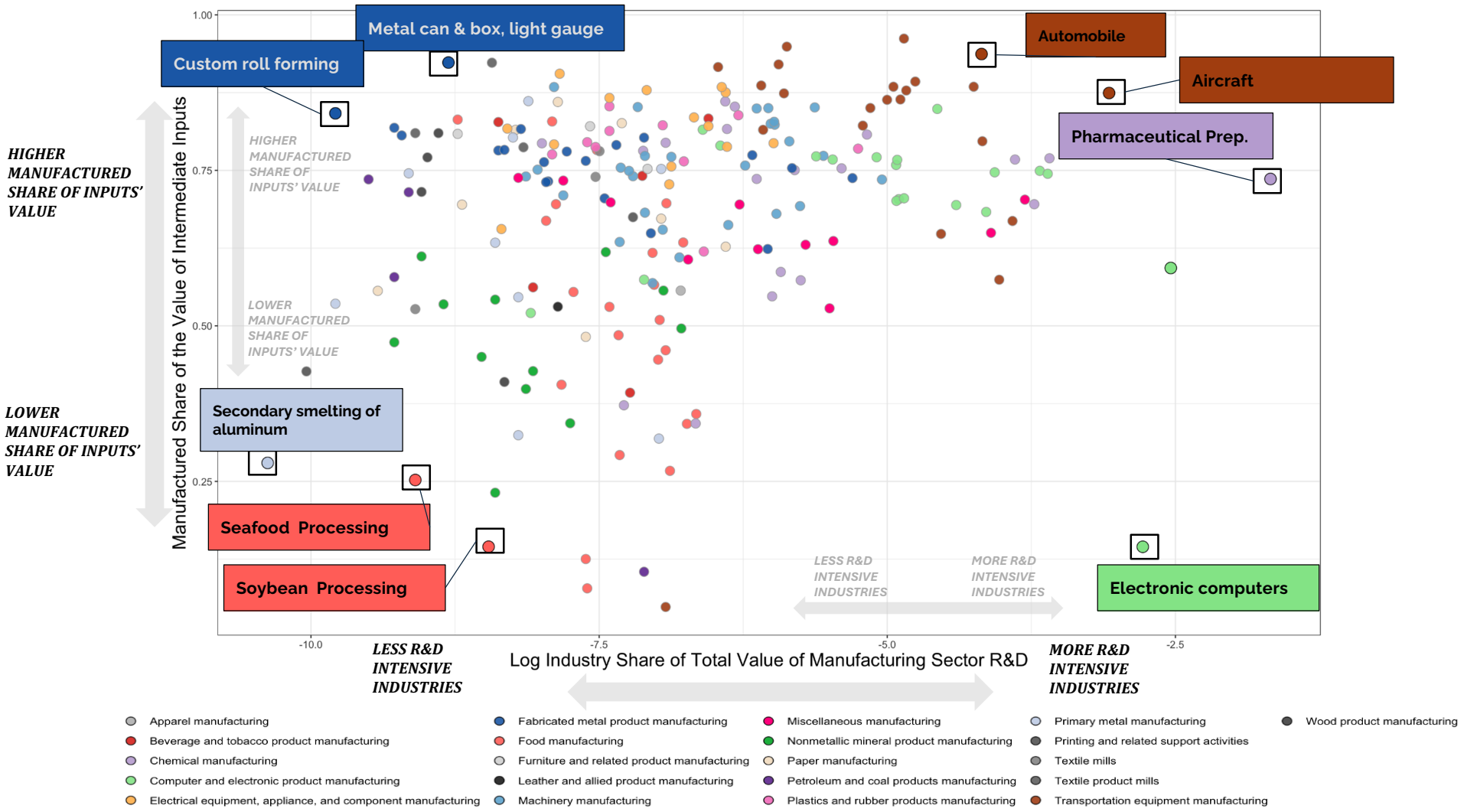


Figure 4: Manufatured Share of Inputs' Value and R&D intensity of each manufacturing industry: Six-digit Industry level log industry share of total value of manufacturing sector R&D (x-axis) plotted against the 6-digit industry level manufactured share of the value of intermediate inputs (y-axis); colors correspond to 3-digit NAICS codes.

For the regression analysis, we return to the raw values of our measures of agglomeration (i.e., without county-normalizing). We aim to understand some of the main correlates between horizontal and vertical agglomeration and the degree to which their correlates differ.

Table 3 reports the summary statistics (Appendix Table A3 reports correlation matrix). Our data covers 20,490 observations (at the county and industry level) and details activity in 229 industries active across 1,899 counties (with an average of approximately 11 industries per county).

Table 3: Summary Statistics for Regression Analysis

	Functional Form	Mean	SD	Min	Max	N
Panel A: DV						
Horizontal Agglomeration	Raw Value	1.05	1.97	0	30.95	20490
	Winsorized	1.01	1.68	0	10.90	
	Normalized	0	1	-0.6	5.9	
Vertical Agglomeration	Raw Value	0.53	1.23	0	21.97	
	Winsorized	0.51	1.04	0	6.88	20490
	Normalized	0	1	-0.49	6.12	
Panel B: Regressors						
R&D Intensity (Industry Share of Total Manufacturing Sector R&D)	Raw Value	0.4%	1.5%	0	18.7%	229
	Winsorized	0.4%	0.8%	0	5.7%	229
Manufacturing Share of Inputs' Value (% Value of Intermediate Inputs from the Manufacturing Sector)	Raw Value	68.9%	17.7%	4.8%	96.2%	229
	Winsorized	68.9%	17.8%	4.8%	93.3%	229
Industry Share of National Employment	Raw Value	81,335	92,537	117	367,019	229
	Winsorized	78,907	85,422	117	314,708	229
County Employment Location Quotient	Raw Value	1.00	1.87	0	13.6	1,899
	Winsorized	0.85	1.18	0	4.48	1,899

Notes: Summary statistics for key variables used in the regression analysis are included at their raw, winsorized (at the 99th percentile), and normalized levels.

5.4.2 Regression Analysis

To examine the association between the various industrial characteristics on horizontal and vertical agglomeration trends, we estimate two OLS regressions.[18]

$$\text{Horizontal Agglomeration}_{i,c} = \beta_1(\text{Employment Intensity})_i + \beta_2(\text{Local Economic Activity})_c + \beta_3(\text{R\&D Intensive})_i + \beta_4(\text{Manufactured Share of Inputs' Value})_i + \beta_5(\text{Vertical Agglomeration})_{i,c} + \epsilon_{i,c} \quad \text{(Eq. 4)}$$

$$\text{Vertical Agglomeration}_{i,c} = \beta_1(\text{Employment Intensity})_i + \beta_2(\text{Local Economic Activity})_c + \beta_3(\text{R\&D Intensive})_i + \beta_4(\text{Manufactured Share of Inputs'Value})_i + \beta_5(\text{Horizontal Agglomeration})_{i,c} + \epsilon_{i,c} \quad \text{(Eq. 5)}$$

Table 4 presents the regression results. Column 1 reports the correlative association for horizontal agglomeration; Column 2 reports the results for vertical agglomeration. Given the skewed features of the data, we winsorize the data at the 99th percentile and include standardized measures for the continuous measures.

We observe contrasting associations between the two regressions. Marginal increases in the contribution of manufactured goods to overall inputs' value are correlated with higher rates of vertical agglomeration and lower rates of horizontal agglomeration. Marginal increases in R&D intensity are correlated with lower rates of vertical agglomeration and higher rates of horizontal agglomeration. These divergences reveal distinct features. Namely, horizontal and vertical agglomeration are meaningfully different dimensions across which industries agglomerate. The relative rates of horizontal and vertical agglomeration correlate with common factors in underlying theory and previous literature on industrial agglomeration discussed above (refer to sections 1 and 2). In addition, the results reveal industry differences in their extent of horizontal versus vertical agglomeration being correlated with those industries' underlying technological characteristics, specifically the contribution of manufactured goods to overall

[18] The regression results are not intended to be causal, but rather to illustrate heterogeneity in the underlying patterns of county and industry rates of vertical and horizontal agglomeration.

inputs' value and their R&D intensity. Industries with a higher manufactured share of inputs' value are correlated with vertical (supplier) agglomeration, while more R&D intensive industries are correlated with horizontal (peer) agglomeration.

Table 4: OLS Regression Results

Dependent Variable	(1) Horizontal Agglomeration Z-Score	(2) Vertical Agglomeration Z-Score
R&D Intensity	0.027 ***	-0.009 *
	(0.004)	(0.004)
Manufactured Share of Inputs' Value	-0.013 **	0.032 ***
	(0.005)	(0.005)
Industry Employment in County	0.048 ***	-0.024 ***
	(0.004)	(0.004)
County Employment Location Quotient	0.036 ***	0.189 ***
	(0.005)	(0.004)
Vertical Agglomeration	0.817 ***	
	(0.005)	
Horizontal Agglomeration		0.742 ***
		(0.004)
Observations	20490	20490
R^2	0.698	0.726

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. All values winsorized at the 99th percentile and standardized.

Additionally, increases in the employment intensity of industries are correlated with higher rates of horizontal agglomeration and lower rates of vertical agglomeration. These results potentially capture shared labor requirements between industries that horizontally agglomerate. Other factors, such as the industry's position along the value chain, the value added of the industry, the global nature of industry supply chains, the need for specialized labor, common skills requirements, or other specialized knowledge, might also correlate with differential rates of horizontal and vertical agglomeration. This regression analysis offers some insight in this regard. We provide a scaffolding for future work to disentangle causal effects on the returns to different

types of agglomeration. Altogether, these results are robust to adjustments in functional form and alternative specifications.[19]

6. Discussion

The anatomy of industrial agglomeration varies across geographies and industries. Whereas previous measures of industrial agglomeration treat agglomeration as a single index, we establish a novel measure with two components for agglomeration, capturing both horizontal (own-industry/peer) agglomeration, as well as vertical (supply-chain) agglomeration. Our results help untangle the question of Marshallian equivalence (Duranton & Puga, 2004) by both highlighting how a distinct group of industries and regions are horizontally agglomerated relative to those that are vertically agglomerated and identifying that the correlates for horizontal agglomeration are uniquely different than the correlates of vertical agglomeration.

We observe that industries may locate to maximize specific benefits over others, with heterogeneity in rates and types of agglomeration correlating with underlying technological characteristics of industries (Diodato et al., 2018, Alcácer & Chung, 2007). We observe distinct heterogeneity in the ways industries agglomerate across geographies, and we argue that such heterogeneity might be due to firms trading off between investing in and maximizing certain Marshallian mechanisms over others.

In this section, we present a conceptual framework that accounts for granular variation in the types of agglomeration at the county and six-digit industry level. We consider the differential impact of industry and county level effects and highlight previously obscured within-industry

[19] For sensitivity checks, we examine a series of alternative specifications. We use establishments instead of employment; we use the value of industry R&D output as a share of total industry output; and we use the share of the value of intermediate inputs that come from both the materials and manufacturing sector. Results are robust to the inclusion of some alternative measures of industry characteristics, such as import intensity. Results available upon request.

regional heterogeneity in semiconductor manufacturing. Moreover, we consider how policy interventions might need to vary depending on the underlying rate and dimension of agglomeration. Lastly, we offer guidance for future scholarship.

6.1 Varieties of Agglomeration

Beyond a binary specification of "low agglomeration" versus "high agglomeration," we differentiate between peer (relatively high horizontal but low vertical) agglomeration, and supplier (relatively high vertical but low horizontal) agglomeration. Based on our results, in Figure 5 we propose a theoretical framework for how industry characteristics may be associated with peer versus supplier agglomeration.

Figure 5: Varieties of Agglomeration Framework

		Horizontal Agglomeration	
		Low	High
Vertical Agglomeration	High	Supplier Agglomeration *Manufactured goods comprise high share of inputs' value*	High Agglomeration
	Low	Low Agglomeration	Peer Agglomeration *R&D Intensive*

Notes: Illustrative 2x2 describing a framework for categorizing variation in horizontal and vertical agglomeration, and associated correlates.

By disentangling horizontal versus vertical agglomeration across both industries as well as counties, our work opens up new ways to characterize how industrial activity and capabilities vary across industries and regions. Industries and/or counties that are highly agglomerated along one component of our measures might not appear agglomerated at all in traditional measures. For example, the employment location quotient of aircraft manufacturing in San Bernardino California is relatively low, but the local peer agglomeration of aircraft manufacturing in San Bernardino is relatively high given its position within a broader, highly peer and supply chain agglomerated set of counties. Similarly, the employment location quotient of motor vehicle

gasoline engine & engine parts manufacturing in Jefferson County, Kentucky is relatively low, but the local supply-chain agglomeration of this industry in this county is relatively high. These nuances are under-observed with existing measures of agglomeration.

6.2 Within-Industry Heterogeneity in Product Characteristics

Our work to date demonstrates industry-level differences in horizontal and vertical agglomeration, and how these differences correlate with industry characteristics such as the use of physical inputs and R&D intensity. However, there can also be substantial differences in the R&D intensity, contribution of manufactured goods to overall inputs' value, and other attributes of products manufactured *within* an industry. We leverage our deep knowledge of the semiconductor industry to illustrate how heterogeneity in industry-county rates of vertical and horizontal agglomeration might reflect differences in the specific products the firms in these different counties manufacture.

The modern semiconductor industry encompasses high heterogeneity across the technological sophistication, end market, and product volume of specific products. Consequently, semiconductor products and production establishments vary in their R&D, skilled labor, and physical input requirements. This range of semiconductor products includes high-end logic chips at the frontier of scientific and production capabilities; commodity memory chips; legacy chips widely used by the energy, transportation, and industrial sectors; custom chips for extreme environments such as the military and space; sensors, transmitters and receivers for the communications sector which require their own production and material systems; and a variety of other highly heterogeneous products. Individual firms specialize in the types of products they manufacture, and the customers that they supply (Berger et al., 2023). These firms are distributed across a variety of regions in the US (72 counties in 2019), and there is heterogeneity in which

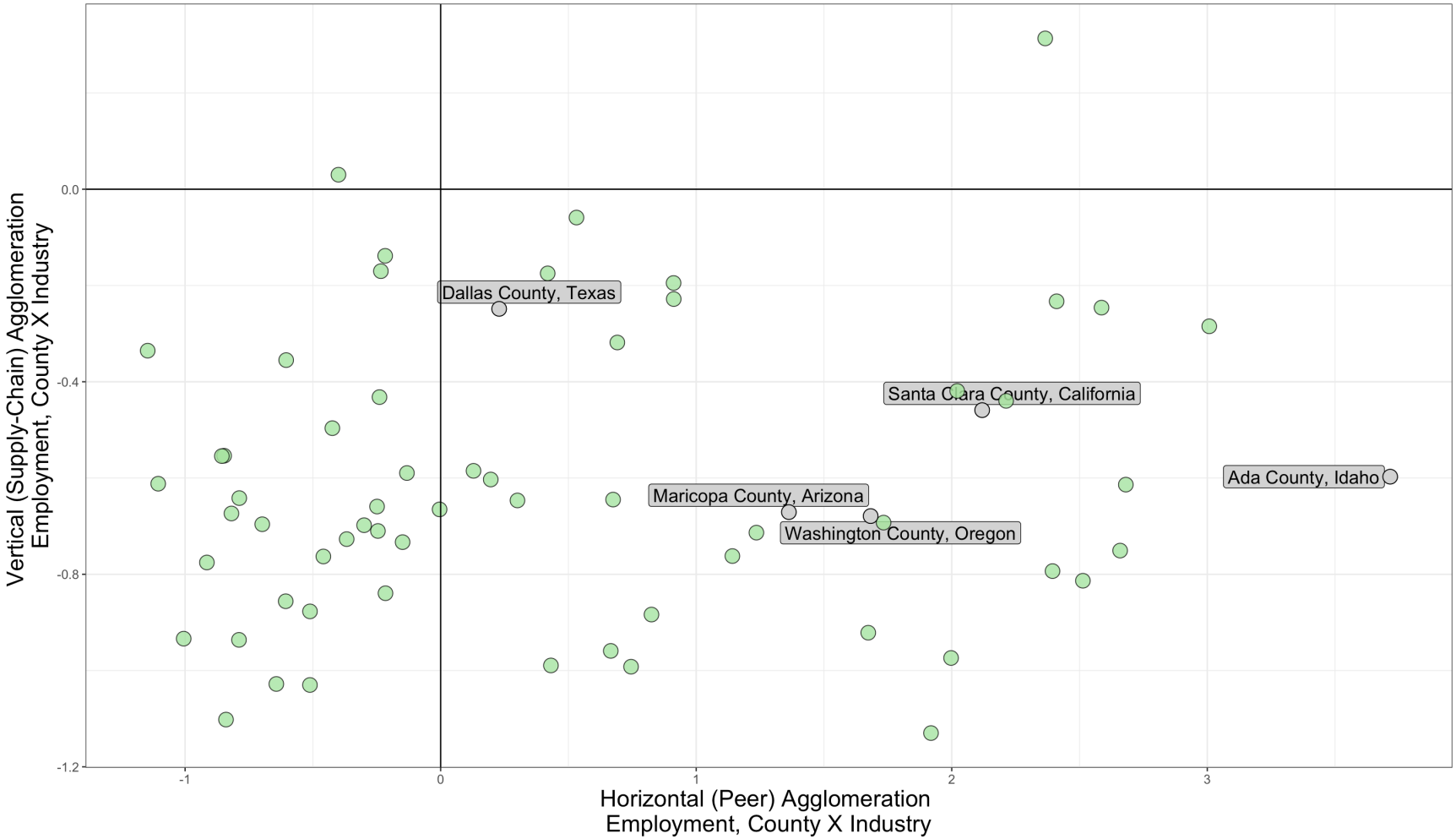
semiconductor products are manufactured in which regions. Existing measures of economic activity and agglomeration are not well positioned to allow stakeholders to capture and explain how differences across individual firms manufacturing specific products in specific regions might result in regionally heterogeneous industrial footprints.

In Figure 6 we zoom in on the distribution of horizontal and vertical agglomeration across counties in which the semiconductor industry operates to illustrate how our novel measure reflects previously obscured within-industry heterogeneity in the regional footprint of semiconductor manufacturing. As in Figure 3, given the underlying skew in our data, we county-normalize our data to highlight the contrast between a specific industry's activity within a county, and the broader county-level activity (e.g. controlling for county fixed effects.)

We focus our discussion on the counties with the top five employment location quotients in 2019: Washington County, Oregon; Dallas County, Texas; Santa Clara County, California; Maricopa County, Arizona; Ada County, Idaho.[20] These counties would be considered "strong" clusters of semiconductor activity according to existing, location quotient-based measures of agglomeration (Ellison, Glaeser, & Kerr, 2010; Delgado et al., 2014.) Semiconductor agglomeration varies slightly in scale across these five counties; however, there are differences in the products the companies in these regions produce, and types of firm activities across these regions.

[20] Washington County, Oregon has the highest employment location quotient at 10.7, while all three of Maricopa County, Arizona (6.9), Santa Clara County, California (6.6), and Ada County, Idaho (6.1) have similar values. Dallas County, Texas (8.5) lies in the middle.

Figure 6: Illustrative Exemplar – Semiconductor Manufacturing Industry



Notes: County-normalized values of horizontal and vertical agglomeration for the semiconductor manufacturing industry. Zoom in of Figure 3 on the Semiconductor Manufacturing industry in particular. Counties in gray (Dallas, County, Texas; Maricopa County, Arizona; Washington County, Oregon; Santa Clara County, California; and Ada County, Idaho) are exemplar counties selected because they have the top five highest employment location quotients in 2019

Washington County is one of Intel's process, design, and R&D hubs. In terms of product differences, the types of chips that are manufactured in Maricopa County (home to Intel and now TSMC) are leading edge chips that require highly specialized skills and knowledge. Comparatively, chips manufactured by Texas Instruments (TI) in Dallas County are lower-end chips that are less R&D intensive and more customized to specific customers (e.g. the automotive industry). Santa Clara County is the birthplace of the semiconductor industry, where Gordon Moore started Fairchild Semiconductor, and is the modern home to the global headquarters of firms such as Intel, with a variety of semiconductor manufacturers serving a myriad of industries, including: computers, communications, electronics, solar energy, and beyond. The largest semiconductor manufacturer in Ada County is Micron, who mostly manufactures memory products. The Ada County location serves as one of Micron's R&D clusters.

Based on these product and facility differences, we might expect that Intel's facilities in Washington County, Santa Clara County, and Maricopa County, together with Micron's facility in Ada County, to have a higher R&D intensity than TI's facilities in Dallas County. While it is more difficult to hypothesize the extent to which each of these facilities differentially depend on high value manufactured inputs, and their individual supply-chain requirements thereof, one might expect manufacturing to comprise a higher share of input value in the Dallas County facilities, followed by the Maricopa County facilities.

Differences in patterns of horizontal and vertical agglomeration across these three counties appear to be consistent with differences in the R&D intensity and manufactured share of inputs' value required by the products that these firms manufacture. County-normalizing our data highlights that the semiconductor industry has high local horizontal agglomeration and low local

vertical agglomeration across the majority of counties in which this industry operates. With this transformation Ada County, Idaho stands out as the most horizontally agglomerated area of semiconductor manufacturing activity, relative to the county average. Maricopa County, Arizona, and Washington County, Oregon appear more similar in their relative rates of local vertical and horizontal agglomeration. However, Washington County, Oregon has slightly higher rates of horizontal agglomeration, which might correspond to the R&D intensive nature of Intel's operations in this county. Santa Clara County, California has slightly higher rates of horizontal agglomeration than either of these counties, and is more vertically agglomerated as well. This may reflect the diversity of semiconductor manufacturing in this area in addition to the many spinoffs and small and medium sized companies that have entered and exited over time (Klepper, 2009). Among these five counties, Dallas County, Texas stands out with the highest rate of local vertical agglomeration. Though, it is also much closer to the county-average rate of horizontal and vertical agglomeration than the other counties.

Capturing the heterogeneity of within-industry differences in product attributes and characteristics is a challenging task, made more difficult by limitations in easily available within-industry data and statistics. Our novel measure may help unpack, describe, and categorize within-industry heterogeneity in which products are produced in which regions. Here, we postulate that counties which have higher rates of horizontal agglomeration, especially relative to their county average, might be home to establishments with more R&D intensive activities, while counties with higher rates of vertical agglomeration might be home to establishments with a higher value of manufactured inputs.

6.3 Policy Considerations

Recently, there has been an increase in support for place-based policies to develop regional ecosystems and industrial clusters (Murray and Budden, 2017; CRS, 2023). Such investments are set to expand in the context of billions of dollars in US federal investment to develop state industrial ecosystems coming down through the Chips and Science Act (CHIPS, passed in August 2022), Inflation Reduction Act (IRA, passed in August 2022), and Infrastructure Investment and Jobs Act (IIJCA, passed in November 2021). In addition, private manufacturing firms are also announcing large investments for manufacturing facilities, totaling over $600 billion in announced investments as of February 2024 (White House, 2024). Such place-based investments are not only occurring in the US, but also in the European Union, China (Chen et al., 2023), and elsewhere. To maximize the impact of such investments, we must hone our approach to measure and understand heterogeneity in contemporary manufacturing activity across regions. We hope this paper positions future scholarship well in this regard.

Efforts to promote economic development, regional resilience, and regional performance might be aided by better visibility into and understanding of the degree of industry and county level variation in rates of horizontal and vertical agglomeration. Regions have limited assets and are constrained in the number and type of investments they can make. Certain investments, such as R&D subsidies, university-industry collaborations, and efforts to attract and retain skilled workers, might boost knowledge spillovers and access to shared labor within a region. On the other hand, regions can make investments in local supply chains and promote vertical linkages, such as through supplier development programs and targeted infrastructure investments (e.g., a port, airport, or cargo processing facility). It is not immediately clear how regions should prioritize their limited funds, especially given heterogeneity in their targeted goals. Should regions cultivate existing agglomeration assets, or should they address agglomeration

weaknesses? How might the "optimal" strategy for a region differ if they are trying to attract an industry that is overall less vertically (or horizontally) agglomerated than the county average? Such questions warrant further investigation and are likely to depend on regional goals and strategies. At the sub-national level, our measure allows regions to quantify which industries have more regional supply chains, which have stronger peer effects, and where industries lag (or lead) regional rates of agglomeration. Here, we propose a theoretical framework for regional and federal stakeholders to follow when evaluating tradeoffs with respect to a specific intervention, into a specific industry, across a set of focus counties in which that industry operates.

First, we propose considering how highly horizontally and vertically agglomerated the specific industry is relative to national averages, to understand *industry-level* patterns of agglomeration. This framing may help policymakers identify industry-specific interventions and to allow interventions to vary depending on the underlying characteristics of the industry to support (e.g., semiconductor manufacturing demands are unique compared to agriculture, aircraft manufacturing, or energy storage demands). Second, we propose considering how highly horizontally and vertically agglomerated the focus counties are relative to the national county-level average. This framing may help policymakers identify how an intervention may need to account for the county-specific context, including both regional assets as well as regional bottlenecks and weaknesses. Previous work has considered the role that "natural assets" play as drivers of agglomeration (Ellison et al., 2010), positing that some regions have attractive assets that are conducive to agglomeration. In addition to certain locations being more conducive to agglomeration overall, we argue that regions might vary in the *types* of agglomeration that they are best positioned to support (e.g., horizontal agglomeration versus vertical agglomeration).

Finally, we propose considering how establishment-specific characteristics (such as R&D intensity and value of manufactured inputs) may differ from industry and county averages. This framing may provide policymakers with additional information about how a specific establishments' agglomeration needs may differ or align with that county's patterns of agglomeration. Comparing these establishment rates of vertical and horizontal agglomeration for a given industry to the county-average rate of vertical and horizontal agglomeration may also help determine how aligned regional assets are to local needs. Moreover, this step might expose possible assets to develop or weaknesses to address. While this theoretical framework – enabled by our novel measure – is not prescriptive, it may help regional and federal stakeholders think through industry needs, regional assets, where the two are aligned, and where they are misaligned.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*, *34*(S1), 141–198.

Agrawal, A., & Cockburn, I. (2003). The anchor tenant hypothesis: Exploring the role of large, local, R&D-intensive firms in regional innovation systems. *International Journal of Industrial Organization*, *21*(9), 1227–1253.

Alcácer, J., & Chung, W. (2007). Location Strategies and Knowledge Spillovers. *Management Science*, *53*(5), 760–776.

Audretsch, D. B., & Feldman, M. P. (1996). R&D Spillovers and the Geography of Innovation and Production. *The American Economic Review*, *86*(3), 630–640.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, *103*(6), 2121–2168. https://doi.org/10.1257/aer.103.6.2121

Berger, A., Khan, H., Schrank, A., Fuchs, E.RF, J. (2023, August 23). A New Policy Toolbox for Semiconductor Supply Chains. *Issues in Science and Technology*. https://issues.org/new-policy-toolbox-semiconductor-supply-chains-berger-khan-schrank-fuchs/

Bernard, A. B., Moxnes, A., & Saito, Y. U. (2019). Production Networks, Geography, and Firm Performance. *Journal of Political Economy*, *127*(2), 639–688. https://doi.org/10.1086/700764

Boschma, R., & Iammarino, S. (2009). Related Variety, Trade Linkages, and Regional Growth in Italy. *Economic Geography*, *85*(3), 289–311. https://doi.org/10.1111/j.1944-8287.2009.01034.x

Carvalho, V. M., & Tahbaz-Salehi, A. (2019). Production Networks: A Primer. *Annual Review of Economics*, *11*(Volume 11, 2019), 635–663. https://doi.org/10.1146/annurev-economics-080218-030212

Congressional Research Service. (2023). Regional Innovation: Federal Programs and Issues for Consideration. https://crsreports.congress.gov R47495

Delgado, M., & Mills, K. G. (2020). The supply chain economy: A new industry categorization for understanding innovation in services. *Research Policy*, *49*(8), 104039. https://doi.org/10.1016/j.respol.2020.104039

Delgado, M., Porter, M. E., & Stern, S. (2014a). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799. https://doi.org/10.1016/j.respol.2014.05.007

Delgado, M., Porter, M. E., & Stern, S. (2014b). *Defining Clusters of Related Industries* (Working Paper 20375). National Bureau of Economic Research. https://doi.org/10.3386/w20375

Diodato, D., Neffke, F., & O'Clery, N. (2018). Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, *106*, 1–26. https://doi.org/10.1016/j.jue.2018.05.002

Duranton, G., & Puga, D. (2004). Chapter 48—Micro-Foundations of Urban Agglomeration Economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2063–2117). Elsevier. https://doi.org/10.1016/S1574-0080(04)80005-1

Ellison, G., & Glaeser, E. L. (1997). Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach. *Journal of Political Economy*, *105*(5), 889–927. https://doi.org/10.1086/262098

Ellison, G., Glaeser, E. L., & Kerr, W. (n.d.). *What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns*.

Feldman, M. P. (1994). *The Geography of Innovation*. Springer Science & Business Media.

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, *43*(2), 409–429. https://doi.org/10.1016/S0014-2921(98)00047-6

Feser, E. J., & Bergman, E. M. (2000). National Industry Cluster Templates: A Framework for Applied Regional Cluster Analysis. *Regional Studies*, *34*(1), 1–19. https://doi.org/10.1080/00343400050005844

Fuchs, E. R. H., Combemale, C., Whitefoot, K. S., & Glennon, B. (2020). The "Weighty" Manufacturing Sector: Transforming Raw Materials into Physical Goods. In *The Role of Innovation and Entrepreneurship in Economic Growth* (pp. 31–94). University of Chicago Press. https://www.nber.org/books-and-chapters/role-innovation-and-entrepreneurship-economic-growth/weighty-manufacturing-sector-transforming-raw-materials-physical-goods

Glaeser, E. L., & Kerr, W. R. (2009). Local Industrial Conditions and Entrepreneurship: How Much of the Spatial Distribution Can We Explain? *Journal of Economics & Management Strategy*, *18*(3), 623–663. https://doi.org/10.1111/j.1530-9134.2009.00225.x

Golman, R., & Klepper, S. (2016). Spinoffs and clustering. *The RAND Journal of Economics*, *47*(2), 341–365. https://doi.org/10.1111/1756-2171.12130

Greenstone, M., & Moretti, E. (2003). *Bidding for Industrial Plants: Does Winning a "Million Dollar Plant" Increase Welfare?* (SSRN Scholarly Paper 423317). https://papers.ssrn.com/abstract=423317

Hausmann, R., Stock, D. P., & Yıldırım, M. A. (2022). Implied comparative advantage. *Research Policy*, *51*(8), 104143. https://doi.org/10.1016/j.respol.2020.104143

Helper, S., & Henderson, R. (2014). Management Practices, Relational Contracts, and the Decline of General Motors. *Journal of Economic Perspectives*, *28*(1), 49–72. https://doi.org/10.1257/jep.28.1.49

Koo, J. (2005). Knowledge-based Industry Clusters: Evidenced by Geographical Patterns of Patents in Manufacturing. *Urban Studies*, *42*(9), 1487–1505. https://doi.org/10.1080/00420980500185249

Marshall, A. (1890). *Principles of Economics* (1st ed.). London: Macmillan and Co., Ltd.

Murray, F. (n.d.). *A systematic MIT Approach for assessing "innovation-driven entrepreneurship" in ecosystems*.

Porter, M. (2003). The Economic Performance of Regions. *Regional Studies*, *37*(6–7), 549–578. https://doi.org/10.1080/0034340032000108688

Safford, S. (2009). *Why the Garden Club Couldn't Save Youngstown: The Transformation of the Rust Belt*. Harvard University Press.

Schrank, A., & Whitford, J. (2011). The Anatomy of Network Failure. *Sociological Theory*, *29*(3), 151–177. https://doi.org/10.1111/j.1467-9558.2011.01392.x

White House (2021, November 6). *Fact Sheet: The Bipartisan Infrastructure Deal*. The White House. https://www.whitehouse.gov/briefing-room/statements-releases/2021/11/06/fact-sheet-the-bipartisan-infrastructure-deal/

White House. (2022, August 9). *Remarks by President Biden at Signing of H.R. 4346, "The CHIPS and Science Act of 2022."* The White House. https://www.whitehouse.gov/briefing-room/speeches-remarks/2022/08/09/remarks-by-president-biden-at-signing-of-h-r-4346-the-chips-and-science-act-of-2022/

White House. *Inflation Reduction Act Guidebook | Clean Energy*. (n.d.). The White House. Retrieved July 8, 2024, from https://www.whitehouse.gov/cleanenergy/inflation-reduction-act-guidebook/

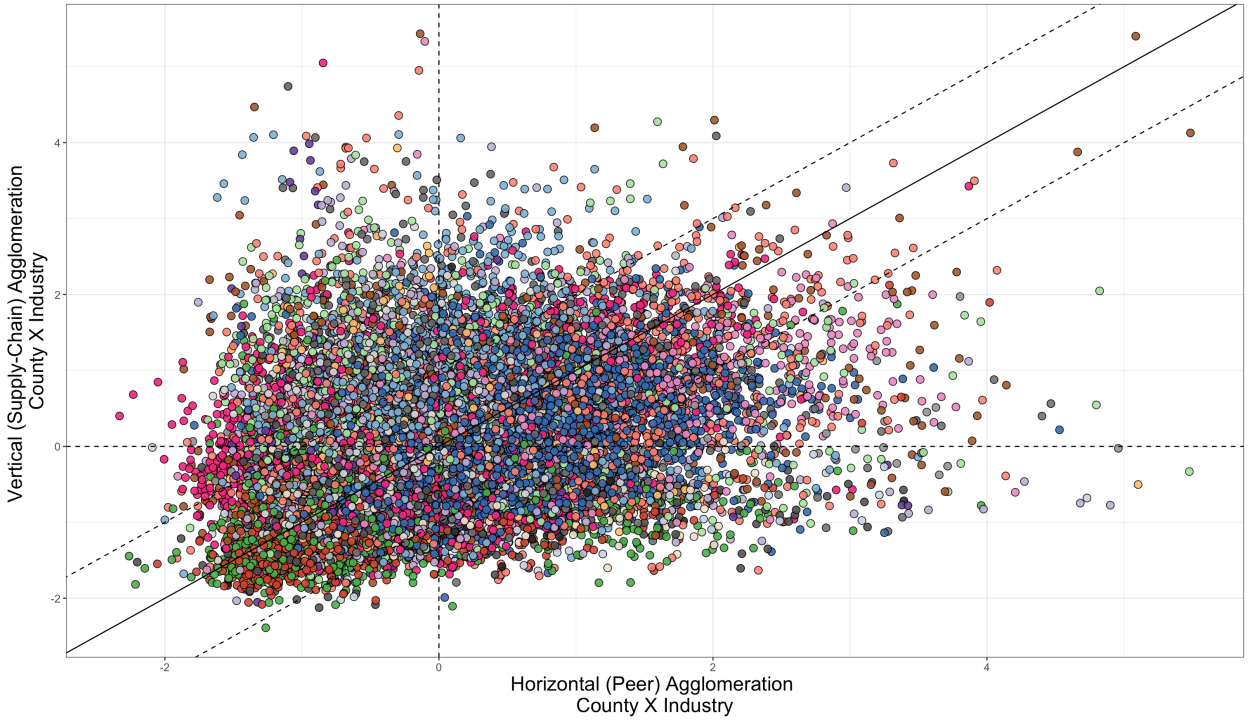
White House. *Investing In America*. (n.d.). The White House. Retrieved February 16, 2024, from https://www.whitehouse.gov/invest/

Whitford, J. (2006). *The New Old Economy: Networks, Institutions, and the Organizational Transformation of American Manufacturing*. Oxford University Press.

Appendix Table A1: Leading Horizontally and Vertically Agglomerated Counties

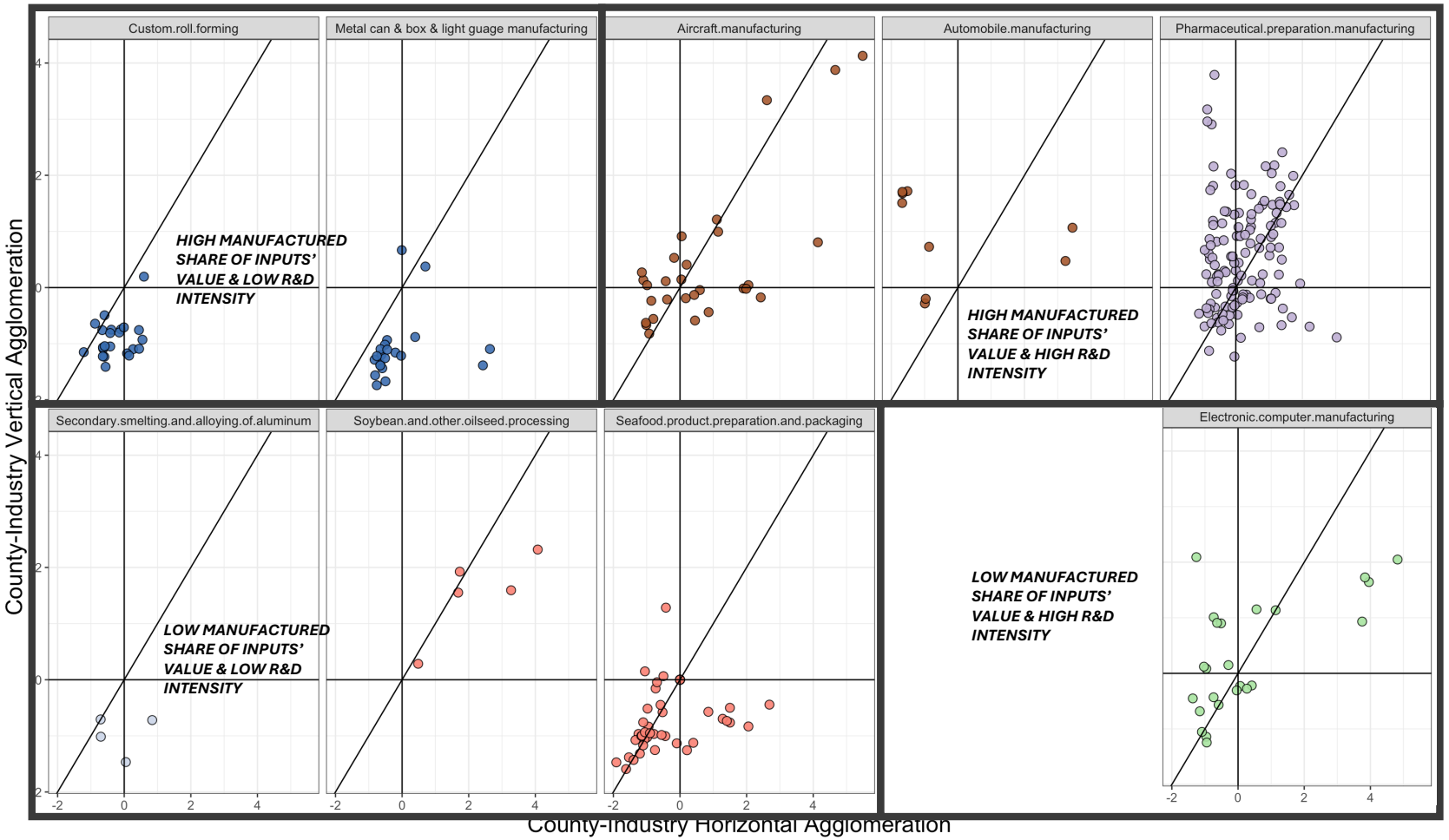
	Leading Counties	Lagging Counties
Vertical Agglomeration	San Diego County, CA; Orange County, CA; Ventura County, CA; Los Angeles County, CA; San Bernardino County, CA	Buckingham County, VA; Bon Homme County, SD; Orange County, VA; Ford County, KS; Wayne County, TN
Horizontal Agglomeration		Juneau City and Borough, AK; Sheridan County, NE; Meade County, SD; Oktibbeha County, MI; Beaverhead County, MN

Appendix Figure A1: County and Industry Trends of Horizontal and Vertical Agglomeration



Notes: County and industry-level rates of horizontal and vertical agglomeration for all industries and counties are reported. Each dot represents an individual manufacturing industry, where values are normalized relative to the county-means. Accordingly, a zero value denotes agglomeration exactly at the county-mean level of agglomeration, with units being standard deviations from the mean. The solid diagonal line highlights where there exists a one-to-one ratio of horizontal to vertical agglomeration, and the dotted diagonal lines demark one standard deviation above and below that one-to-one ratio.

Appendix Figure A2: Variation in rates of horizontal and vertical agglomeration across select industries



Notes: County-normalized values of horizontal and vertical agglomeration for the industries at the corner values of industry contribution of manufactured goods to overall inputs' value and industry R&D intensive. Observations are colored based on their 3-digit NAICS code. Each dot represents an individual manufacturing industry, where values are normalized relative to the county-means. Accordingly, a zero value denotes agglomeration exactly at the county-mean level of agglomeration, with units being standard deviations from the mean, denoted by the dotted lines

Appendix Table A2: Constructs of industrial characteristics

Constructs	**Measure Description**	**Source**	**Measure**
Employment Intensity	Labor intensity of a specific industry	CBP Industry Employment (2019)	Industry employment / National employment
Location Economic Activity	Intensity of economic activity in a particular location	CBP Industry Employment (2019)	County Employment Location Quotient
R&D Intensive	Technological complexity, R&D requirements of different industries, position along value chain	IO Account Scientific R&D Commodity Use & Supply (2017)	Industry Total Value of Scientific R&D Output / Total Value of Manufacturing Sector R&D Output
Manufactured Share of Inputs' Value	Measure of reliance on manufactured inputs, position along value chain	IO Account Manufacturing Commodities Use & Supply (2017)	Industry Total Value of Inputs from the Manufacturing Sector / Total Value of Intermediary Inputs

Appendix Table A3: Correlation matrix

		1	2	3	4	5	6
1	Horizontal Agglomeration	1.00					
2	Vertical Agglomeration	0.83	1.00				
3	Industry Employment in County	-0.03	-0.08	1.00			
4	County Employment Location Quotient	0.42	0.48	-0.26	1.00		
5	R&D Intensity	0.08	0.06	0.01	0.08	1.00	
6	Production Intensity	0.06	0.08	0.00	0.09	0.07	1.00

Notes: Cross-Tabulations of sectoral heterogeneity based on prominent correlates to agglomeration.

Appendix B: Details from the Bureau of Economic Analysis Use and Supply Data

B1: Mapping Use and Supply Tables in the Input Account Data to US County Business Pattern Data

There are a total of 360 manufacturing industries at the 6-digit NAICS level of granularity. Certain 3-digit NAICS "sectors" have more granularity than others. For example, "Food Manufacturing (NAICS 311) has more than 40 individual 6-digit NAICS industries. On the other hand, "Leather and allied product manufacturing (NAICS 316)" only has four individual 6-digit NAICS industries. On average, each 3-digit "sector" describes 17 distinct 6-digit industries. However, the Input-Output account data only cover 232 individual manufacturing industries. In certain cases, Input-Output accounts provide granularity at the 6-digit NAICS level. At the 3-digit level, IO data on average cover 60% of all the 6-digit NAICS code industries. However, certain 3-digit NAICS families are far better described in the IO accounts than others. For example, the IO accounts cover 25/27 (or over 92%) of the "Transportation equipment manufacturing (NAICS 336)" sector, while only covering 1 out 7 of the "Apparel manufacturing (NAICS 315)" sector. In this work, we use the maximum level of granularity provided by BEA input-output data. As such, for certain industries, we have a 6-digit level of granularity, while for other industries we only have a 3 digit level of granularity. We refer to this maximum level of granularity as "industry" level detail, and occasionally abstract up to 3-digit NAICS code "sectors" of groups of manufacturing industries.

B2: List of Semiconductor Industry Outputs

Semiconductor and related device manufacturing; Scientific research and development services, Household appliances and electrical and electronic goods; Custom computer programming services; Other electronic component manufacturing; Major household appliance manufacturing; Printed circuit assembly (electronic assembly) manufacturing; Computer storage device manufacturing; Photographic and photocopying equipment manufacturing; Lighting fixture manufacturing; Electric lamp bulb and part manufacturing; Search, detection, and navigation instruments manufacturing; Other basic inorganic chemical manufacturing; Electricity and signal testing instruments manufacturing; Aluminum product manufacturing from purchased aluminum; Broadcast and wireless communications equipment; Air and gas compressor manufacturing; Manufacturing structures; Ornamental and architectural metal products manufacturing; Semiconductor machinery manufacturing; Nonferrous metal (except copper and aluminum) rolling, drawing, extruding and alloying; Irradiation apparatus manufacturing; All other miscellaneous electrical equipment and component manufacturing