Bidding for Firms: Subsidy Competition in the U.S.

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Abstract

State and local governments in the U.S. compete to attract firms by offering discretionary subsidies. I use a private value English auction to model the subsidy bidding process and quantify the welfare effects of competition. The allocation of rents between states and firms depends on the heterogeneity in states' valuations for firms and the substitutability of locations. I find that competition increases welfare by less than 5% over a subsidy ban, and states compete away the surplus, transferring all of the rents to firms. These findings dampen any interpretation of subsidy competition as an effective place-based policy.

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1 Introduction

In 1976, after dozens of governors traveled to Germany to make their pitch to Volkswagen executives and multiple rounds of bidding, Volkswagen decided to locate their first U.S. plant in Pennsylvania. The German automobile manufacturer promised to create 5,000 jobs and received a discretionary subsidy worth $100 million. Forty years later, discretionary incentives are a mainstay of local economic development policy in the United States. In 2017 alone, states promised over $6 billion in tax incentives and subsidies—one third of their economic development budget—to just 20 firms.

Some policymakers have proposed a ban on subsidy competition, arguing that it is a zero-sum game that only serves to transfer rents from local governments to firms (Farmer, 2019; Burstein and Rolnick, 1995). However, discretionary subsidies can increase welfare if they compensate firms for locating where they will create more value, improving the match between firms and locations. If subsidy competition improves matches, allowing states and local governments to offer specialized tax breaks and incentives can increase the allocative efficiency of firm location, and may be an effective place-based policy to address rising geographic economic inequality within the United States.

In this paper, I model the subsidy "bidding" process and quantify the welfare effects of subsidy competition. The English auction model I use allows local governments to value both firm and location characteristics when submitting bids, and allows firms to take both subsidies and location characteristics into account when choosing their location. In order for subsidy competition to strictly improve welfare, it must be that competition induces some firms to choose locations that they would not choose in the absence of a subsidy. If all governments have the same valuation for attracting a firm, subsidy competition will still allocate firms to the highest profit place. Similarly, if government valuations and firm profits are strongly positively correlated, then total welfare and profits are strongly positively correlated and subsidy competition, which allocates firms to the highest welfare location, will not impact the location choice. However, if valuations are sufficiently heterogeneous, or, if valuations and profits are strongly negatively correlated, then subsidies will change firms' location choice, thereby increasing welfare. The size of this welfare gain is a function of the heterogeneity in valuations for firms. I estimate the joint distribution of firms' preferences over location characteristics and local governments' (revealed) valuations for firms that rationalizes observed subsidies.

I offer three main findings. First, valuations for firms are heterogeneous and firm profits and valuations for firms are slightly negatively correlated. This means that subsidies can have a meaningful effect on firm location decisions. In the counterfactual, I find that 52% of firms would locate in another state if there was no incentive spending. Taken together, subsidy competition increases total welfare by 4% by allocating firms to places with higher valuations, but lower profits. Second, there is not enough heterogeneity in valuations, so states compete away most of the surplus created by improving match values, transferring the majority of rents to firms in the form of discretionary subsidies. In the aggregate, state and local governments would be better off in the absence of subsidy competition. Third, higher valuations for firms are correlated with low personal income per capita and higher unemployment rates. This suggests that valuations reflect the location-specific economic benefit of winning a firm. However, economic benefit is not the sole determinant of willingness to pay. A firm's "value" to a location is also correlated with politicians' career concerns—states with governors facing re-election value firms more than their term-limited counterparts. Therefore, the government valuation of winning a firm does not necessarily reflect the benefit the firm will create for their constituents.

Glaeser (2001) notes, "Tax incentives seem to be a permanent part of the urban economic landscape. However, economists do not yet know why these incentives occur and whether they are in fact desirable." Two major obstacles stymie progress in this area. First, there is a lack of coherent data on subsidies, due to limited transparency from state and local governments on the subsidy-setting process. Most empirical work focuses on one tax credit or incentive program, but states have many levers and programs to build a subsidy deal for an individual firm. Second, even if researchers did have data on subsidy deals, the observed subsidy is an equilibrium outcome—the result of the firm location decision, the willingness to pay of the local governments, and a competition between localities. To this end, this paper makes two contributions to the literature. First, I introduce a new, hand-collected data set on state-level incentive spending and firm-level subsidy deals across the United States. This data set is unique because it includes details on the terms of each subsidy deal, the runner-up location, and the number of competitors in the subsidy competition. Second, I develop and estimate a tractable model of the subsidy competition "market," which encompasses many real world features of subsidy competition in the United States. I leverage the new data together with techniques from the empirical auction literature to estimate the model and quantify the welfare effects of subsidy competition.

In the first part of the paper I describe the institutional background of subsidy competition in the United States, introduce new data on subsidy-giving, and present reduced-form evidence. The data set has two parts: total state-level incentive spending and firm-level discretionary subsidies. I collect the state-level incentive spending data set by reading state budget documents and tax expenditure reports from each state. I collect data on the firm-level discretionary subsidies from the policy group *Good Jobs First*, the *Site Selection Magazine* annual "Top Deals" report, and by reading news articles and press-releases on each subsidy deal. The sample I use for analysis in this paper is a set of subsidy deals for which I know the firm, location, subsidy size, number of jobs promised, industry, and runner-up location in the competition. These subsidies generally include contributions from both the state and local governments—I use the term "state" as the government of interest in most of the paper, but one can think of the state and local government determining the subsidy offer together. I collect all deals between 2002 and 2017 that included competition between localities and that were worth over $5 milion to the firm, resulting in 387 firm-level deals. The average firm promises to create 1,400 jobs and receives a subsidy worth $150 million over 10 years, which is about $107,000 per job promised or $10,700 per job per year.

According to policymakers, the primary purpose of giving subsidies for firm locations is job creation. However, the number of new jobs the firm promises only explains about 10% of observed subsidies. This may be due to differences in location characteristics; a less attractive place needs to offer a larger subsidy than its more attractive counterparts, all else equal. In fact, local characteristics that may be favorable to a firm, e.g. right-to-work laws and the prevalence of research universities, are correlated with smaller discretionary subsidies. There may also be differences in the location-specific valuation of new jobs. In the aggregate data, states that experience decreases in the employment population ratio are more likely to increase per capita incentive spending. I use a model to disentangle differences in firm profits in a given location from the underlying location valuations for firms.

In the model, state governments compete for firms with subsidies and firms choose the location that offers the highest payoff, where payoff is a function of both the subsidy offered and the location-specific profit. I model this as an open outcry ascending (English) scoring auction. This modeling approach captures many real world features of subsidy competition in the United States: subsidies are not the only factor in a firm's location decision, there are multiple rounds of bidding in competition, and states know the offers of their competitors.[1]

The argument that subsidy competition can increase the allocative efficiency of firm locations relies on the assumption that a firm will create different amounts of value in different localities. By

[1]The English auction can resemble markets with negotiated or bargained prices, and in my setting it captures the negotiation between the firm and multiple locations. Recent work uses the English auction to model mortgage and consumer loan markets (Allen, Clark and Houde, 2019; Cuesta and Sepúlveda, 2019).

modeling subsidy competition as a private value auction I assume that each state can accurately anticipate the value a firm will create in its jurisdiction. There is no winner's curse—subsidy competition must be efficient. Although I estimate a model that presumes efficiency gains, my results on the distribution of rents and the determinants of states' willingness to pay do not follow directly from this modeling choice. In fact, this presumption is conservative with respect to my results because it is optimistic about the gains from competition, which I find to be negligible.

In most empirical auction applications, the observation of the winning bid and the number of bidders is sufficient to recover the underlying distributions of valuations for the object. However, in my setting subsidies and location characteristics are substitutes—the winning location need not be the place that offers the largest subsidy.[2] In order to achieve identification of state governments' valuations for firms, I also need to know the scoring rule, e.g., the firms' preferences over location characteristics. I identify the scoring rule using the model: the observed winning bid is the subsidy that sets the payoff in the winning and runner-up location equal. In other words, the winning subsidy is equal to the difference in the firm profits in the runner-up and winning location plus the runner-up bid. Therefore, the variation in the winning subsidies and the differences in winning and runner-up location characteristics allow me to identify firms' preferences over location characteristics.

To see the intuition for this approach, imagine two subsidy deals for automobile manufacturing facilities of identical size. One plant locates in Alabama with a subsidy of \$100 million and the other locates in Ohio with a subsidy of \$140 million. In both cases, the runner-up in the subsidy competition is South Carolina, so the runner-up valuation and profit are held constant. Now suppose Alabama and Ohio have almost all of the same location characteristics: the same tax rate, the same wages, the same skilled workforce. The only difference between the two states is that Alabama is a right to work state and Ohio is not. Then, the \$40 million difference in the two observed subsidy deals can be attributed to how much automobile manufacturers prefer to locate in a right to work state.[3]

[2] It is evident that the subsidy size is not the only factor in firms' location decisions. In the case of Amazon HQ2, Atlanta, GA, Chicago, IL, Newark, NJ, Columbus, OH, Philadelphia, PA, and Montgomery County, MD each offered more than the two winning cities' bids, combined (Mak, 2018).

[3] In this step I also estimate the correlation between runner-up location characteristics and the runner-up valuation. Imagine, in this case, two subsidy deals for identical manufacturers won by the same state, Indiana. For one deal, Indiana pays a subsidy of \$300M and the runner-up is Georgia. For the other, Indiana pays a subsidy of \$270M and the runner-up is Tennessee. If Georgia and Tennesse have identical location characteristics, except for the fact that the unemployment rate in Georgia is 7% and the unemployment rate in Tennessee is 5.5%, the difference between the two observed subsidy deals can be attributed to a higher valuation for firms in higher unemployment locations, on average.

Once I have an estimate of firms' preferences over location characteristics and runner-up valuations, I predict each firm's payoff in its runner-up location. The runner-up location gives the firm the second highest payoff, which is equivalent to the second highest level of welfare (where welfare is defined as firm profit plus state valuation). This means that I can use the order statistic identity to recover the full distribution of welfare across locations (Athey and Haile, 2002). I then exploit the relationship between valuation, profits, and welfare, and invert the distribution of welfare to recover the distribution of location valuations.

I use the estimated distributions of state valuations and firm profits to evaluate a counterfactual policy in which state and local governments do not offer any discretionary tax breaks or economic development tax credits.[4] In the counterfactual, up to 48% of the firms stay in the winning location, and 25% choose the runner-up locations. I simulate valuations in the winning and new locations and find that total welfare decreases by about 4% when I implement a subsidy ban, because higher valuation places are not able to express those values through bidding. This is, in part, a mechanical result—the independent private values auction says that competition must be weakly efficient.[5]

My results on the allocation of welfare between locales and firms, which are due to the heterogeneity in the distribution of valuations and firm profits across locations, are not mechanical. I find that all of the aggregate gain from subsidy competition due to increased match values is transferred to the firms; the total subsidy spending over the sample amounts to over $40 billion, while state valuations increase by about $13 billion under competition. The payoff accrued to winning localities under subsidy competition is less than half of the payoff accrued to localities under the subsidy ban.

Although, in the aggregate, states are better off under the ban, my results suggest that any type of subsidy "truce" would likely be hard to sustain—there are clear winners and losers across geographies. These distributional implications across space are due to firms' preferences over location characteristics. Many of the states in the Midwest and South lose the majority of the firms that they had attracted with subsidies, while states like New York, California, Texas and Virginia retain all their firms or are net gainers of firms under a subsidy ban.[6]

[4] This is a partial equilibrium analysis. I do not allow states to change the corporate tax rate or invest in changing other location characteristics.

[5] I estimate a negative correlation between profits and valuations, which suggests that competition will induce some firms to choose higher valuation locations. However, it is not only the relationship between profits and valuations that matters for welfare; the degree of heterogeneity in the distribution of valuations plays an important role.

[6] Perhaps unsurprisingly, the states with more attractive fundamentals are more likely to advocate for multi-state truces in the post-Amazon HQ2 landscape. Lawmakers in New York State have introduced the "End Corporate Welfare Act" bill, and are encouraging other states to do the same (Farmer, 2019).

A few additional considerations temper the estimated welfare gain from subsidy competition. First, firms have costs to engaging in subsidy competition that are not explicit in the model. Namely, firms hire site selection consultants to research locations and negotiate with governments. When I incorporate a conservative estimate of consulting costs into the analysis, the welfare gain from competition shrinks from 4.3% to 1.2% . Second, states may overestimate the benefit of winning any particular firm. In a back of the envelope estimate I find that if states are slightly over-optimistic about the valuation of a firm, the welfare gain from subsidy competition quickly dissipates. Third, states with governors facing re-election are willing to pay more for a manufacturing firm, all else equal. This raises the issue that the "welfare" of the state decision maker may not necessarily align with that of a social planner. In short, although the private value auction model I estimate is one in which efficiency gains are expected, I find that the scope for discretionary subsidies to be an effective tool to reduce geographic inequality is extremely limited.

Related Literature

This paper contributes to the analysis begun by Black and Hoyt (1989), Bartik (1991), Martin (2000*a*), Glaeser (2001), and Garcia-Mila and McGuire (2002), all of which present the argument that subsidy competition is not necessarily a zero-sum game, but can actually lead to efficiency gains. Moreover, Black and Hoyt (1989) and Martin (2000*a*) explicitly model the subsidy competition as an auction and highlight the importance of the heterogeneity in a location's value for winning a firm for total welfare. This motivates my approach.

A set of recent papers take the theory to the data. In contemporaneous work, Kim (2020) estimates the efficiency of subsidy competition with a model of competition between states. He uses a first-price private value sealed-bid auction and a larger sample which includes smaller, non-discretionary deals. His model has the innovation that there is an unobservable component to firms' profit, creating uncertainty in location choice from the perspective of the state. Despite the difference in approach, he also finds that, in the aggregate, low profit places have higher values for firms. However, he finds that firms are much less responsive to subsidies, which is mostly driven by the difference in our samples. Ferrari and Ossa (2023) calibrates a quantitative economic geography model using total state manufacturing subsidies. He finds that states have strong incentives to subsidize firm relocations in order to gain at the expense of neighbor states, a gain which is mostly driven by agglomeration externalities. Mast (2020) estimates a model in which New York counties compete for mobile establishments.

He finds that eliminating tax breaks has a very small effect on equilibrium firm locations, limiting the scope for gains in allocative efficiency.[7] In this paper I am able to explicitly focus on cases for which there was competition between localities for a given firm, and provide a simple framework with which to analyze subsidy competition and evaluate counterfactual policies.

This paper also relates to a more general literature on discretionary subsidy policy, which includes research on the effect of subsidy-giving on local economic outcomes (Greenstone, Hornbeck and Moretti, 2010; Patrick, 2016; Slattery and Zidar, 2020; Setzler and Tintelnot, 2021).[8] This literature takes an ex-post approach—what happens in a location after it wins a subsidy competition? Alternatively, I evaluate subsidy competition at the time of the subsidy deal—why do local governments offer subsidies and do subsidies improve the allocative efficiency of firm locations?

There is a substantial literature on the effect of taxes and incentives on business location and activity. Using data on firms and establishments in the United States, most researchers find very little evidence that corporate tax cuts boost entry (Carlton, 1983; Bartik, 1985; Papke, 1991; Ljungqvist and Smolyansky, 2016). With all the tax credits and subsidies available to large firms, one reason that researchers haven't found strong evidence of a response could be that the corporate tax rate does not reflect the price that larger firms are facing.[9] Suárez Serrato and Zidar (2016) and Fajgelbaum, Morales, Suárez Serrato and Zidar (2018) use spatial equilibrium models to estimate the welfare effects of changes in state taxes on firms and workers. These papers consider (among many other factors) the location-specific productivity of firms, but abstract from any location-specific benefits for the locations. My paper not only studies firm behavior, but also highlights the government objective function, and provides some insights to the government's willingness-to-pay for different types of firms, which is not the focus of most of the literature on taxes or place based policies.

[7] This result, he notes, may arise because he studies a sample of smaller firms that are spatially constrained.

[8] More broadly, there is a robust literature on the effect of place based policies, see, for example, Kline and Moretti (2013) and Busso, Gregory and Kline (2013).

[9] Firms also can respond to tax rates on the intensive margin, Giroud and Rauh (2019) find that multi-establishment firms respond to tax cuts by reallocating activity to the lower cost location. The location of foreign direct investment, R&D, start-up activity, and highly-productive scientists responds to tax policy across states (Hines, 1996; Wilson, 2009; Curtis and Decker, 2018; Moretti and Wilson, 2017). Taxes, grants and agglomeration have also been found to affect location choices of multinationals and manufacturing plants in Europe (Devereux and Griffith, 1998; Devereux, Griffith and Simpson, 2007; Becker, Egger and Merlo, 2012; Criscuolo, Martin, Overman and Van Reenen, 2019).

2 Background and Data

2.1 Subsidies and Site Selection

In this section I give a brief history of subsidy competition in the United States, as well as an overview of the "industry" in its current state. This includes institutional details on the composition of subsidies and the process of bidding for firms.

The practice of states offering discretionary incentives in exchange for firm locations dates back at least to the 1970s. As noted in the introduction, the earliest evidence I can find of states competing with discretionary tax incentives is in 1976, when Volkswagen received $430 million (in 2017 dollars) to locate their first U.S. plant in Pennsylvania. Volkswagen chose Pennsylvania after narrowing down their search to thirteen states and receiving multiple rounds of bids. This subsidy included financial (e.g. property tax abatements, low-interest loans) as well as in-kind (e.g. rail and highway extensions, job training) incentives. Perhaps partly enticed by the success of Volkswagen, other foreign auto manufacturers followed, each spurring a subsidy competition between states.[10]

As in the 1980s, many subsidies in the last 20 years have gone to automobile manufacturers. However, recent subsidy deals also include R&D intensive industries such as pharmaceuticals and software, as well as wholesale trade, retail, and corporate headquarters. This may be a result of more companies actively seeking out subsidies from local governments, as "site selection" has become an industry of its own. A magazine by the same name gives companies information about expansion planning and subsidy deals, with a feature titled "Incentives Deal of the Month," which highlights deals other firms have received.[11] There are also consulting firms that specialize in site selection. Companies looking to relocate can hire a consultant to identify potential sites and negotiate subsidies with local governments, advertised as "Public Incentive Identification & Negotiation." A company will often start with a list of hundreds of potential sites, but, with the help of the consultants, narrow that list down to a much shorter list of the most attractive locations. These shortlisted locations are

[10]Mazda located in Michigan in 1984 for $125 million, Mitsibushi and Toyota the next year in Kentucky ($147 million) and Illinois ($249 million) respectively. The VW deal is detailed in the book *The Last Entrepreneurs: America's Regional Wars for Jobs and Dollars* (Goodman, 1979). Information on the Mazda, Mitsubishi, and Toyota deals are from the *Good Jobs First* Subsidy Tracker (Mattera and Tarczynska, 2019). All of the state-level large deals tracked by *Good Jobs First* before 1987 are for foreign auto-manufacturers.

[11]*Site Selection* is not the only player, there is also *Business Facilities* (`https://businessfacilities.com/`), which markets themselves as "The leading source of intelligence for corporate site selection, expansion, relocation & area economic development solutions" and *Area Development* (`http://www.areadevelopment.com/`), "the leading executive magazine covering corporate site selection and relocation."

then contacted and negotiations begin.[12]

The subsidy that a firm will receive is not a lump-sum payment from the governor, but sourced through various programs and state funds. One subsidy deal may consist of (1) tax credits and programs that the state already has in place to create jobs and investment, (2) tax abatements for the individual firm, (3) infrastructure projects, (4) low-cost loans, (5) job training programs, and (6) exemptions from state regulations. It often includes local level incentives as well, such as a property tax exemption. The governor and the state economic development agency decide the subsidy offer from the state, and the city and county decide the contribution from the local government. The state legislature (and city council) may need to approve the offer, or pass a bill to enact any specialized legislation for the firm.

There are significant differences across states and firms in the composition of subsidy deals. For example, consider Foxconn, an electronics manufacturing company that received a subsidy worth almost $5 billion dollars to locate a plant in Wisconsin. The deal consists of 15 years of corporate tax abatements, amounting to about $2.85 billion. Due to two existing tax credits Foxconn would have little to no state tax liability, and would receive the $2.85 billion in cash from the discretionary tax abatement. The state also agreed to make road improvements worth over $252 million, and give sales tax breaks for construction worth $150 million. The locality created a Tax Increment Financing district, which amounts to an additional $1.5 billion. Lastly, Foxconn was also exempted from various state environmental regulations, the savings from which are hard to measure.

In California, however, the aerospace and defense company Lockheed Martin received a subsidy composed entirely of two tax credits. California passed a new tax credit specifically for Lockheed, in exchange for locating their production of new bombers for the Air Force in the state. The legislature enacted the *New Advanced Strategic Aircraft Program*, which specifically gives a credit of 17% of wages to "qualified taxpayers that hire employees to manufacture certain property for the United States Air Force." Lockheed also qualifies for California's R&D tax credit on any R&D expenses, which is the highest in the U.S. at 15%.[13] This is worth an estimated $420 million to Lockheed

[12]Take, for example, a description of the site selection process for Volkswagen's 2008 assembly plant (Bruns, September 2008). "A team of 25 people with Staubach worked on the project, helping VW consider an initial pool of more than 100 candidate sites, all located in the central or eastern U.S. because of time-zone proximity to Germany. "What you look for is mostly problems sites have—readiness, labor, logistics infrastructure," says Greg Lubar, project leader and senior vice president at Staubach. VW said it short-listed 25 sites. "It was then a dozen or so we were in discussions with until the three finalists," says Lubar."

[13]Unlike at the federal level, state level R&D tax credits are used less to encourage innovation and more to attract businesses. In California, a report to the Council on Science and Technology reads " California is perceived as a high-tax

Martin.

2.2 Data

A difficulty for empirical research on state and local business incentives in general is the absence of a comprehensive and centralized data set of state taxes, incentives, and subsidies. States vary widely in the structure of their corporate and individual income taxes and payroll, not to mention their economic development and incentive programs. Also, states and local governments do not make the subsidies they offer to individual firms public knowledge.[14] To this end, most empirical work to this point has focused on posted tax rates or a single credit program at a time.[15] In order to evaluate subsidy competition I need the full picture of all the incentives offered. A major contribution of this paper is the introduction of a detailed data set on individual incentive deals.

Data Collection

The *Good Jobs First* Subsidy Tracker (Mattera and Tarczynska, 2019) collects data on state and local discretionary incentives from a variety of sources: state documents, FOIA requests, news articles, and press releases. If a state does not publish establishment level incentive spending, then the coverage for that state is not exhaustive. However, the Subsidy Tracker takes care to track the largest subsidy deals, due to publicity and media interest. For this reason, the *Good Jobs First* data cannot be used as a measure of the exact amount of tax credits and incentives each establishment in a state received, but is an extremely useful starting point to study large discretionary deals.

I start with the set of all Subsidy Tracker entries over $5 million. I then limit the sample to entries that involve a discretionary program or mention expansion or relocation. I then add any firm location decisions described in *Site Selection Magazine*'s annual "Top Deals" report. I arrive at a sample of over 500 establishments receiving discretionary subsidies over the period 2002-2017. At a minimum the *Good Jobs First* will include the company name, location, year, agency or program that gave the subsidy, and the value of the subsidy. The higher quality observations also include information on the

business environment by firms contemplating setting up business or expanding...An R&D-related tax measure targets the particular types of firms that California desires to attract in spite of its relatively high position in the "tax" league tables."

[14] Recent examples include this New York Times article on transparency issues "Cities' Offers for Amazon Base Are Secrets Even to Many City Leaders," and the New York Times opinion piece by political scientist Nathan Jensen, "Do Taxpayers Know They Are Handing Out Billions to Corporations?"

[15] The notable exception being Suárez Serrato and Zidar (2018), who leverage the new database on tax rates and credits created by Bartik (2017).

number of jobs that will be created, wages, planned investment and the industry of the firm, as well as a description of the project and details breaking down the subsidy into its various components.

Appendix Figure A.5 shows the range in information available in the Subsidy Tracker. Toyo Tire agreed to locate their tire plant in Georgia and create 900 jobs at an average of $15 per hour. Toyo would also make a capital investment of $392 million. In exchange, they would receive $71 million from the state and county combined. The subsidy contains infrastructure, land, state tax credits, and exemption from certain state and local taxes. The only additional information that I need for the analysis is the runner-up location and the number of competitors in the subsidy competition. Meanwhile, the Subsidy Tracker reports that Microchip received a discretionary property tax abatement from the state of Oregon, worth $13 million, in 2002. From the project description I know that Microchip is a semiconductor firm. However, I do not know whether Microchip is a new entry to Oregon or expanding an existing facility, how many jobs they are creating, and whether they qualified for any existing non-discretionary state tax credits or programs.

In order to fill in the number of jobs and planned investment I take a brute-force approach, and read articles and press releases about each deal.[16] For the Microchip example, there is an article in the trade publication *Site Selection* titled "Oregon Incentives, Idle Plant Are 'Fab' for Microchip's Expansion Plan." From the article I learn how many jobs are planned (688) and the runner-up location (Puyallup, WA).[17] I also add any non-discretionary incentives that the firm would qualify for in the state, if it is not included in the subsidy entry or news article. I know each economic development program and tax credit available in a state because I download each tax expenditure report and budget document from state websites, creating a state-year-incentive program spending data set.[18] In Microchip's case, Oregon has a 5% R&D tax credit for eligible R&D spending, which would mean an additional $2.2 million in savings, given the number of jobs promised and average industry wage.

Runner-up locations are almost never included in the Subsidy Tracker entries, so creating an establishment-level subsidy dataset that includes the number of competitors and the identity of the

[16] When there is no information on the industry of the firm I match the company name to Compustat, if not in Compustat it is also sourced from the news articles. Over 50% of the observations in the sample have missing jobs or investment, which I fill in.

[17] From the article: "Spurred by US$17.3 million in state incentives, Microchip Technology (www.microchip.com) has hired the first 60 of what may be as many as 688 employees at its newly acquired facility in Gresham, Ore....In 2000, Microchip bought an existing Matsushita fab in Puyallup, Wash., 155 miles (249 kilometers) north of Gresham. The Puyallup fab, which is also currently idle, was the clear frontrunner in Microchip's U.S. expansion plans."

[18] In the cases that these documents are not available online I call the state budget offices and request the document from the archive. See more details on the state level tax expenditure and economic development budget data in Appendix Section A.

runner-ups is a considerable task. Sources include *Site Selection* and other trade magazines, local newspapers, state documents, and company press releases.[19] I was able to find some information about the runner-up for 95% of the subsidy deals in my sample. Of course, the runner-up "location" is sometimes not a location but a threat to shut-down or not expand. In 77% of cases I can identify a runner-up location in the U.S.[20] The final sample that I use in this paper is the set of 387 subsidy deals for which I have evidence there was a competition for the project, I know the runner-up location, and the runner-up location is within the United States.

Lastly, I normalize all the amounts by the length of the subsidy deal. In the majority of deals firms receive tax credits or abatements for a period of 10 years, so I standardize all deals in the data to the 10-year value. The bulk of the new data comes in the form of the runner-up locations, number of competitors in the subsidy competition, non-discretionary incentive spending, promised job numbers, and planned investment amounts.

Limitations of the Data

The ideal data set would consist of the detailed contract between the firm and state (or city), as well as administrative data on state, county, and city costs, and firm savings for each year following the deal. Of course, those data are confidential, and still might not include all of the variables I would like, for example, the dollar value of in-kind subsidy items to a given firm or the exact set of sites the firm was considering in the competition. In this section I will briefly discuss the limitations of the data I do have.

Good Jobs First takes the value of the deal as given from the source (state document, news article, press release), and states may calculate the present discounted value differently, and include or exclude certain costs when reporting the value of the subsidy deal. Similarly, certain parts of the subsidy deal are in-kind, for example, the state gives the firm land or builds an exit to the highway. I rely on the estimate from the state on how much that is worth, and no distinction is made between how much it costs for the state to provide and how much it is worth to the firm.[21]

[19] Collecting runner-up locations from *Site Selection* is at the heart of the identification strategy in Greenstone, Hornbeck and Moretti (2010). See examples from other sources in Appendix Section A.1.

[20] For about 10% of the sample the runner-up is outside of the U.S., and the remaining firms reportedly do not consider other locations, but claim that they would not expand or shut down without the subsidy.

[21] Consider the two examples of subsidy deals I presented in Section 2.1. In the case of Foxconn, the subsidy deal reportedly included exemptions from state environmental regulations. I have no way to estimate how valuable that would be to Foxconn, and it is not included in the dollar amount of the deal. In the case of Lockheed Martin, the *Good Jobs First* data only includes the value of the discretionary tax credit, but Lockheed is also eligible for California's very generous

In the analysis I will treat the jobs promised and the investment planned in the winning location as fixed in the competition. That is, if I observe a subsidy for BMW creating 2,000 jobs in South Carolina, I assume BMW was promising 2,000 jobs in all of the potential locations competing. For assembly plants this is likely close to reality, but it might not be the case for other types of establishments, like a regional headquarters. This type of measurement error can introduce bias in the estimate of firm profits and runner-up valuations, which I discuss further in Section 5.

In terms of selection, I know the runner-up and winning location, and for the majority of the deals I know the number of locations the firm is considering. However, I do not necessarily know the identity of each of these locations. Therefore, in the counterfactual analysis, I will have to make an assumption on the set of locations the firm will choose between. I do not explicitly model entry, but I use characteristics of locations that enter the firm's profit function to select the set of locations. This is motivated by the institutional details on the site selection process.

Another consideration is the selection of firms that receive subsidies. If a firm relocated without any discretionary subsidy it is not considered in this data set, because I do not have administrative data on establishment entry. Therefore, all of the analysis is with respect to this subset of "special" firms which receive discretionary subsidies. See Appendix A.3 for a discussion of various checks of the integrity and coverage of the *Good Jobs First* and *Site Selection* data.[22]

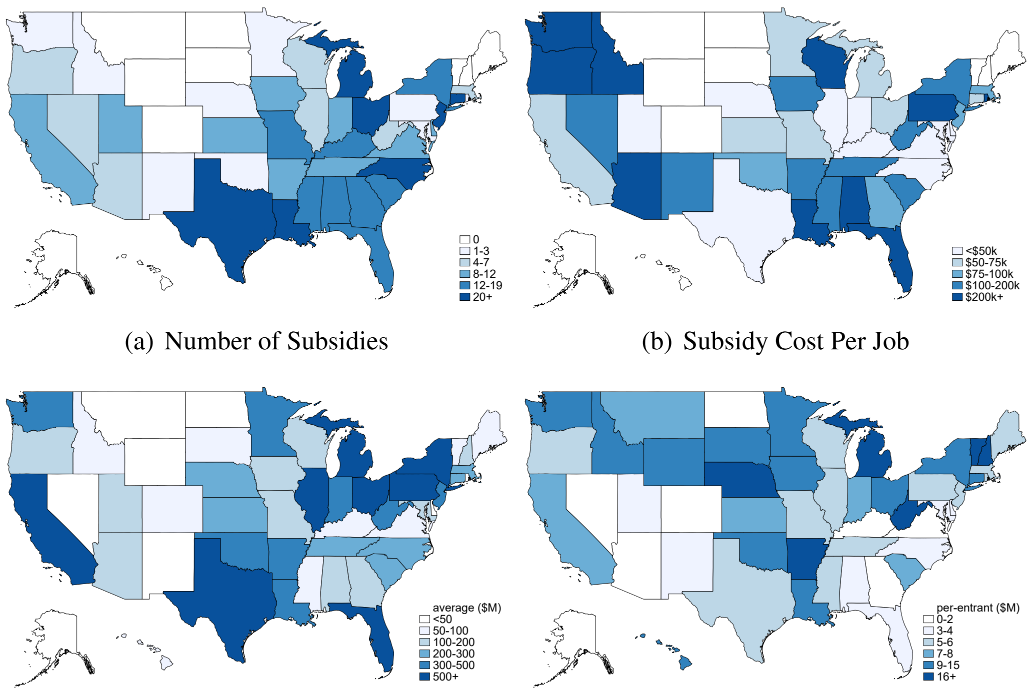
2.3 Descriptive Statistics

The number of discretionary subsidies per year has grown over the sample period: from just over 10 in 2002 to a peak of almost 35 in 2012 (Appendix Figure A.6). Over this period the size of the subsidies did not follow the same trend; there is substantial heterogeneity in total subsidy size and the subsidy cost per job within and across years, industries, and states. On average a firm receives a subsidy worth \$149.5 million over 10 years and promises to create just under 1,400 jobs. This amounts to about \$107,000 per job, or \$10,700 per job per year. At the 10$^{\text{th}}$ percentile the total cost

R&D tax credit. I do not know the size of Lockheed's research and development expenses in California, so I will have to estimate the value of the credit using the number of jobs they will create, the expected wages of those jobs, and the proportion of R&D employment in that industry. Lockheed Martin is a publicly traded firm, so they do report their R&D expenditure to the SEC in the Form 10-K. However, this is not broken down by location of expenditure, and Lockheed operates "significant operations" in 22 locations across 16 states, according to their 2016 10-K.

[22] In Slattery and Zidar (2020) we compare the data collected for this paper with previous efforts and approaches to collect data on incentive spending and subsidy deals. In that paper, we use the same data, but we do not restrict the subsidies to deals for which we know there was a competition and we know the runner-up, therefore we have over 500 deals in the sample for the descriptive analysis.

Figure 1: Geographic Distribution of Subsidy-Giving and Incentive Spending



(a) Number of Subsidies

(b) Subsidy Cost Per Job

(c) Total Business Incentive Spending

(d) Spending Per Establishment

Notes: The four figures above show the geographic distribution of subsidy-giving and spending. Figure (a) is the number of subsidies given by each state over the sample period (2002-2017). Figure (b) is the average cost-per-job of subsidies given in each state. Figure (c) is the yearly average of each states' total business incentive spending, which is not limited to discretionary subsidies. Total business incentive spending includes all tax credits and economic development programs that the state has available to new and expanding businesses. Figure (d) is the average per-establishment incentive spending. This is calculated as the states' total economic development spending in year t, divided by the number of establishments with 100+ employees that entered the state in year t. Data on subsidies and total business incentive spending is collected by the author. Establishment entry is from the Census Business Dynamics Statistics data.

per job is $15,000, and at the 90$^{\text{th}}$ it is $522,000.

Figure 1 highlights geographic patterns in subsidy-giving, cost per job, total business incentive spending, and spending per establishment entry. Note that large states, such as Texas, California, and New York are all top incentive spenders (Panel c), but do not necessarily give the most discretionary subsidies (Panel a) or spend much per subsidy job (Panel b). When spending is normalized by the number of establishments with at least 100 employees that entered the state (Panel d), it is states such as Idaho, West Virginia and Oklahoma that are the top spenders. These are potentially less productive locations for new establishments, so firms require large incentives to locate there.[23]

There is also a considerable amount of heterogeneity in subsidy-giving across industries (Table

[23]Note that many smaller states are never observed giving large discretionary subsidies to firms. This may be due to budget constraints, which I discuss in Section K. I provide more details on the state budget process in Appendix Section A.

Table 1: Terms of Subsidy Deals

Industry (NAICS)	# of Deals	Mean # Bidders	Subsidy ($M) Mean	Subsidy ($M) Med.	Jobs Promised Mean	Jobs Promised Med.	Invest ($M) Mean	Invest ($M) Med.	Cost/Job ($K) Mean	Cost/Job ($K) Med.
Mining, Utilities (21-22)	3	4.0	753.7	314.2	215	225	3,215	2,277	3,506	1,397
Manufacturing (31-33)	204	5.8	203.9	89.3	1,388	900	1,768	472	147	99
Chemical manuf. (3251-3)	15	2.6	293.6	186.8	314	180	1,943	1,255	936	1,038
Automobile manuf. (3361)	35	7.3	271.9	154.1	2,911	2,000	1,012	613	93	77
Aerospace manuf. (3364)	22	7.6	389.0	107.6	1,615	1,020	7,123	688	241	105
Wholesale, Retail Trade (42-45)	15	6.4	68.7	41.1	1,302	820	288	160	53	50
Transport/Warehousing (48-49)	13	3.0	82.2	69.3	1,887	1,050	232	228	44	66
Information Svc. (51)	27	6.6	85.1	74.4	730	450	612	171	117	165
Finance, Insurance, RE (52-53)	44	3.0	50.4	33.3	1,794	1,495	160	75	28	22
Financial activities (5239)	18	3.3	59.0	26.8	1,970	1,825	204	67	30	15
Prof., Scientific, Tech Svc. (54)	43	5.3	119.7	56.3	1,431	700	262	53	84	80
Scientific R&D (5417)	17	3.1	136.5	62.8	549	303	181	95	248	207
Management, Other Svc. (55-81)	38	3.7	59.3	37.5	1,404	972	182	89	42	39
Full sample	387	5.2	149.5	59.5	1,399	907	1,084	214	107	66

Notes: This table displays sector and industry level descriptive statistics on subsidy deals. For each industry group, the table presents the mean and median subsidy size, number of direct jobs promised by the firm (this includes new and retained jobs), and planned investment. I also list the number of subsidy deals in each category, and the average number of locations in competition for the firms in that category (the number of bidders). For large sectors (in terms of subsidy deals), such as manufacturing, I break out the statistics for certain industries. This is for a sample of large subsidy deals for which there was competition between localities and the runner-up location is known. The data were collected by the author. The sample period is 2002-2017.

1). Over half of all subsidies in the sample go to firms in manufacturing industries, with subsidy deals for automobile manufacturers making up about 10% of all observations. Automobile manufacturers promise over 2,000 jobs per deal, so although they receive larger subsidies than average, the cost per automobile manufacturing job remains relatively modest. Meanwhile, subsidies in the chemical manufacturing and mining industries have extremely large cost per job numbers, promising low levels of direct employment and high levels of investment. It is also striking that dissimilar industries, such as management (headquarters) and transport/warehousing, receive similar size subsidies per job on average, at $42,300 and $43,500 per job respectively. The question remains—what explains the generosity of any one subsidy deal?

The most commonly cited motivation for giving a discretionary subsidy is job creation. This is evident from both the legislative text and interviews with policymakers.[24] However, jobs do not go

[24] For example, the legislation enacting North Carolina's Job Development Investment Grant (JDIG) program states: "The purpose is to stimulate economic activity and to create new jobs for the citizens of the State.." In an interview with the Washington Post about the Amazon HQ2 bidding war, Maryland State Senate President Thomas 'Mike' Miller says "Whether in Baltimore City, Prince Georges County or Montgomery County, we need to make it happen. It's jobs, jobs, jobs and more jobs" (Nirappil and Wiggins, 2018).

very far in explaining subsidy size. For the majority of the sample (the 99% of deals with job promises under 10,000), the relationship between total jobs promised and subsidy size is fairly modest; an additional job is correlated with an $18,000 increase in subsidy size.[25]

The unobserved indirect job creation of each firm, that is, jobs expected to be created through spillover, may help rationalize this lack of correlation between direct jobs and subsidy size. Spillovers are another oft-cited justification for the size of a subsidy or competition for a given firm, as well as a motivation for subsidy competition in the theory.[26] Heterogeneity between states, differing valuations of jobs in certain industries, revenue considerations, and economic conditions also could have a role in explaining subsidy size. I explore these possibilities in Table 2, with a linear regression of subsidy size on all of the observed "terms" of the subsidy deal, as well as on state and local characteristics.

The first three columns of Table 2 only consider deal-specific determinants of subsidy size: new jobs promised, investment planned, and the local employment, or "jobs," multiplier. I use the local employment multipliers at the industry level to proxy the average expected spillover job creation.[27,28] A promise of 1,000 more jobs is correlated with a $34 million increase in subsidy size, an additional $1 billion in investment is correlated with a $54 million increase in subsidy size, and an increase of one additional indirect job per promised job is correlated with an $8 million increase in subsidy size. Taken together, investment, jobs, and the jobs multiplier explain about forty percent of the variation in observed subsidies.

If firms create different value across space, state and local governments should vary in their willingness-to-pay for an identical establishment. This could be due to the expected revenue from new economic activity—a state with a higher corporate income tax can expect to collect more revenue from increased business activity in the state. It could also be due to differences in the value of a new job—local residents who are employed at the new establishments will enjoy welfare gains that

[25]In Appendix Figure A.7 I plot the total number of jobs promised by a firm with the size of the subsidy it received. Total jobs promised includes the new jobs the firm promises to create and the jobs the firm promises to retain. When the subsidy deal is for an expansion then retained jobs are often part of the deal; the firm is promising to stay and expand in their current location, instead of picking up and moving elsewhere.

[26]However, there is limited data on firm-state specific spillovers. North Carolina provides predicted "indirect job creation" in the documentation of their discretionary grant program. They often estimate the indirect jobs created by attracting a given firm will be an order of magnitude greater than the direct jobs. See Figure A.1 in the Appendix.

[27]In a previous draft I explicitly model expected spillovers by estimating the effect of large firm location decisions on the location of smaller firms, in a discrete choice framework (Berry, 1994). Results available upon request.

[28]The multiplier represents the predicted number of jobs created in the local economy for every one new job in the industry. The Economic Policy Institute (EPI) uses Bureau of Economic Analysis data to create these employment multipliers. I check the EPI multipliers against the North Carolina data and find similar magnitudes. For example, North Carolina predicted that the pharmaceutical firm Novo Nordisk would have a jobs multiplier of 6.2, while the EPI reports a multiplier of 5.7 for the pharmaceutical industry.

Table 2: Reduced Form Evidence: Determinants of Subsidy Size

	Dependent variable: Subsidy ($M)					
	(1)	(2)	(3)	(4)	(5)	(6)
Deal Characteristics:						
New Jobs Promised (1,000)	42.98***	34.09***	34.13***			37.31***
	(6.86)	(5.86)	(5.66)			(5.70)
Investment Planned ($B)		60.95***	54.20***			54.21***
		(5.09)	(5.09)			(5.04)
Industry Multiplier			8.33***			6.95***
			(1.62)			(1.67)
State Characteristics:						
Corp. Tax Rate (%)				6.78	3.94	7.75**
				(3.66)	(3.65)	(2.95)
Income Tax Rate (%)				-12.30***	-10.85**	-7.66**
				(3.35)	(3.49)	(2.82)
Right-to-Work					-51.34**	-20.99
					(17.33)	(14.92)
Local Characteristics:						
Unemp. Rate (%)				20.39***		13.86**
				(5.57)		(4.64)
Log(Income per Capita)				-2.86		103.85
				(42.84)		(59.88)
Concentration of Industry Estab.					-46.87**	-12.00
					(15.12)	(12.80)
Local Industry Wage ($1,000)					0.07	-0.22
					(0.30)	(0.24)
House Prices ($1,000)					-0.05	-0.18
					(0.10)	(0.10)
Research University					-23.61	-14.51
					(18.34)	(14.32)
Airport					2.58	4.67
					(19.80)	(15.87)
Observations	380	380	380	380	380	380
R-squared	0.11	0.36	0.41	0.08	0.10	0.46

Notes: This table presents the results of a linear regression of subsidy size on subsidy deal characteristics, state characteristics, and local (commuting zone) characteristics. The coefficients represent correlations between observed subsidy size and observed characteristics. Each observation is a subsidy deal, the sample is 2002-2017, and regressions include year fixed effects. The sample is restricted to subsidies under $1 billion, which means that 7 subsidy deals with extremely large subsidies (for example, Foxconn) are not included. Data on promised jobs, investment, subsidy size, and industry of the firm are compiled by the author. The jobs multiplier is from the Economic Policy Institute (2019). Sources for state and local characteristics include the CSG Book of the States (1950-2018) (tax rates), U.S. Bureau of Economic Analysis (1967-2017) (per capita income), National Conference of State Legislatures (2019) (right-to-work), Bureau of Labor Statistics (1990-2017) (unemployment), County Business Patterns (1997-2017) (establishments, wages), National Science Foundation (2000-2017) (research universities), Zillow (1996-2020) (housing prices), and Federal Aviation Administration (2019) (airports).

depend on their prior wages and employment status.[29] Column 4 of Table 2 considers the location characteristics that might affect the state and local governments' willingness-to-pay for the firm. This includes tax rates, the local unemployment rate, and per capita income. A one percentage point increase in the unemployment rate in the winning county of the subsidy deal is correlated with a $20 million increase in the subsidy size, but, on their own, location characteristics that might explain willingness to pay only explain 8% of the variation in observed subsidy size.[30]

Column 5 of Table 2 displays the correlation between subsidy size and the location characteristics that the firm might consider when making their location decision. If the firm has a lower expected productivity in a given location, they should demand a larger subsidy to compensate them for not going to a higher productivity location, all else equal. For example, firms value certain pro-business policies, such as right-to-work laws (Holmes, 1998*a*), so they are willing to accept lower subsidies in right-to-work states. The same is true for local amenities, such as whether there is a research university, or airport, in the county. In the final specification I include all of the variables: deal characteristics that affect how much a firm's establishment is worth to a locality, location characteristics that affect the state and local government's willingness to pay, and location characteristics that affect the firm's location decision.

Table 2 provides insights on how firm characteristics, government willingness-to-pay, and location profitability can affect subsidy size. Of course, there is one important element missing in this analysis: competition. The observed subsidy size is not only a function of the profitability of the location and the local government's willingness-to-pay, it is a result of competition between locations. In order to incorporate competition, I introduce the model.

3 Model

In this section I develop a model of subsidy competition. I use anecdotal evidence from reporting on subsidy deals and the site selection process, institutional details from internal reports, and discussions with state economic development agencies and company officials to inform my modeling approach. To be specific, I model subsidy competition as a private value open outcry ascending (English) scor-

[29] In Slattery and Zidar (2020) we show that in the aggregate higher corporate tax rates are correlated with higher per-capita business incentives. We also show that in the individual subsidy data, poorer counties pay more per job.

[30] Appendix Table A.2 shows how state-level economic and political characteristics correlate with per capita business incentive spending, using the state level data.

ing auction. You can think of firms "shopping" across locations for the highest payoff (the sum of the location-specific profit and the subsidy offer). Firms can use other locations' offers to negotiate better subsidy deals. Then, the firm will locate in the highest payoff location, with a subsidy that leaves the second-highest payoff location with a zero payoff, after accounting for differences in firm profits between the two locations.[31]

The model captures many real world features of subsidy competition in the United States. First, firms do not always locate in the highest subsidy place: they care about other location characteristics that affect their profits, like human capital, wages, and labor laws. Therefore, we can think of the competition as a scoring auction, where the locations submit bids which are scored on subsidy (traditionally, this is price) and profit (traditionally, this is quality). As noted in the introduction, many of the subsidy offers that Amazon received were larger than the subsidies offered by the winning locations.[32]

Second, there are often multiple rounds of bidding in a subsidy competition. That means that a local government can submit one subsidy offer, and then, after learning that they are still not the highest payoff place, offer a larger subsidy. This is why I chose the ascending auction—the bidder (local government) can increase its bid over the course of the auction.[33]

The third institutional detail that I capture is that local governments know the subsidy offers of their competitors.[34] In the auction framework this is an open outcry auction. This is an important feature, because it disciplines the bidders to increase their bids only when they know they have been outbid, and the current bid is lower than their valuation. The open-outcry ascending auction is also called an "English" auction, and is strategically equivalent to the second price auction.[35]

The last feature of the auction is that it is private value. In this context, this means that the local governments know with certainty the benefit or value the firm will create in their jurisdiction. This value is location-specific: the firm is not expected to create the same amount of value in each locality.

[31] Recent work on consumer loan and mortgage markets take a similar approach, as markets with negotiated prices often resemble English Auctions (Allen, Clark and Houde, 2019; Cuesta and Sepúlveda, 2019). For example, Cuesta and Sepúlveda (2019) use an English auction to model the process in which consumers shop across banks for the best contract offer. The consumer signs the contract with the lowest cost bank, at the interest rate that leaves the second-lowest cost bank with zero profits.

[32] I usually do not have data on the size of the subsidy in the runner-up, but this is true for the Hyundai plant in Alabama (2002), the Samsung plant in Texas (2006), and the Foxconn factory in Wisconsin (2017), among others.

[33] Firms and consultants often cite being in "discussions" with multiple locations throughout the site selection process. Over this time the locations can refine the subsidy offer.

[34] See Appendix Section C for evidence of this assumption.

[35] Allen, Clark and Houde (2019) and Cuesta and Sepúlveda (2019) also use the 2nd price auction equivalence in their applications.

This is the crux of the allocative efficiency argument—competition can improve the allocation of firms to localities if localities have different values for a job, or different agglomeration externalities. There may be some correlation in valuations, based on firm characteristics. This is incorporated in the model, where state and local governments draw a valuation conditional on firm observables.[36]

To summarize, I will use a private value English scoring auction to model the subsidy competition. Bidding for a firm begins when the firm contacts the states it is considering for an expansion or relocation, and continues as states learn of other bids and adjust their subsidy offers. The firms that are being "auctioned" have a discrete choice problem; they locate in the state that gives the highest payoff, where payoff is a function of the subsidy offer and the profit they would receive in that state.

The model captures the mechanism through which states compete for firms, and allows me to clearly separate the government valuation for firms and the firm preferences over locations. This will allow me to explain how state and local governments make subsidy decisions, and how subsidies influence firm locations.

3.1 Model Set-up

There are two types of agents in the model: State (and local) Governments and Firms that receive discretionary subsidies.[37]

The state, s, has a valuation for each firm, i, which is a function of location characteristics x, and firm characteristics, z. This valuation is denoted $v_{is}(x,z)$. The value a firm brings to the state, v, can depend on a variety of factors, including the revenue the state and municipality anticipate receiving from increased tax collections as well as any positive externalities the firm is predicted to create create via increasing demand for services, attracting other firms, or increasing local housing prices. It can include negative things like congestion or the cost of raising funds. This function may differ substantially across locations. Given the heterogeneity across states in the spillover and revenue impact of any given firm, this is modeled as a private valuation—the benefit of firm i locating in state s is different across states, conditional on firm characteristics.

The firm, i, has a profit in each location, denoted $\pi_{is}(x,z)$. This will also be a function of location

[36] See Section K for an extended discussion of this assumption.

[37] Throughout this section I will simplify by using the word "State" to denote the state and local government. In reality, the state and local government may both contribute to the subsidy deal, and the "state" valuation for the firm will depend on the specific location within the state that the firm is considering locating. I allow for this in estimation, but stick to the state as the relevant location in the model to simplify notation.

and firm characteristics, x and z, such as the wages and taxes in the location, and the size of the planned investment of the firm.

3.2 Example: Auction with 2 States

I will illustrate how the auction for firms works with a simple example (also shown in a diagram in Figure 2). Suppose there are two states, State 1 and State 2, competing for a firm, Firm A. Firm A has a profit of \$10 million in State 1, which values Firm A at \$3 million, $\{\pi_{A1}, v_{A1}\} = \{10, 3\}$. In State 2, $\{\pi_{A2}, v_{A2}\} = \{7, 7\}$.

In absence of subsidy competition, Firm A would locate in the state that gives the highest profit, State 1, receiving a payoff of \$10 million. State 1 would receive their value for the firm, \$3 million, for a total welfare $(\pi + v)$ of \$13 million.

If the states compete for the firm in an English auction, State 2 can start the bidding with a subsidy offer of \$3 million + ε, making the payoff Firm A would receive in State 2 ε higher than its' payoff in State 1. However, State 1 can respond to that, and states will continue to increase their subsidy bids until one of the states reaches its valuation for the firm. In this example, State 1 will not bid higher than \$3 million. Firm A receives a payoff of \$13 million in State 1 when it bids up the subsidy to its total value; State 2 responds by offering a payoff that is ε higher than \$13 million, which means it offers a subsidy of \$6 million + ε. Therefore, State 2 offers the highest payoff for Firm A, and Firm A locates in State 2.

Note that the total welfare when Firm A locates in State 2 is \$14 million; welfare has increased due to subsidy competition. Therefore, in this simple example, subsidy competition is not a zero-sum game. This is due, in part, to heterogeneity in the state valuations for the firm. Competition allows the state that would experience a larger benefit from the firm's entry to compensate the firm for its location-specific externality.

In this example, subsidy competition reduces the total payoff captured by the states. Without competition, State 1 would receive a payoff of \$3 million, its total valuation for Firm A. With competition, State 2 has a payoff of $v_{2A} - b_2 = 1 - \varepsilon$, just under \$1 million. Therefore, although total welfare increases with competition, this welfare gain is captured by the firm, and total state welfare decreases. If the difference in the two states' valuations were larger, both state and firm payoffs could increase under competition. The distribution of any welfare gain between the firm and the state

Figure 2: Subsidy Competition Example with 2 States

State 1	**State 2**
$\pi_{A1} = 10, v_{A1} = 3, W = 13$	$\pi_{A2} = 7, v_{A2} = 7, W = 14$
$\vdots$	$b_2 = 3 + \varepsilon$
$b_1 = v_{A1} = 3$	$\pi_{A2} + b_2 = 10 + \varepsilon$
$\pi_{A1} + v_{A1} = 13$	$\vdots$
- - - - - - - stop - - - - - - -	$b_2 = 6 + \varepsilon$
	$\pi_{A2} + b_2 = 13 + \varepsilon$

Notes: This figure diagrams an example of subsidy competition between two states.

depends on not only the welfare in the winning location, but the valuation in the runner-up.

One could easily formulate an example where competition is a zero-sum game. Consider the same case as the example above, except that the valuation of State 2 is \$5 million instead of \$7 million. Competition would still result in Firm A locating in State 1, but more rent would be transferred from the state to the firm. It is the correlation between π and v, as well as the heterogeneity in v, that dictate whether allowing competition will change the location decisions of the firm.

In Appendix D I generalize this example, and use the model to predict the change in welfare and division of welfare gain, under different assumptions on the number of bidders and the joint distribution of v and π. The results of the model simulations corroborate the predictions from the simple example. Appendix Figure D.1 shows how the share of simulated deals with a strictly positive welfare gain (e.g. the share of cases where allowing competition induced the firm to choose a higher welfare location) changes with the covariance of v and π (left panel) and the variance of v (right panel). As the correlation between v and π grows the highest profit place is more likely to be the highest welfare place, decreasing the share of deals that induce firms to choose a different location. However, even though the correlation is important to predicting competition's effect on location choice, it is not the most important object. The simulations highlight that, given the baseline level of heterogeneity in valuations and profits, even a positive correlation in valuations and profits will still predict many firms choosing alternate locations due to subsidy competition. Meanwhile, as the variance of v increases, so does the instance of welfare gain. With more heterogeneity in valuation, subsidy competition is more likely to allocate a firm to a location that has a very high value for winning that firm.

I also use the simulations to predict the total welfare gain and the split in welfare between firms and states (Appendix Figures D.2 and D.3). Here, it is the variance in v that is much more important than the correlation between v and π, at least in the range of values that may be feasible in this setting. The simulations emphasize that the heterogeneity in valuations will be the key to the welfare results. This has implications for both the number of location choices that subsidy competition has the ability to affect, as well as the size of the welfare gain given those relocations. More variance in valuations also will allow the locations to capture more of the welfare gain, as it will increase the difference between the payoff in the winning and runner-up states.[38]

The goal of this paper is to estimate the distribution of π and v with the subsidy data, in order to quantify the welfare gains from subsidy competition and the distribution of the welfare gain between firms and states. Now I will provide model details and formal notation.

3.3 Model Details

I will start with the timing of the game and then detail the optimization problem for each agent. The timing of the game is as follows:

(t=0) *Firm i* decides to expand or relocate, and conducts research about all potential sites, $s \in S$.[39]

(t=1) *Firm i* contacts a short list of n sites, $s \in S^n$, about the locating in s.

State governments, $s \in S^n$, bid for firm i.

(t=2) *Firm i* locates in the site with highest payoff.

Model Primitives

Each location $s \in S$ independently draws a profit level and a private valuation for firm i, $\{\pi_{is}, v_{is}\}$, from the joint distribution $H^0_{\Pi,V}(\pi, v|z)$. The sum of profit and valuation, $w_{is} = \pi_{is} + v_{is}$, represents the total welfare created if firm i locates in location s.

[38] This is consistent with a key result of theoretical work on subsidy competition (Martin, 2000*a*).

[39] Multiple firms may conduct searches and choose locations each year (and at different times within a year). I assume there are no immediate synergies between firms; winning one auction does not explicitly increase (or decrease) my willingness to pay for the second firm. However, to the extent that winning a firm changes a location's characteristics, I allow this in estimation. Therefore, winning a firm can indirectly have an effect on both the probability of winning future deals and the state's valuation of subsequent firms.

Firm chooses a shortlist

Firm i does research on each site, s, to learn π_{is}. The firm then chooses the sites with profits above an exogenous, firm-specific profit cutoff, $\bar{\pi}_i$.[40] Here, $\pi_{i(|S|)}$ is the profit in the location that gives the highest profit to firm i and $\pi_{i(|S-n+1|)}$ is the lowest profit location that still gives profits higher than $\bar{\pi}_i$ ($\pi_{i(|S-n+1|)} \geq \bar{\pi}_i$ while $\pi_{i(|S-n|)} < \bar{\pi}_i$).

The resulting short list, S^n, has n_i of a possible $|S|$ total sites, with profit levels $\{\pi_{i(|S|)}, \pi_{i(|S-1|)}, \dots, \pi_{i(|S-n+1|)}\}$. The process of doing research on a large number of locations and then negotiating with a short list of those locations follows the institutional details of the site selection process (see Section 2.1 and Appendix E for more details).[41]

Locations bid for firm

Locations that are on the firms' short list, S^n, compete for the firm in a private valuation English auction. The English auction is a open-outcry ascending auction, which means that a state can announce a bid and then increase their bid once another state makes a more attractive offer.[42] This is strategically equivalent to the 2nd price auction, in which every bidder bids their value, and the highest value bidder wins the good, paying the price of the second highest bidder. The optimal strategy for the state is straightforward—it bids up to its value, v_{is}, for the firm. Due to the process by which firms shortlist locations, the locations competing for the firm draw valuations from the truncated distribution:

$$H_{\Pi,V}(\pi, v|z) = H^0_{\Pi,V}(\pi, v|z, \pi \geq \bar{\pi}).$$

If firm i chooses to locate in state s, the state receives a payoff of $v_{is} - b_{is}$, where b_{is} is the subsidy paid to the firm.

[40] Firms face costs to negotiating with each locality in both time and consultant fees. Moreover, only certain locations might have the exact combination of characteristics a firm is looking for, such as the appropriate labor market and a large enough plot of open land that is ready to build. This is the micro-foundation of having a shortlist. At some point, due to the increased costs, it is not worth adding more locations, even if that increases chance of having higher subsidy draw. It could also be rationalized as v being small, relative to π, different time horizons of π and v, and relatively low variance in v. A notable exception is Amazon HQ2, where all localities were invited to submit bids, and the Amazon team had the resources to go through them all (though it is likely that the company had some locations in mind to start with). I will note that in the data none of the firm or deal observables are correlated with the number of locations on the shortlist.

[41] One concern is that firms are strategically soliciting bids, and inviting locations that may have relatively low π_{is}, but high expected v_{is}, essentially creating artificial competition to push up the winning bid in one of the locations with higher profits. This may be more successful in some industries than others. I am assuming the firms are shortlisting the most profitable locations, as they describe in interviews with site selection trade publications (Appendix E). However, if this assumption is violated, one would expect the winning bids to be closer to the valuation of the winning location. I repeat the analysis under this assumption in Appendix J.

[42] As the firm receives subsidy offers, it updates the competing states about whether or not they are still offering the highest payoff. I will discuss this assumption further in the next section.

Firm chooses a location

The firm's objective is to maximize payoffs. This means that the winning state is not always the one with the highest subsidy offer. Instead the firm will locate in the state that gives them the highest payoff, which is the sum of their profit in the state and the subsidy offered by the state.

I model firm i's payoff from locating in state s as:

$$p_{is} = b_{is} + \pi_{is} \tag{1}$$

where b_{is} is the final bid (subsidy offer) of state s, and π_{is} is the profit of firm i in state s.

Firm i locates in s if it gives the highest payoff of all states in S:

$$y_{is} = \mathbb{1}[\underbrace{b_{is} + \pi_{is}}_{p_{is}} \geq \underbrace{b_{im} + \pi_{im}}_{p_{im}} \ \forall\, m \in S^n].$$

Outcome

The English auction ends when there is only one bidder remaining. Therefore, the winning location will offer a subsidy that would result in zero payoff in the runner-up location, after accounting for the profit difference between the two locations.

The outcome of the model is a set of equilibrium subsidies and firm locations, $\{b^*_{is}, y^*_{is}\}$ s.t.

$$\begin{aligned}
\text{losing subsidy offers: } & b_{ij} = v_{ij}(x_j, z_i) \\
\text{winning subsidies: } & b^*_{is} \leq v_{is}(x_s, z_i) \\
\text{locations: } & y^*_{is} = \mathbb{1}[\pi_{is} + b^*_{is} \geq \pi_{ij} + b_{ij} \ \forall\, j \in S^n].
\end{aligned}$$

4 Identification

The primitive from the model that I would like to identify is the joint distribution of profits and valuations $H_{\Pi,V}(\pi, v|z)$.[43] I have data on firm locations, winning subsidy bids, runner-up locations, and location and firm characteristics.

Identification challenges arise because I only have data on winning subsidies and not the profits in the winning location (i.e., I do not observe winning payoffs, where payoffs represent the firm profit plus the subsidy). If firms only cared about the subsidy, and not other location characteristics, this

[43] Recall that this is the truncated distribution of H^0. The aim is to identify the distribution of profits and valuations of locations on the firm's shortlist.

would be a straightforward problem.[44] However, because locations compete on payoffs, and I do not observe the winning payoff, there are multiple steps.

In the first step I recover the parameters of the firm profit function and the runner-up valuation. I use the equilibrium condition from the model—the winning location should give the firm the same payoff as the runner-up. In the second step, I use the estimated profits and valuations to calculate the welfare in the runner-up location. This allows me to apply the order statistic identity, and recover the full distribution of welfare. Finally, because total welfare is a function of state valuations and firm profits, I can exploit the relationship between profits and valuation in the runner-up states to invert the distribution of welfare and recover the marginal distribution of state valuations for firms. I take the rest of the section to provide intuition and details.

4.1 Firm Profits

From the model we know that firm i goes to the state (bidder) that gives the highest payoff. We also know the optimal bidding strategy of each state is to offer a subsidy up to their value, until no other state can raise their bid. This means that the winning state can stop bidding when the payoff they give the firm just exceeds the welfare in the runner-up state. Essentially this is an auction on "total welfare," and, like the second price auction, the winning state will guarantee the firm the second highest welfare as payoff:

$$\underbrace{\pi_{\text{winner}} + b_{\text{winner}}}_{\text{payoff in winning location}} = \underbrace{\pi_{\text{runner-up}} + v_{\text{runner-up}}}_{\text{welfare in runner-up location}} \tag{2}$$

To formalize the argument, I assume:

Assumption 1 *States compete for firm i in a private-value English auction. In this auction, the seller (firm) updates the bidders (states) when their offer has been dominated.*

As discussed in the start of Section 3, states learn competitors' subsidy offers through discussions with the firm (see Appendix Section C for evidence). Therefore, I am assuming that the firm is truthful about which location is most desirable throughout the auction process. I have discussed the issue of non-truthful firms with state economic development agencies. In the event that states are suspicious that the firm is not accurately representing the alternative options, many agencies request

[44] I would not need to recover profits, and the winning subsidy would represent the second order statistic from the distribution of state valuations. Therefore, identification of the distribution of valuations would be achieved using the order statistic identity (Athey and Haile, 2002).

documentation of both offers from other locations and costs in other locations to verify a firm's claims.[45,46]

Assumption 1 gives way to the following result:

Proposition 1 *The winning location will bid up to the firm's payoff in the runner-up location. For ease of notation, let us call the location with the highest payoff, the winner of the auction, location 1, and the runner-up location 2.*

$$b_{i1}^{*} + \pi_{i1} = b_{i2} + \pi_{i2} \tag{3}$$

Due to the structure of the English auction, location 1 will never offer a subsidy higher than b_{i1}^{*}, as defined in Equation 3, because it will not change the probability of winning, but it will lower their payoff, $v_{i1} - b_{i1}$.

In the English auction all losing states must have offered subsidies equal to their valuations, which is their stopping rule. This means that $b_{i2} = v_{i2}$ and I can rewrite Equation 3 as:

$$b_{i1} = v_{i2} + \pi_{i2} - \pi_{i1}. \tag{4}$$

Equation 4 is a function of both profits and valuations, two primitives that I do not observe. Because I only have data on winning bids, I will not be able to separately identify these two objects without further assumptions. Here, I will characterize both firm profits and the runner-up valuation as a function of observable firm and location characteristics:

Assumption 2 *Profits of firm i, in locality c and state s, are a function of observed location characteristics, x_{cs}^{π}, observed firm characteristics, z_i, and unobserved firm characteristics, η_i:*

$$\pi_{ics} = x_{cs}^{\pi} \beta_i$$

where $\beta_i = \beta + z_i \beta^o + \sigma \eta_i$ *and* $\eta_i \overset{\text{iid}}{\sim} N(0,1)$.

The random coefficients model allows firms that are similar on observables to have different preferences over location characteristics, for reasons that are unobservable to the econometrician.

[45]Alternatively, one could assume that states observe both subsidy offers from competing states, $\mathbf{b}$ *and* firm profits across all states, $\boldsymbol{\pi}$. If there is asymmetric information in profits, the state may not know the payoff they have to offer the firm to ensure they win the competition, causing them to "overbid". However, given the state has a long history of competing for firms and observing location choices, as well as access to financial information for publicly traded firms, this is not necessarily far from reality.

[46]This is a related issue to the assumption that the short list is only selected on profits, and that high valuation locations are not included to increase the competition.

Assumption 3 *The valuation in the runner-up location is a function of observed location characteristics, x^v_{cs}, observed firm characteristics, z_i, and an unobserved location-firm specific match, ε_{ics}. The unobservable portion of the valuation is additively separable and normally distributed:*

$$v_{ics} = \alpha(x^v_{cs}, z_i) + \varepsilon_{ics} \tag{5}$$

where $\alpha(x^v_{cs}, z_i) = z_i\alpha_z + x^v_{cs}\alpha_x + z_i x^v_{cs}\alpha_{zx}$ and $\varepsilon_{ics} \sim N(0, \sigma_\varepsilon)$.

Note that location characteristics, $\mathbf{x}_{cs} = \{x^\pi_{cs}, x^v_{cs}\}$, enter both the firm profit function and the runner-up's valuation. There are location characteristics that may affect both profits and valuations, so the intersection of these two sets is non-empty.

I plug in equations (4) and (5) into equation (3),

$$\underbrace{x^\pi_1\beta_i}_{\pi_{i1}} + b_{i1} = \underbrace{x^\pi_2\beta_i}_{\pi_{i2}} + \underbrace{\alpha(x_2, z_i) + \varepsilon_{i2}}_{v_{i2}}$$

and arrive at an expression for observed winning subsidies as a function of observed firm and location characteristics:

$$b_{i1} = (x^\pi_2 - x^\pi_1)\beta_i + \alpha(x^v_2, z_i) + \varepsilon_{i2}. \tag{6}$$

In order to identify the parameter of interest, β, I need one additional assumption on the structure of the location unobservables that affect valuations, ε.

Assumption 4 *The unobservable portion of the valuation in the runner-up location, ε_2, is independent of the difference in location observables that affect profits in the winning and runner-up locations, $\mathbb{E}(\varepsilon_2 | x^\pi_2 - x^\pi_1) = \mathbb{E}(\varepsilon_2)$.*

Independence of ε_2 and Δx^π is necessary for consistent estimates of β. A concern here is the bias induced by the selection inherent in the auction process; locations that are less profitable for firms are only likely to become the runner-up by virtue of having a large ε_2.[47] In Appendices F and G I discuss potential unobservables that enter ε. Most of these unobservables are politics and budget related, and therefore unlikely correlates with the *difference* between the location fundamentals in the winning and runner-up locations. Appendix Tables F.1 and F.2 also show that there are no location observables that seem to be systematically over- or under-represented in winning locations (compared to runner-ups).

Of course, neither of the above arguments are smoking guns; the selection inherent in the auction leads to a relationship between low profits and high valuations in runner-up places (or, high profits

[47]The same logic holds runner-ups that are very profitable to a firm, but end up the runner-up due to a small ε.

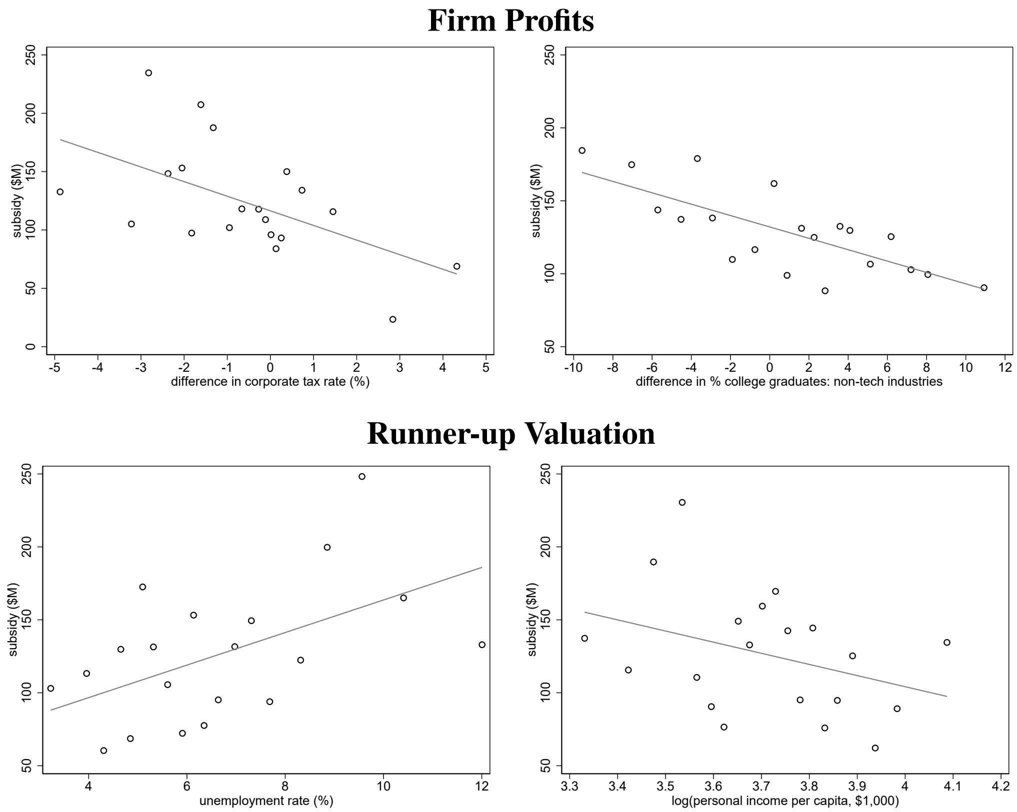
and low valuations). In the Appendix I take an alternative approach that does not rely on Assumption 4. The alternative approach requires independence of ε and x, but the assumption is not specific to the unobservable valuation of the runner-up. See Appendix J.2 for further discussion and results.

To see the intuition for my approach, imagine two subsidy deals for two pharmaceutical manufacturing plants of identical size. One plant locates in New Jersey with a subsidy of \$90 million and the other locates in Pennsylvania with a subsidy of \$80 million. In both cases, the runner-up in the subsidy competition is Virginia, so the runner-up valuation and profit are held constant. Now suppose Pennsylvania and New Jersey have almost all of the same location characteristics: the same infrastructure, the same wages, the same skilled workforce. The only difference between the two states is that the corporate tax rate is 11.5% in New Jersey and 10% in Pennsylvania. Then, the \$10 million difference in the two observed subsidy deals can be attributed to how much pharmaceutical manufacturers value a 1.5 percentage point lower corporate tax rate.

Figure 3 presents the graphical representation of this identification strategy for two variables that enter the firm's profit function: corporate tax rates and the education of the workforce. Each figure is a binned scatter plot, which controls for the other variables that enter profits and state's valuation. The figure on the top left shows the relationship between the observed winning subsidy and the difference in the corporate tax rate in the runner-up and winning location, holding other location and firm characteristics constant. This shows a negative relationship between winning location tax rates and subsidy size. As the winning state's tax decreases relative to the runner-up, the subsidy size decreases, as the relative profitability of the location has increased.

The bottom panel of Figure 3 shows two variables that enter the runner-up location's valuation for winning the firm: local unemployment and personal income per capita. Note that these characteristics, of the *runner-up* location, are correlated with the subsidy in the *winning* location. If the winning and runner-up are not competing, as laid out in the model, one would not expect any correlation between runner-up characteristics and winning subsidies. However, the valuation parameters, α, that I estimate for the runner-up location do not have any causal interpretations, and instead should be interpreted as correlations.

Figure 3: Identification via Runner-up



Notes: These figures show the variation in the data that allow me to identify the parameters of the profit function and correlates of the runner-up valuation. Each figure is a binned scatter plot, which controls for the other differences in location characteristics, firm characteristics, and runner-up location characteristics (Equation 6). The top two figures show the relationship between the observed winning subsidy and the difference between the runner-up and winning location characteristics that may enter the firm's profit function. The bottom two figures show the relationship between the observed winning subsidy and the runner-up location characteristics that may affect the runner-up's valuation.

Given the estimates of the profit parameters, $\{\beta, \beta^o, \sigma\}$, I can use the out-of-sample (non winner or runner-up) location characteristics, x, to predict firm profits across competing locations: $\hat{\pi}_{is} = x^{\pi}_{cs}\hat{\beta}_i$, giving way to an empirical marginal distribution for profits in the shortlisted locations: $\hat{H}_{\pi}$.

The model, following the site selection process, dictates that selection on π results in the short list of locations, while selection on $\pi + v$, via the auction, gives us the winning and runner-up locations. Therefore, heterogeneity in v might be substantial across the short list, and "observing" v in the runner-up location might not be a good proxy for v in the 3rd or 4th choice location. The rest of this section focuses on pinning down this distribution, H_v.

4.2 Welfare

Given the parameters of the firm profit function and of the runner-up valuation, I have the empirical joint distribution of runner-up profits and valuations, and I can calculate welfare in the runner-up location:

$$\hat{w}_{i2} = \underbrace{x_2^{\pi}\hat{\beta}_i}_{\pi_{i2}} + \underbrace{\hat{\alpha}(x_2^{v}, z_i) + \hat{\varepsilon}_{i2}}_{v_{i2}}. \tag{7}$$

The estimates of welfare in the runner-up locations give way to the distribution of the second order statistic of welfare. The last assumption that I need to make before proceeding to the estimation is on the distribution of welfare:

Assumption 5 *Welfare across locations, w, is distributed i.i.d.* $F(w|z)$.

This assumption precludes bidder types—strong versus weak locations. Of course, some locations have higher profits than others, but the selection of the short list means that the profits should be relatively similar—all of the bidders have high enough profits to be on the shortlist. There is no obvious way to classify bidders by type ex ante, and the types would need to classify bidders by their valuation as well as their profitability.[48] This assumption also precludes correlation in bidder valuations over time, which I discuss in Appendix K.

I can nonparametrically identify the distribution $F(w|z)$, using the distribution of runner-up welfare, $F(w|z)^{(n-1:n)}$. Identification of $F(w|z)$ comes from the order statistic identity. The i-th order statistic from an i.i.d. sample of size n from an arbitrary distribution F has distribution (Arnold, Balakrishnan and Nagaraja, 1992; Athey and Haile, 2002):

$$F^{(i:n)}(w|z) = \frac{n!}{(n-i)!(i-1)!}\int_0^{F(w|z)} t^{i-1}(1-t)^{n-i}dt \tag{8}$$

where n is the number of bidders. Therefore the distribution of welfare in all states, $F(w|z)$, is identified from data on the 2nd order statistic of welfare, $w_i^{(n-1:n)}$.

Number of Bidders

Equation 8 requires knowledge of the number of bidders in the competition. I have data on the number of bidders for over 90% of the sample. For the subsample of observations for which I do not know the number of bidders, I use the mean from the data, which is 5. The median number of bidders

[48] In the Appendix I take an alternate approach that does not rely on assumption of i.i.d. bidders, but requires additional assumptions on the structure of the problem. See Appendix J.2 for more details and results under this alternative approach.

in the sample is 3. As the number of bidders is fairly low in most cases, for 50% of the sample I not only know the number of bidders but I also know their identities.[49,50]

Given the identification of the parameters of the profit function and the distribution of welfare, I proceed to the final object of interest, the marginal distribution of the state valuation of firms, $H_V(v|z)$.

4.3 Valuations for Firms

Recall, the goal is to identify the joint distribution of firm profits and state valuations $H_{\Pi,V}(\pi,v|z)$. From the model, I know the relationship between welfare (w), profits (π) and state valuations for the firm (v): $w = v + \pi \sim F$. From Section 4.2, I know the distribution of welfare, $F(w|z)$. From Section 4.1, I know the marginal distribution of profits, $H_\Pi(\pi|z)$. I also can approximate the joint distribution of runner-up profits and runner-up valuations, $\hat{H}_{\Pi V}^{runner-up}$. The challenge remains to recover the joint distribution of firm profits and government valuations across short-listed locations.[51]

In order to achieve identification I will employ a copula, which allows the representation of the joint distribution, $H(\pi,v|z)$, as a function of the two marginal distributions and a dependence parameter. I can rewrite $H(\pi,v|z)$ as $C(H_\Pi, H_V|z)$, where C represents the dependence structure between the two marginals, H_Π and H_V, with dependence parameter ψ. Then, the distribution of welfare is just the convolution of the marginal distributions of profits and valuations:

$$\begin{aligned} H_V(t|z) = \Pr(v < t|z) &= \Pr(w - \pi < t|z) \\ &= \Pr(w < t + \pi|z) \\ &= \int F(t+\pi|z)h(\pi|t,z)d\pi, \end{aligned} \tag{9}$$

I can solve for ψ, given a parameterization of C and the assumption that the correlation between valuations and profits in the runner-up locations (recovered in Section 4.2) is the same as the correlation between valuations and profits throughout the distribution:[52]

[49] See Appendix B for a discussion and to see the distribution of number of bidders in the data.

[50] A usual concern in the estimation of English auctions is that the number of bids is a lower bound on the actual number of bidders (Haile and Tamer, 2003). However, the data on the number of bidders is not from bidding data, where this would be a concern. It is from the firm's shortlist. This is the number of locations that the firm invites to bid. There may be locations on the shortlist that do not have a sufficiently high valuation and do not submit bids, they will still be included in the number of bidders. There may be locations that would love to submit bids but are not on the shortlist, they are not considered by the firm and they are not included in the number of bidders.

[51] When profits and valuations are independently distributed then the probability density function of the sum of dependent random variables is equivalent to the product of the transforms of each random variable (Springer, 1979). However, the dependence between v and π makes this a more complicated problem.

[52] See Appendix I.2.1 for details on the parameterization of the copula C.

Assumption 6 $\rho(v^{runner-up}, \pi^{runner-up}) = \rho(v, \pi)$.

So I can rewrite Equation 9 as:

$$\begin{aligned} H_V(t) &= \int F(t+\pi)h(\pi|t)d\pi \\ &= \int F(t+\pi)c(H_V(t), H_\Pi(\pi))h_\Pi(\pi)d\pi \end{aligned} \tag{10}$$

and I have only one unknown to solve for, the marginal distribution of valuations: $H_V(t)$.

5 Estimation and Results

The estimation argument closely follows the identification argument. I follow the steps below:

Step 1 Estimate Equation 11 via simulated maximum likelihood. Predict runner-up profits and valuations, given these estimates.

Step 2 Calculate welfare in the runner-up location, given profit and valuation from Step 1. Use the order statistic identity to recover the distribution of welfare across the short listed locations.

Step 3 Invert the distribution of welfare (Step 2) to recover the marginal distribution of valuations. I difference out the distribution of profits. This requires information on the profit parameters and the correlation between runner-up profits and valuation (Step 1).

5.1 Step 1: Profit Parameters

From Section 4.1, the equation of interest is repeated below:

$$\varepsilon_{i2} = (x_2^\pi - x_1^\pi)\beta_i + \alpha(x_2^v, z_i) - b_{i1}. \tag{6, rearranged}$$

where b_{1i} is the winning subsidy offer, z_i are the firm characteristics, x_1 are the characteristics of the winning location and x_2 are the characteristics of the runner-up location. The profit parameters, β_i, include interactions with observed (z_i) and unobserved ($\eta_i \sim N(0,1)$) firm characteristics. The level of observation for the location characteristics is the state-commuting zone pair. I estimate this model via simulated maximum likelihood, with the following simulated likelihood function:

$$L_i(\varepsilon_{i2}|x,z) = \frac{1}{R}\sum_{r=1}^{R} f(\varepsilon_{i2r}; 0, \sigma_\varepsilon^2), \tag{11}$$

where f is the probability density function of the standard normal distribution with mean 0 and variance σ_ε and R represents the number of simulations of η.[53]

The location characteristics (x) that enter the profit function include taxes (state corporate, sales, income taxes and local property taxes), other costs (local housing prices, local industry wages, industrial electrical prices), proximity to suppliers (local industry concentration), regulations (local zoning, state right-to-work status), infrastructure (large airport, road network), and workforce (population with bachelors degree, local research university, employment in relevant occupations). I allow the industry group of the firm, the number of jobs promised at the subsidized establishment, and investment planned to enter the profit function in z_i. I estimate the model separately for manufacturing and trade/services firms. The goal is to allow for as much heterogeneity as possible in the profit function, given the relatively small sample size. I discuss the variable selection process in detail in Appendix F, and I show the descriptive statistics for the set of all potential location characteristics in Table F.1.

Tables 3 and 4 display the estimates of the parameters of the profit function, $\hat{\beta}$ and $\hat{\sigma}$, and the correlates of the runner-up valuation, $\hat{\alpha}$, for the manufacturing and trade/services sub-samples respectively. The dependent variable is the winning subsidy (in $ million).

The profit parameters are estimated off of the differences between runner-up and winning state and local characteristics.[54] The coefficients can be interpreted as the change in subsidy size needed to win a firm, given a change in the difference in runner-up and winning characteristics. For example, if the winning state increases the corporate tax rate by one percentage point, the state needs to offer $11 million more in subsidies to attract the average sized manufacturing firm, all else equal.[55]

The profit parameters also highlight location characteristics that firms value. For example, high-tech manufacturing firms value both college educated population and agglomeration, as measured by the industry establishment share in the location. A location that experiences a one standard deviation increase in the proportion of the population that has a college degree (6ppt) will be able to

[53] I use the OLS estimates of β and α (i.e. estimating Equation 6 without random coefficients), as starting parameters for the optimization procedure. I set 10 as the starting parameter for the random coefficient parameters.

[54] In about 30% of cases I have more than one runner-up location listed in a subsidy deal, and I cannot distinguish which is the true runner-up and which is the third place location. The results are not sensitive to randomly choosing one as the "true" runner-up, or to using them all, but weighting by number of included runner-ups. The results I show in Tables 3 and 4 do the former. When I do not know the runner-up county (only the state) I assign the commuting zone (CZ) that has the highest concentration of industry establishments in that state. The results are not sensitive to other choices of CZ within the runner-up state, or using the state average.

[55] This uses the average investment for a manufacturing firm, $900M. If the establishment is in a trade/services industry, the state needs to offer a $8 million larger subsidy.

Table 3: Manufacturing

Variable	Coefficient	Estimate	Std. Error
Profits:			
Δ Corporate Tax (%)	β_{corp}	-8.04	3.76
Δ Corporate Tax $\times$ Investment ($B)	$\beta_{corp\times invest}$	-3.54	0.84
Δ Corporate Tax: Random Effect	σ_{corp}	-10.42	3.89
Δ Income Tax (%)	β_{inc}	4.78	3.14
Δ Income Tax: Random Effect	σ_{inc}	9.86	2.93
Δ Property Tax (%)	β_{prop}	-4.64	7.77
Δ Industry Wage ($1,000)	β_{wage}	-2.11	0.50
Δ Industry Wage: Random Effect	σ_{wage}	2.06	0.47
Δ Industrial Electricity Price (c/KwH) $\times$ Investment ($B)	$\beta_{utility\times invest}$	4.58	1.89
Δ Industrial Land Supply $\times$ Investment ($B)	$\beta_{landsupply\times invest}$	99.31	26.45
Δ Auto Network Density $\times$ Traditional Manufacturing	$\beta_{auto\times trad}$	60.38	20.89
Δ Pop. in Relevant Occupation (1,000)	β_{occ}	-2.62	1.12
Δ Pop. in Relevant Occupation $\times$ Jobs Promised (1,000)	$\beta_{occ\times jobs}$	2.85	0.97
Δ Pop. in Relevant Occupation: Random Effect	σ_{occ}	-3.76	0.85
Δ Population with BA+ (%) $\times$ High-Tech Manufacturing	$\beta_{college\times high-tech}$	5.96	2.94
Δ Population with BA+ (%) $\times$ Traditional Manufacturing	$\beta_{college\times trad}$	-3.08	1.53
Δ Industry Estab. Share (%) $\times$ High-Tech Manufacturing	$\beta_{estab\times high-tech}$	261.41	144.73
Valuation:			
Jobs Promised (1,000)	α_{jobs}	111.21	33.59
Investment Planned ($B)	α_{invest}	58.48	4.91
Indirect Jobs (Jobs $\times$ Multiplier)	$\alpha_{multiplier}$	2.10	0.40
Income Tax (%)	α_{inc}	-4.36	3.98
Corporate Tax (%)	α_{corp}	6.93	4.32
Term Limit	α_{term}	-7.88	15.79
Log(Income per capita)	$\alpha_{log(income)}$	-14.88	15.53
Relevant Occupation Wage ($1,000)	α_{wage}	6.67	4.45
Relevant Occupation Wage $\times$ Log(Income per capita)	$\alpha_{wage\times log(income)}$	-1.62	1.08
Unemployment (%)	α_{unemp}	4.61	4.83
Unemployment $\times$ Jobs Promised	$\alpha_{unemp\times jobs}$	-6.70	4.75

Notes: Table 3 displays the profit parameter estimates: $\{\hat{\beta}, \hat{\sigma}\}$, for the Manufacturing sample. The sample is restricted to deals worth under $1 billion (See Appendix Figure I.1(a)), for a sample of 200 deals. Descriptive statistics for location characteristics are in Appendix Table F.1, and more details on the selection of these characteristics is in Appendix F. The mean subsidy size for this sub-sample is $144 million, and the median is $83 million. The table also shows the estimated correlates of the runner-up valuation function, $\hat{\alpha}$. Table 4 follows with the estimates for the Trade/Services subsample.

Table 4: Trade/Services

Variable	Coefficient	Estimate	Std. Error
Profits:			
Δ Corporate Tax (%)	β_{corp}	-8.05	2.30
Δ Corporate Tax: Random Effect	σ_{corp}	9.60	1.65
Δ Income Tax (%)	β_{inc}	7.51	2.01
Δ Income Tax $\times$ Jobs Promised (1,000)	$\beta_{inc\times jobs}$	-2.45	1.00
Δ Income Tax: Random Effect	σ_{inc}	-7.60	1.40
Δ Property Tax (%)	β_{prop}	-21.40	8.91
Δ Property Tax: Random Effect	σ_{prop}	0.44	7.94
Δ Right-to-Work State	β_{r2w}	4.26	7.93
Δ Right-to-Work State: Random Effect	σ_{r2w}	35.92	7.59
Δ Housing Price ($1,000)	$\beta_{housing}$	0.05	0.05
Δ Housing Price ($1,000) $\times$ Investment ($B)	$\beta_{housing\times invest}$	-0.08	0.05
Δ Industry Wage ($1,000) $\times$ High-Skill Services	$\beta_{wage\times high-skill}$	0.05	0.45
Δ Industry Wage $\times$ Trade/Other Services	$\beta_{wage\times other}$	-1.17	0.82
Δ Commercial Electricity Price (c/KwH)	$\beta_{utility}$	-2.44	1.88
Δ Auto Network Density	β_{auto}	14.56	9.62
Δ Large Airport $\times$ Trade	$\beta_{airport\times trade}$	55.79	15.35
Δ Research University $\times$ Services	$\beta_{univ\times services}$	4.34	5.50
Δ Research University $\times$ Trade	$\beta_{univ\times trade}$	-40.96	16.11
Valuation:			
Jobs Promised (1,000)	α_{jobs}	14.06	4.00
Investment Planned ($B)	α_{invest}	57.16	10.01
Industry Multiplier	$\alpha_{multiplier}$	1.20	1.87
Income Tax (%)	α_{inc}	-5.23	2.24
Corporate Tax (%)	α_{corp}	10.14	2.59
Sales Tax (%)	α_{sales}	1.37	2.51
Property Tax (%)	α_{prop}	33.40	9.47
Term Limit	α_{term}	13.80	8.05
Unemployment (%)	α_{unemp}	2.66	1.60
Relevant Occupation Wage ($1,000)	α_{wage}	0.23	0.21
Log(Income Per Capita)	$\alpha_{log(income)}$	-23.24	7.69
	σ	33.99	3.25

Notes: Table 4 displays the profit parameter estimates: $\{\hat{\beta}, \hat{\sigma}\}$, for the Trade/Services sample. The sample is restricted to deals worth under $400 million (See Appendix Figure I.1(b)), for a sample of 177 deals. This is the estimation of equation 6, where the dependent variable is the winning subsidy (in $ million). Descriptive statistics for location characteristics are in Appendix Table F.1, and more details on the selection of these characteristics is in Appendix F. The mean subsidy size for this sub-sample is $78 million and the median is $45 million. The table also shows the estimated correlates of the runner-up valuation function, $\hat{\alpha}$.

offer a \$36 million smaller subsidy to attract the high-tech manufacturing firm, all else equal. For the trade/services sub-sample, a location that experiences a one standard deviation increase in auto network density, which is a proxy for highway access, will be able to offer a \$5 million smaller subsidy to attract the trade/services firm, all else equal.[56]

Tables 3 and 4 include the correlates from the runner-up's valuation function, $\hat{\alpha}$. These coefficients are meant to provide insights into the determinants of a location's willingness-to-pay, but should not be interpreted as causal.[57] As expected, willingness to pay is positively correlated with the following deal characteristics: jobs promised, investment planned, the expected wage for the jobs, and the expected indirect job creation. Also, there seems to be some evidence that places that are struggling (either in terms of unemployment or income) value firms more. For manufacturing firms, unemployment seems to be a good predictor of valuation, and richer regions are also willing to pay less for high-paying manufacturing jobs, while richer regions in general are willing to pay less for all firms in the trade and services sub-sample. This is consistent with Slattery and Zidar (2020), where we show in the raw data that poorer counties pay more per job. Moreover, locations with higher unemployment rates are willing to pay more for smaller projects, in terms of jobs promised. These struggling locations may not be able to compete with the blockbuster subsidies that the larger projects attract.

Model Fit: Runner-up Valuations

In order to check the model fit, I use $\hat{\alpha}$ and $\hat{\varepsilon}$ (Tables 3 and 4) to predict valuations in the runner-up locations, and then compare these predicted valuations with the subsidy offers in the runner-up locations. These bids should represent the runner-up valuation, as the runner-up bids up to their own

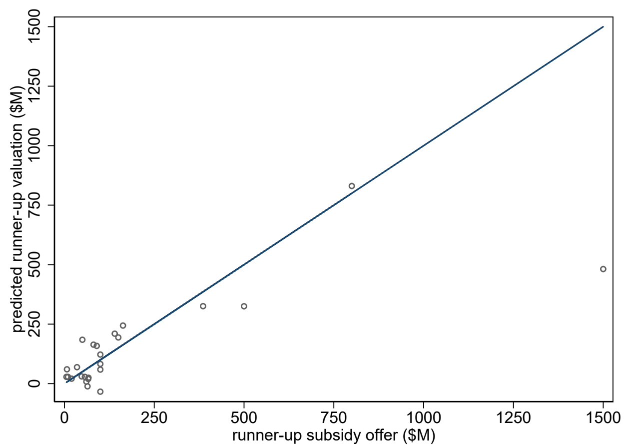
[56]Some of the variables that should likely enter firm profits, for example, state right-to-work status for manufacturing firms, are noticeably absent. This is due to a lack of variation in differences between winning and runner-up right-to-work status. For over 70% of subsidy deals in the manufacturing sub-sample, both the runner-up and winner have the same value, so the difference between the location characteristic is 0. Therefore, I cannot recover, for example, how much the manufacturing firms value being in a right-to-work state. The value of locating in a right-to-work state is likely high, because of the selection of mostly right-to-work states into the competition, and from what we know from previous work (Holmes, 1998*a*). This proposes a problem for the welfare analysis—there is a minimum profit level that I have not recovered; I only identify profits up to a level shift when I predict profits using $\hat{\beta}$. Therefore, I make the following assumption: profit in the winning location must be weakly positive. This shifts the value of predicted profits by the minimum value of predicted profits in the sample, given that the minimum value is negative.

[57]Moreover, states may have very different considerations when determining their own willingnesss-to-pay, and I will remain agnostic about the functional form of v when I recover the distribution. Including the potential determinants of the runner-up's valuation is important to both start understanding what factors may influence willingness-to-may, and also, econometrically, to avoid omitted variable bias in the estimation of Equation 6.

value in the English auction.

I have the reported runner-up subsidy offers in a small subset of subsidy competitions, split between manufacturing and services firms. Figure 4 shows a scatter plot of runner-up subsidy offers (data) and predicted runner-up valuations from estimation ($\hat{v}_2$). The correlation coefficient between runner-up subsidy offers and predicted valuations is 0.77 for the full sample, and 0.91 for the sample with runner-up subsidy offers under $1 billion.

Figure 4: Model Fit: Runner-up Subsidy Offers and Predicted Valuations



Notes: This is a scatter plot of the reported subsidy offer in the runner-up location, and the estimated valuation of the runner-up location, $\hat{v}_2$. I have data on subsidy offers in the runner-up location in 25 subsidy competitions, 13 of which are manufacturing firms, and 12 are services firms. The correlation coefficient between runner-up subsidy offers and predicted valuations is 0.77 for the full sample, and 0.91 for the sample with runner-up subsidy offers under $1 billion.

Runner-up Profits and Valuations

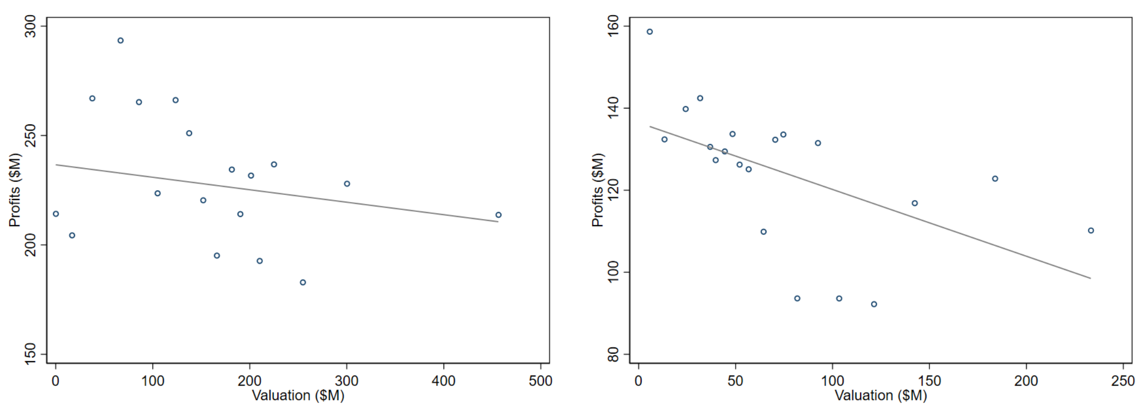
I will use the estimates of $\hat{\beta}$ to predict the profits in the runner-up location. One issue in estimating profits off of the difference in location characteristics is that there is no variation in some characteristics that are used to select shortlisted locations. Some of these are observable (i.e. right-to-work status), and some are unobservable (i.e. having a plot of sufficient size to build a factory, as discussed in Appendix G). Therefore, in order to accurately capture the magnitude of firm profits, I make the following assumption:

Assumption 7 *Profits in the winning and runner-up location are weakly positive.*

In order to enforce this assumption I make a very simple adjustment, and shift all estimated profits $\hat{\pi}$ by the minimum predicted profit in the sample. Therefore, the lowest predicted profit resulting from this exercise is zero.[58]

Figure 5 shows the relationship between $\hat{\pi}_{i2}$ and $\hat{v}_{i2}$, conditional on firm characteristics, z (I take the average jobs promised, investment planned, and multiplier for each sub-sample). The two objects are slightly negatively correlated: the correlation coefficient for trade/services is -0.28 and the correlation coefficient for manufacturing is -0.06. This result suggests that subsidy competition is likely to strictly increase welfare, as the negative correlation will induce more firms to choose locations that they would not have chosen in absence of a subsidy. However, I cannot predict the extent to which competition changes firms' location choices without the distribution of valuations and profits.

Figure 5: Runner-up $\hat{\pi}$ and $\hat{v}$ (Step 1)



(a) Manufacturing (b) Services

Notes: This figure is the binned scatter plot of predicted profits and valuations in the runner-up location ($\hat{\pi}_{2i}$ and $\hat{v}_{2i}$). The profits and valuations are predicted using the estimated parameters from Tables 3 and 4. The correlation coefficient for services is -0.28 and the correlation coefficient for manufacturing is -0.06. The profits and valuation are conditional on firm characteristics; I use the average jobs promised, investment, and multiplier for the respective sub-sample. In Appendix Figure H.1 I correlate the predicted profits with the runner-up location subsidy offers, which reflect runner-up valuations. Though this is for a much smaller sample, the results are consistent: the correlation coefficient for services is -0.12 and the correlation coefficient for manufacturing is -0.11.

5.2 Step 2: Distribution of Welfare

The next step is to calculate welfare in the runner-up location. As a reminder, welfare is defined as the sum of the firm profit and the state and local government's valuation for the firm. Therefore, given the predicted profits and valuations from Step 1, I have the predicted runner-up welfare. The empirical distribution of runner-up welfare, $F^{n-1:n}(w|z)$, is shown in Appendix Figure I.2.

[58] I look up each deal for which profits are predicted to be negative. The majority of these deals are retentions and expansions. See Appendix I.1 for more details.

Given the empirical distribution of welfare in the runner-up location, I apply the order statistic identity (Equation 8), to recover the full distribution of welfare across short-listed locations. The number of bidders varies across auctions (see Appendix Figure B.1), so I estimate Equation 8 separately for each number of bidders.[59]

5.3 Step 3: Welfare Inversion

The last step is to recover the marginal distribution of valuations, $H_V(v|z)$.

Given the estimates of $\hat{\beta}$ and $\hat{\sigma}$ from Step 1, I can use the out-of-sample (non winner or runner-up) location characteristics, x, to predict firm profits across competing locations, $\hat{\pi}_{is}$, giving way to an empirical marginal distribution for profits $\hat{H}_{\pi}$ in shortlisted locations.[60] Then, given the empirical distribution $\hat{F}(w|z)$ from Step 2, I have enough information to estimate $H_V(v|z)$.

Following the identification strategy in Section 4.3, H_V can be estimated by simulating draws of π_t from the copula $\hat{C}(\pi|v<t,z)$ and calculating the sample average:

$$H_V^M(t|z) = \frac{1}{M}\sum_{m=1}^{M}\hat{F}(t+\pi_t|z). \tag{12}$$

More details on the procedure follow in Appendix I.2. Here, I impose that valuations are strictly positive, by fitting H_V to a log-normal distribution. Appendix Figure I.3 shows the figures for the marginal distribution of state valuations, separately for manufacturing and services firms.

5.4 Model Fit

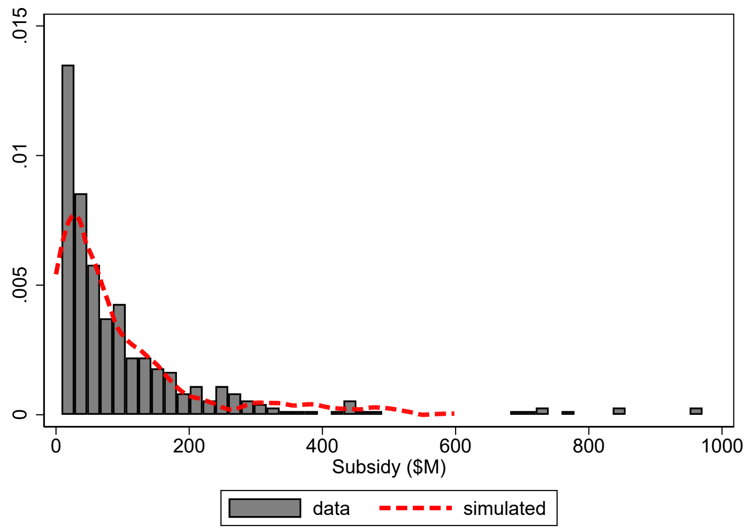
Given the distribution of valuations, I can proceed to the counterfactual policy analysis. However, before simulating a counterfactual subsidy ban, I will simulate the subsidy competition game to assess how well the model fits the data.

Figure 6 shows the model fit. The histogram represents the observed subsidies (data), and the dashed red line shows the kernel density of the simulated subsidies. These simulated subsidies are the result of simulating profits and valuations for each firm in the data. The simulated subsidy game is played 1,000 times, and the resulting subsidy is the difference between the profit in the winning location and the profit and valuation in the second highest payoff location. Then, I take the median

[59] All of the auctions with more than 5 bidders are estimated together, because there are not enough observations for each number of bidder above 5. I assign $n = 11$, which is the average for this subset. The resulting distribution, $\hat{F}(w|z)$, is a mixture, given the distribution of bidders across the sample.

[60] Appendix I.6 describes the procedure for determining potential shortlisted locations.

Figure 6: Model Fit: Simulated Subsidy Competitions



Winning Subsidy ($M)

		Simulated	
Pctile	Data	Med.	Mean
25^{th}	26.98	21.36	37.65
50^{th}	57.21	51.95	57.21
75^{th}	128.48	119.02	128.48
90^{th}	250.64	220.31	274.30
Mean	108.38	90.89	119.85
SD	143.09	109.73	120.78

Notes: The figure on the left and table on the right show the distribution of subsidies in the data, and the size of subsidies predicted by the model. These simulated wins are the result of playing the subsidy game by simulating profits and valuations for each firm in the data. The simulated subsidy game is played 1,000 times, and the resulting subsidy is the difference between the profit in the winning location and the profit + valuation in the second highest payoff location. I take the median/mean of the simulated subsidies for each subsidy deal (the figure shows the median). Appendix Table I.1 shows the fit with respect to the identity of the winning state, and Appendix Figure I.4 shows the fit at the simulation level (instead of aggregating simulated subsidies to the deal level).

or mean of simulated subsidies over subsidy deals. The model underpredicts subsidies in the $20-40 million range, and does not predict subsidies over $600 million (of which there are 9 in the data). The mean subsidy in the sample data is $108.4 million and the mean in the simulation is $91-$120 million. Appendix Figure I.4 shows the fit over each simulation, instead of aggregating simulations over subsidy deals. This shows more dispersion over simulated subsidies, and a larger average simulated subsidy.

Appendix Table I.1 shows the fit with respect to the identity of the winning state. To the extent that winning locations in the data can differ from the winning locations predicted by the simulations, I will correct for this misspecification when predicting location choices in the counterfactual simulation.[61]

[61] For example, Table I.1 shows that the model predicts that under subsidy competition 9.1% of manufacturing firms in the sample will locate in Texas, but only 6.0% of manufacturing firms locate in Texas in the data. Most of this misspecification, in the case of Texas, is driven by the model predicting that firms that are observed locating in Louisiana in the data should instead be located in Texas. Therefore, in the counterfactual where I ban subsidy spending, I could potentially over-estimate the number of firms that would choose alternative locations in the absence of subsidy competition, which would inflate the welfare gain from competition. I will detail the correction procedure in the next section, when I explain the details of the counterfactual. Thank you to an anonymous referee for this suggestion.

6 Counterfactual Subsidy Regime

In the early 1990s, United Airlines was holding a bidding war for the location of a new maintenance facility. United set up their negotiations at a hotel, where representatives from the airline would meet up with representatives from cities and states. Jim Edgar, the governor of Illinois at the time, called for a truce with the other states. "If you've got some states doing it, it's hard for the others not to do it. It's like unilaterally disarming," Edgar recalls (Story, 2012). Ultimately, not all states would join in the truce, and subsidy competition for individual firms continues to be part of the economic development landscape. However, a subsidy "truce" between localities, or a federal ban on discretionary subsidy giving, remains a topic of discussion for legislators and concerned citizens.

In fact, the European Union mostly restricts member countries from offering "state aid" to companies (European Commission, 2008). In the U.S., legal scholars have posited that discretionary subsidies are in violation of the commerce clause of the Constitution (Enrich, 1996).[62] In the summer of 2019 the governors of Kansas and Missouri signed a truce to stop offering discretionary tax breaks to attract firms from the other side of the border in the Kansas City metro area (Hardy, 2019). Meanwhile, lawmakers in New York State have introduced the "End Corporate Welfare Act" bill, and are encouraging other states to do the same (Farmer, 2019).

6.1 Implementation

In this counterfactual exercise I eliminate incentive spending and predict where firms would locate in the absence of subsidies. Eliminating incentive spending means that the large firms would have to pay the state's posted corporate tax rate, and receive no tax credits or non-discretionary incentives. This is the most severe potential policy change, which will illustrate the upper bound on the effect of limiting incentive spending. Also, this is a partial equilibrium analysis. States who lose firms when they are not able to compete with discretionary subsidies or tax credits would likely adjust by changing their corporate tax rate or investing in other location characteristics.

The counterfactual proceeds in two steps. First, the firms choose their location in absence of subsidies. This is a function of the predicted profit, which I calculate using $\hat{\beta}$ and $\hat{\sigma}$ (Estimation Step

[62] In fact, a 2004 case brought against DaimlerChrysler and the state of Ohio, for an investment tax credit given to the car manufacturer, used this argument. The U.S. Court of Appeals in Cincinnati found the credit unconstitutional, but the ruling was struck down by the Supreme Court for a procedural flaw (Holder, 2018).

1). Second, given the profit level in the counterfactual location, I simulate the valuation for winning the firm, from $\hat{H}_V(v|\pi)$.[63]

In order to run this analysis I need to make an assumption on the set of locations on the shortlist.[64] Of course, I do not explicitly estimate the selection of the shortlist, but I can use characteristics of locations that enter the firm's profit function to select the set of potential locations. Appendix Section I.5 provides the details, but, in short, I select locations on size, industry concentration, and relevant employment. Appendix Table I.2 shows that this results in a set of locations that are similar to winning and runner-up locations on population, wages, the auto road network, large airport, right-to-work, employment in relevant industries, college population, and the concentration of industry establishments. Each firm has a set of 60-80 locations on the "potential shortlist," which was reduced from 700 locations across the U.S. to start. Then, for each iteration of the simulation, I randomly select locations to compete for the firm. The number of locations in competition for each firm in the simulation is set to equal the number of bidders from the data. By default, the runner-up location listed in the data is included in the shortlist.

Given this set of competitors, the counterfactual location is simply the location that gives the firm the highest profit. I calculate firm profits in each state-commuting zone, using $\hat{\beta}$ from Table 3, simulating over shortlists, S^n and random coefficient draws, η. I also adjust for the fact that even with subsidy competition, the model does not always predict that the firm will locate where it is observed locating in the data.[65]

6.2 Location Results

In the counterfactual simulations many firms stay put. Over the sample, 52% of firms choose alternative locations: 29% of firms relocate to what was the runner-up location in the competition and 23% choose another, non-runner-up, location.[66]

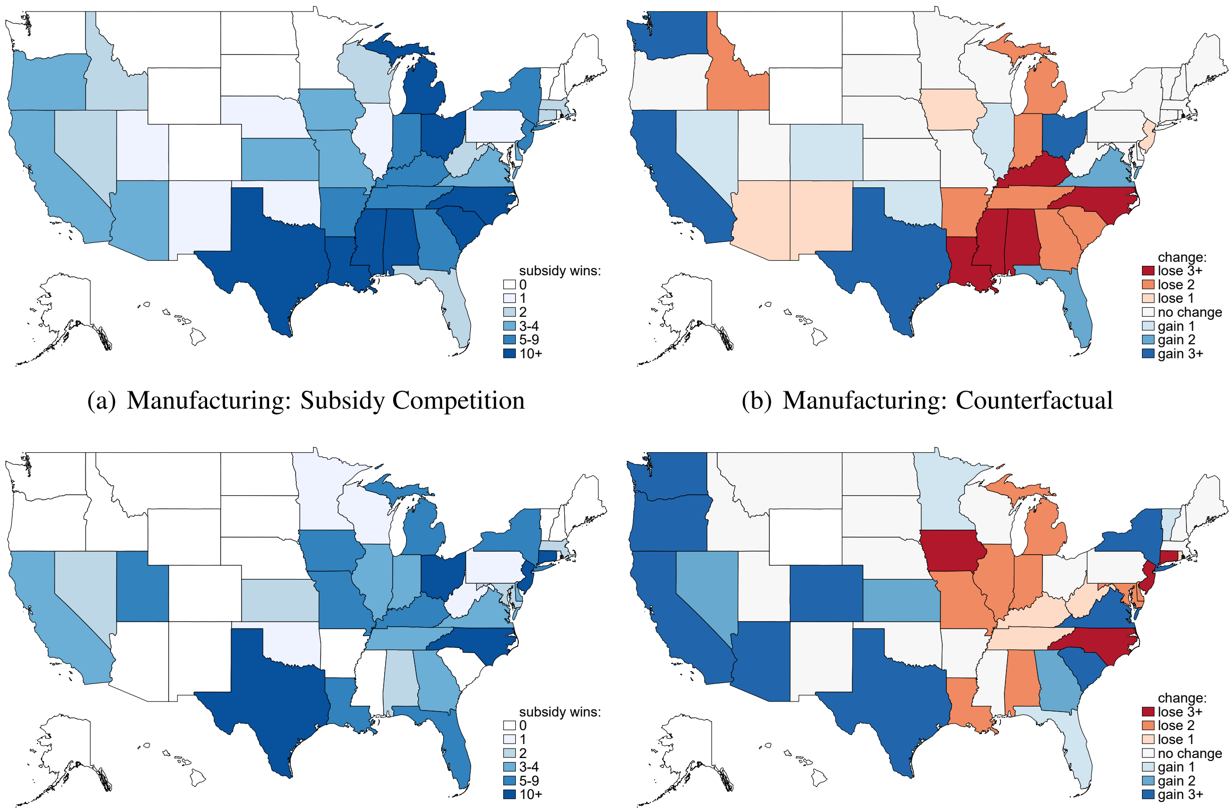
[63] In Appendix I.6 I give further details on the simulation procedure.

[64] For 49% of the sample, when the number of bidders is small, I know all of the locations on the shortlist.

[65] To give a concrete example, take the case of Valero Refining. In 2013, Valero received a $247 million subsidy to construct a methanol plant in St. Charles Parish, Louisiana. When I simulate the subsidy game, the model predicts that Valero will locate in Louisiana 58% of the time, and will locate in Texas 26% of the time. When I ban subsidies, the model predicts that Valero will locate in Texas 52% of the time. I adjust for the fact that the model predicts Valero would have chosen Texas even with subsidies and attribute 26% of those subsidy ban wins to misspecification, arriving at the result that Valero will locate in Texas in 39% of simulations of the subsidy ban regime.

[66] The share of firms that choose alternate locations in the counterfactual is larger than "but for" percentages found in the literature (and summarized by Bartik (2018)), but these estimates are mostly based on studies with very different samples—my sample has much larger firms making larger investments and receiving larger subsidies than the firms

Figure 7: Counterfactual Changes in Firm Locations



(a) Manufacturing: Subsidy Competition

(b) Manufacturing: Counterfactual

(c) Services: Subsidy Competition

(d) Services: Counterfactual

Notes: In order to determine the counterfactual location I calculate firm profit in each shortlisted commuting zone, using $\hat{\beta}$ from Table 3, drawing shortlisted locations, S^n, and firm unobservables, η. I simulate the counterfactual location decision 1,000 times. The counterfactual location is simply the state that gives the firm the highest profit, given that subsidies are set to 0. This figure shows the distributional results of the counterfactual. The shading in panels (a) and (c) represents the number of firms that locate in each state under the subsidy competition regime. The shading in panels (b) and (d) represents the change in the number of firms that locate in each state.

Figure 7 shows the distributional results of this exercise. The shading in (a) and (c) represents the number of firms that locate in each state under the subsidy competition regime. The shading in (b) and (d) represents the change in the number of firms that locate in each state, given the subsidy ban. In manufacturing, states in the deep south and Midwest are the most likely to lose firms they attract with subsidies, while states like Texas and Florida are net gainers. This pattern of middle America losing the most firms in the absence of subsidies matches a similar pattern found by Austin, Glaeser and Summers (2018), where the non-employment rate has risen more from Louisiana up through Michigan than in most of the rest of the country.

studied by the previous literature. Moreover, my sample is selected on the premise that firms are choosing between locations for a new investment, not the marginal effect of changes in a regional or state tax credit program, for example.

Table 5: Welfare Analysis

Policy	Movers	Simulated v (\$B)	π (\$B)	Sub (\$B)	Payoffs (\$B) States	Firms	Total Welfare
Subsidy Ban	-	48.4	84.6	0.0	48.4	84.6	133.0
Competition	51.6%	61.2	77.5	40.9	20.4	118.4	138.8
				Δ welfare from competition:	-57.9%	39.9%	4.3%

Notes: Table 5 displays the results of the counterfactual welfare analysis. For the "competition" policy, locations are observed, and I calculate profits using $\hat{\beta}$ and $\hat{\sigma}$ (Tables 3 and 4) and then simulate the valuations of the winning locations from $\hat{H}_V(v|\pi)$. For the "subsidy ban" policy, locations are predicted, as depicted and described in Figure 7. The first column shows the % of firms that "move" (choose an alternate location) due to the subsidy competition. The second column shows the sum of the simulated valuations. The third column shows the sum of simulated profits. Under either policy, state payoffs are equal to the total valuations less the total subsidy spending (which is equal to 0 if there is a ban). The firm payoffs are equal to the total profits plus the total subsidy spending. Total welfare is the sum of state and firm payoffs. Appendix Table I.3 breaks down the counterfactual welfare by sector (Manufacturing vs Trade/Services).

In trade and services, Texas, California, New York and Virginia, which already offer subsidies in competition, win even more firms in the subsidy ban. Given these findings, it is perhaps unsurprising that New York is one of the states pushing for a ban on subsidy competition. Meanwhile, Alabama won 11 subsidy competitions for manufacturing firms in the last 15 years, and is predicted to win 5 of them in the counterfactual. These results suggest that any type of subsidy "truce" would likely be hard to sustain—there are clear winners and losers across states in the subsidy ban.

6.3 Welfare Results

Given the observed and counterfactual locations, and the simulated profits, I simulate the valuation in each location from $\hat{H}_V(v|\pi,z)$.[67] Table 5 displays the results from this exercise. Each row in the table corresponds to a policy: subsidy ban or competition. The total amount spent on discretionary subsidies in my sample (2002-2017) is about \$41 billion. This is the subsidy spending under competition, the current policy. Under a subsidy ban, subsidy spending would be \$0, mechanically.

Table 5 shows the total simulated valuations for winning locations under the ban is \$48 billion, while it is much larger, \$61 billion, under competition. However, these locations also have lower profits. Total profits for firms are \$85 billion under the ban, and \$77 billion under competition.[68]

The allocative efficiency argument for subsidy-giving is evident in this simulation—when there are no subsidies firms locate in higher profit locations, which can have lower valuations for winning the firms. With competition, the simulated valuations are substantially higher—the higher valuation

[67] I can link the marginal distributions $\hat{H}_\Pi$ and $\hat{H}_V$ via copula, where the dependence structure relies on the estimated correlation between runner-up valuations and profits, as detailed in Section 4.2.

[68] See Appendix Table I.3 for the same table broken out separately for manufacturing and trade/services.

locations now can express that valuation in the form of a subsidy. However, these higher valuation places have lower profits.

I use the simulated valuations and profits to calculate the payoffs for each agent. The payoffs for the states is the total valuation, v, in winning states, less the subsidy payment. The payoffs for the firms is the total profits, π, in the chosen location, plus the subsidy payment. It is clear that the firms are the winners of subsidy competition: firm payoffs increase by 40%, while state payoffs decrease by 58%. Taken all together, the total welfare gain is small. The sum of state and firm payoffs under the subsidy ban is \$133.0 billion, compared to \$138.8 billion in the subsidy competition. This amounts to a welfare gain of 4.3%.

Total state payoffs are about \$28 billion lower under subsidy competition than under the subsidy ban. This result is due to the degree of heterogeneity in $\hat{H}_V(v|z)$. If the valuations were even more heterogeneous, it would not be the case that most of the surplus is competed away. I show this in Appendix Table I.4, where I exclude the random coefficients from the firm profit function, instead using the $\hat{\beta}$ estimated in the OLS model (Appendix Tables F.2 and F.3). I repeat all of Section 5 with this model, and use the resulting distribution of valuations for the counterfactual analysis. Here, because less heterogeneity is being attributed to profits in the absence of the random coefficients, more heterogeneity loads on to valuation. This increased heterogeneity in valuation results in more movers due to competition, larger differences in winning and runner-up payoffs, and a *much* higher total welfare gain of over 20%, instead of 4%.

A potential concern is that the results are sensitive to the assumptions of the model. Namely, a firm could potentially add "unrealistic" locations to the short-list, that have high valuations but low profits, in order to bid up the subsidies in their preferred location. Therefore, in Appendix J I repeat the estimation process and counterfactual simulations under an alternative model.[69] In this model, the assumption is that the winning location bids up to, or close to, their valuation. I provide more details in the appendix, but the take-away for the counterfactual is very similar—subsidy competition leads to a 2.6% increase in welfare over the subsidy ban, with states experiencing a 38.6% decrease in payoffs, and firms experiencing a 25.2% increase.

[69]Thank you to an anonymous referee for this suggestion.

6.4 Additional Considerations

A few considerations may dampen the estimated welfare gain from subsidy competition. First, there are unobserved costs to engaging in subsidy competition. This cost, from the perspective of the state and local government, can be part of their valuation, and is a reason that some places may have very low valuations for winning a firm. However, for the firm, the cost is not incorporated in the model. This cost comes in the form of hiring a team of consultants to research locations and negotiate with governments (the site selectors that I described in Section 2.2). In conversations with practitioners, I learned that site selectors often earn a commission on the subsidy size, which can be as large of 30% for smaller subsidy deals. For the projects that I study in this paper, a more realistic fee structure would be a 5-10%, and many large firms have an in-house team, so contingency fees are less common. Still, if we take the 5-10% contingency fee seriously, incorporating these costs into the welfare analysis results in a welfare "gain" from competition of 0.0% to 2.0% for manufacturing deals and 3.1% to 4.6% for trade and services deals (compared to 3.6% and 6.1% respectively at the baseline, see Appendix Table I.3). In aggregate, the total welfare gain, under the assumption of a 10% fee, would be only 1.2% (and 2.8% under the 5% fee assumption).

Second, states may not be able to accurately predict the benefit a firm will have in their jurisdiction. If governors are present-biased, they may put more weight on the short-term benefits of winning a firm, and discount the future costs. Or, it may be that all states are over-optimistic about the benefit of winning any particular firm, because they are using inflated multipliers that lead to high spillover predictions. In a back of the envelope exercise, I find that if states overestimate their valuation of a firm, the welfare gain from subsidy competition quickly dissipates.[70] The results are shown in Appendix Figure I.6. In this exercise, I find that if states are just 8% over-optimistic about the value a firm will create, the total welfare gain from competition disappears. The exercise also shows that in about 20% of subsidy deals the state offers a subsidy roughly equal to their simulated willingness-to-pay.

Third, politics is a potential distortion. Appendix Table F.2 shows that being a term-limited governor is associated with a lower willingness-to-pay for manufacturing firms, on the order of $20

[70]This is a thought experiment. There is no systematic evidence that governments over estimate the benefit, although the multipliers used are very high. There is some recent work suggesting the wage effects from plants owned by multinationals are large and positive (Setzler and Tintelnot, 2021). However, this paper also comes to the conclusion that the firm is able to extract a large portion of the welfare gain.

to $40 million. This raises the issue that the "welfare" of the state decision maker may not align with that of the social planner. Recent work explores potential political distortions in this setting (Kim, 2023; Slattery, 2024).

Throughout this section, I have taken total welfare as the sum of firm and state payoffs, where all payoffs receive a weight of one. The social planner could weigh differently the payoffs in different locations. For example, the planner could put a higher weight on job creation in high unemployment, low income areas. This will be unlikely to have substantially different welfare implications, but it would depend on the weights the planner chooses. For the manufacturing sample, the per capita income in winning places under competition is about $1,920 less than under the ban, while unemployment is about 0.50 percentage points higher, at the median.[71] Notably, the places that retain firms in the counterfactual (i.e. the places that won firms with subsidies and still win the firms without the subsidy) have better economic characteristics than the average subsidy winning place: unemployment is 0.22 percentage points lower and per capita income is $1,860 higher.

7 Conclusion

States and local governments offer generous tax credits and subsidy deals to attract individual firms to their jurisdiction. The extent to which these incentives improve allocative efficiency depends on the firm's profitability in the locality and the locality's valuation of the firm. Therefore, in order to understand the welfare effects of subsidy competition one must know both (1) how state and local governments determine discretionary subsidies, and (2) the effect of subsidies on firms' location choice. Due to the lack of transparency of the subsidy setting process, the lack of data on realized subsidy deals, and the equilibrium nature of the observed outcome, these two questions have historically been difficult to answer.

To make progress on this line of inquiry, I introduce a new data set on discretionary subsidies, which I create by reading state budget documents and tax expenditure reports, as well as press releases and news articles on each subsidy deal. Then, I use an open outcry ascending auction to model the bidding process. To capture the fact that, all else equal, a less "attractive" location must offer a larger subsidy to attract a firm, I embed the location choice problem of the firm within the auction

[71] For the trade/services sample the differences are smaller, subsidy winning locations having about $770 lower in per capita income but the same median unemployment rates as the counterfactual choices.

framework.

I find that competition increases welfare by about 4% over a counterfactual subsidy ban, but this surplus is captured entirely by the firms. In the aggregate, states are better off in the subsidy ban, but my results suggest that any type of subsidy "truce" would likely be hard to sustain—there are clear winners and losers across geographies.

There is still much to learn about discretionary subsidy-giving and its role in state and local economic development policy. Future work should consider the trade-offs between spending on discretionary subsidies for a few large firms and more broad-based incentive programs. There are opportunity costs to states spending on incentives for a few large firms; they could instead lower taxes for citizens, invest in public goods, or create incentive programs for small businesses. Also, giving discretionary tax breaks to a few large firms may have anti-competitive effects on the product market, as these firms now have lower costs then their competitors.[72] We also need to know more about distributional impact once the establishment opens—who is hired and what happens to local prices? The poorest places, with the highest unemployment rates and potentially the highest values for jobs, are never observed winning a subsidy deal (Slattery and Zidar, 2020).

In short, this paper identifies an important force we should use to think about discretionary subsidy-giving, which is a popular economic development tool in the United States and worldwide. The model allows us to learn about state and local governments' willingness to pay for a firm with limited data. Although there is scope for subsidy competition to increase the allocative efficiency of firm locations, the influence on politics on government valuations of firms, and the difficulty in forecasting the effect of any individual establishment, greatly limit the potential gains. Understanding the disconnect between state government valuations and the actual benefit a firm creates for constituents is crucial to evaluating the welfare implications of subsidy-giving. The data introduced in this paper can be used to push research in this arena further.

[72] Rossi-Hansberg, Sarte and Trachter (2018) find that although national product market concentration is increasing, when the top firm in an industry opens a plant, local concentration declines. The effect of discretionary subsidies on product-market competition, both at the local and national level, as yet to be studied.

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Appendix

A Institutional Details: State Economic Development and Data

State Budget Process

The budget process of the state generally follows these steps:[73]

1. Each department and agency of the state government prepares a budget request and submits it to the governor. This process begins at least one year before the budget year, when the governor sends instructions on what level of resources the department should plan for.

2. The governor receives the agency budget proposals in the Fall, and prepares the final budget proposal, submitting it to the state legislature by late January/early February.

3. The budget is received by the appropriations committee in the House and then sent to the Senate. If the budget approved by the state Senate differs from that approved by the House the two groups must work out a compromise in conference committee.

4. The budget is sent back to the governor, who signs it, vetoes the entire bill, or vetoes certain line items.

Differences in state budget processes lie in the governors ability to line-item veto, biennial or annual budget setting, the rigidity of the balanced budget requirement, and super-majority legislature rules.[74]

Unlike at the federal level, most of the power lies at the governor. The governor must submit a budget in balance, which makes it more difficult for the legislature to make changes. The governor also has a full-time staff and generally has more information and time for budget setting than the legislature, especially in states where the legislature is a part-time job and only convenes for a couple of months. Lastly, 43 states give the governor the power to line-item veto items from the budget.

State Legislative Process

The budget process determines how much money goes to existing programs. Changing and enacting tax credits and economic development programs requires legislation. States' legislative processes are much more heterogeneous than the budget process. Each state may establish its own rules for procedure, which means that it has its own process for considering and enacting bills. In broad strokes, the bill will be introduced in the House or Senate, or in committee, and then goes through steps of being debated, opened to public opinion, and amended, with votes at various parts of the process, in both chambers of the state legislature. In the last step it goes to the governor, who has veto power. 46 state legislatures meet annually, so those states may enact new legislation each year.

[73] This is written with a July 1-June 30 fiscal year, though four states follow a different schedule.

[74] 19 states have a biennial budget setting process, which means that they set the budget for two years. However only 4 states have biennial meetings, so most states still meet annually, and enact supplemental budgets to amend the biennial budget. For this reason, many argue that setting a biennial budget is wasteful, as the state will need to amend and set supplemental budgets in the "off" year.

States can also call special, or extraordinary sessions, in order to address unfinished business or special topics, such as emergencies and natural disasters. Governors sometimes call special sessions in order to approve incentive packages for discretionary subsidy deals.

Data Collection: State-level spending

There are two primary ways a state can create financial incentives for businesses. The first is to offer a tax credit, or to lower the tax rate, which lowers the tax bill of the business. States track the amount spent (revenue foregone) on each credit program in their Tax Expenditure Reports. The second way to provide for incentives is to allocate money for economic development programs in the state budget (e.g. grant, discretionary fund, infrastructure project). States track the amount allocated and spent on each program in their annual (or biennial) budget documents.

In order to create my dataset I download each tax expenditure report and budget document from state websites for the years 2006-2016. If those items are not available I contact the state Department of Revenue and/or Budget Office. The tax expenditure reports and budget documents vary widely in formatting, not only across states but over time. New economic development programs and tax credits are introduced over the sample period, names often change, and programs can be reorganized between departments. This makes any machine learning technique extremely difficult, so I read each document to identify tax credits and budget items targeted at businesses, and collect the data by hand.

The amount foregone in tax revenue due to tax credits is recorded in the states' tax expenditure reports. Figure A.2 provides two examples of tax expenditure reports, from Virginia and North Carolina. In Virginia's document, each credit is listed, along with the number of returns filed that take the credit, and the total amount that was claimed on those returns. In North Carolina, the state reports the description of each credit along with an estimate of the amount that will be claimed in each fiscal year.

Figure A.3 provides an example of budget documents in both states (Virginia and North Carolina). Virginia has a website for their budget, which allows you to search for keywords, e.g. "economic development." However, the line items are not very specific, as evidenced in the figure. The footnote provides more information, detailing that these "Economic Development Services" are used at the discretion of the Governor to attract economic development prospects to locate or expand in Virginia. North Carolina's budget has very specific line items, and the amount spent and authorized each year. Another section of the document provides descriptions of each of the line item programs.

I record each program and credit in a state level dataset that covers the years 2007-2014. Based on the text description of the program (if any) I can classify the spending by stated purpose or target: Business Attraction, Jobs, Job Training, Investment, Manufacturing, R&D, High-Tech, and Small Business. In the state-program level data I note that funds are often earmarked for discretionary spending, e.g. "Strategic Attraction," and when states do break out tax credit expenditures by firm, the majority of spending goes to a few firms. Firms receive different tax treatments within one state, thus one needs firm-level data to understand state incentive spending policies.

In Section 2.2 I also mention anecdotal evidence that states consider *indirect* job creation when determining their subsidy offers. Figure A.1 provides such an example. This is an excerpt from a report on North Carolina's discretionary grant program. North Carolina is one of the few states to publish spending at the firm level. The table lists the number of expected (direct) jobs the firm will create and the number of indirect and induced jobs. In this paper, these are the "spillover" jobs the state might care about, and it is proxied with the industry multiplier. The table also suggests that the state cares about the firm's effect on GDP and state revenue.

Figure A.1: Discretionary Spending: North Carolina

J·D·I·G
JOB DEVELOPMENT INVESTMENT GRANT

Award Year	Company Name	Grant Term (Years)	Expected Jobs	Indirect and Induced Jobs	Total Jobs	Estimated NC GDP Impact (millions)	Estimated Net State Revenue Impact (millions)
2015	Novo Nordisk Pharmaceutical Industries, Inc. III	12	691	4,276	4,967	$7,361	$208.8
2015	Premier Research International LLC	12	260	683	943	$568	$9.5
2015	RBUS, Inc. II	12	500	701	1,201	$583	$12.9
2015	Royal Appliance Mfg. Co.	12	200	398	598	$613	$14.5
2015	**Total (Grant Term is average)**	**12**	**4,788**	**13,363**	**18,151**	**$15,995**	**$354.4**
2016	Aurobindo Pharma USA Inc.	12	275	1,231	1,506	$1,126	$15.8
2016	Avadim Technologies Inc.	12	551	1,359	1,910	$1,817	$43.2
2016	Citrix Systems, Inc. II	10	400	640	1,040	$659	$8.1
2016	Corning Optical Communications LLC (Cable)	12	205	345	550	$460	$8.7
2016	CSX Intermodal Terminals, Inc.	12	149	170	319	$2,485	$97.1
2016	Everest Textile USA, LLC	12	610	698	1,308	$733	$15.5
2016	GF Linamar LLC	12	350	349	699	$606	$8.4
2016	GKN Driveline Newton, LLC II	12	143	284	427	$307	$5.9
2016	GKN Driveline North America, Inc. III	12	159	316	475	$449	$10.7
2016	INC Research, LLC II	8	550	836	1,386	$750	$6.2
2016	JELD-WEN, Inc. II	12	206	313	519	$456	$7.2
2016	K-Flex USA L.L.C.	12	100	125	225	$231	$4.4
2016	LendingTree, LLC	12	314	1,061	1,375	$1,106	$22.7
2016	PrescientCo Inc.	12	205	258	463	$444	$9.6
2016	Relias Learning LLC	12	470	790	1,260	$1,583	$43.5
2016	**Total (Grant Term is average)**	**12**	**4,687**	**8,775**	**13,462**	**$13,212**	**$307.0**

Notes: This is an excerpt from North Carolina's 2013 Job Development Investment Grant Report. For each firm they receives a discretionary subsidy from the program, there is a description of the characteristics of the firm: the expected direct jobs, indirect jobs, total jobs, increase in state GDP, and increase in state revenue.

Figure A.2: Examples of Tax Expenditure Reports

Table 3.1
Fiscal Year Tax Credits
Returns Processed During Fiscal Year 2015

Code Section(s)	Credit	Year Enacted	Credit Claimed Against	Number of Returns	Amount
§§ 58.1-439.18 et seq.	Neighborhood Assistance Act Credit	1981 (effective July 1, 1981)	Individual, Corporate, Insurance and Bank	4,393	$14,512,830
§ 59.1-280	Enterprise Zone Business Tax Credit	1982 (effective July 1, 1982)	Individual, Corporate, Insurance and Bank	12	1,218,516
§§ 58.1-334 & 58.1-432	Conservation Tillage Equipment Credit	1985 (effective 1985)	Individual and Corporate	255	486,727
§ 58.1-435	Low-Income Housing Credit	1989 (effective 1990)	Individual, Corporate, Insurance and Bank	*	15,542
§§ 58.1-337 & 58.1-436	Advanced Technology Pesticide and Fertilizer Application Equipment Credit	1990 (effective 1990)	Individual and Corporate	99	156,193
§ 58.1-438.1	Tax Credit for Vehicle Emissions Testing Equipment and Clean-Fuel Vehicles and Certain Refueling Property	1993 (effective 1993)	Individual and Corporate	41	9,482
§ 58.1-439	Major Business Facility Job Tax Credit	1994 (effective 1995)	Individual, Corporate, Insurance and Bank	74	4,109,769
§ 58.1-439.2	Coalfield Employment Enhancement Tax Credit (Refundable)	1995 (effective 1996)	Individual and Corporate	49	28,363,515
§ 58.1-439.1	Clean Fuel Vehicle and Advanced Cellulosic Biofuels Job Creation Tax Credit	1995 (effective 1996)	Individual and Corporate	191	307,062
§ 59.1-280.1	Enterprise Zone Real Property Investment Tax Credit (Refundable)	1995 (effective July 1, 1995)	Individual and Corporate	0	0
§ 58.1-339.2	Historic Rehabilitation Tax Credit	1996 (effective 1997)	Individual, Corporate, Insurance and Bank	1,038	97,998,279
§ 58.1-439.4	Day-Care Facility Investment Credit	1996 (effective 1997)	Individual and Corporate	0	0
§§ 58.1-339.3 & 58.1-439.5	Agricultural Best Management Practices Tax Credit	1996 (effective 1998)	Individual and Corporate	471	1,144,933
§ 58.1-439.6	Worker Retraining Tax Credit	1997 (effective 1999)	Individual, Corporate, Insurance and Bank	6	160,926
§ 58.1-439.7	Recyclable Materials Processing Equipment Credit	1998 (effective 1999)	Individual and Corporate	91	623,285
§ 58.1-332.1	Foreign Tax Credit	1998 (effective 1998)	Individual Only	1,689	507,562
§ 58.1-339.4	Qualified Equity and Subordinated Debt Investments Tax Credit	1998 (effective 1999)	Individual Only	241	2,096,539
§ 58.1-439.10	Waste Motor Oil Burning Equipment Credit	1998 (effective 1999)	Individual and Corporate	62	124,387
§ 58.1-439.9	Tax Credit for Certain Employers Hiring Recipients of Temporary Assistance to Needy Families (TANF)	1998 (effective 1999)	Individual and Corporate	0	0
§ 58.1-512	Land Preservation Tax Credit	1999 (effective 2000)	Individual and Corporate	3842	67,668,579
§ 58.1-339.6	Political Candidates Contribution Tax Credit	1999 (effective 2000)	Individual Only	17,357	604,377
§ 58.1-339.7	Livable Home Tax Credit	1999 (effective 2000)	Individual and Corporate	284	823,494
§ 58.1-433.1	Virginia Coal Employment and Production Incentive Tax Credit	1999 (effective 2001)	Corporate Only	7	8,909,576
§ 58.1-339.8	Low-Income Taxpayer Credit	2000 (effective 2000)	Individual Only	364,370	133,791,162
§§ 58.1-339.10 & 58.1-439.12	Riparian Forest Buffer Protection for Waterways Tax Credit	2000 (effective 2000)	Individual and Corporate	98	229,754
§ 58.1-339.9	Rent Reductions Tax Credit	2000 (effective 2000)	Individual and Corporate	0	0
§ 58.1-339.11	Long-term Care Insurance Tax Credit	2006 (effective 2006)	Individual Only	4,081	1,174,845
§ 58.1-439.12:02	Biodiesel and Green Diesel Fuels Producers Tax Credit	2008 (effective 2008)	Individual and Corporate	0	0
§ 58.1-439.12:05	Green Job Creation Tax Credit	2010 (effective 2010)	Individual and Corporate	*	752
§ 58.1-439.12:04	Tax Credit for Participating Landlords (Community of Opportunity)	2010 (effective 2010)	Individual and Corporate	20	42,041
§ 58.1-339.12	Farm Wineries and Vineyards Tax Credit	2011 (effective 2011)	Individual and Corporate	63	180,535
§ 58.1-439.12:03	Motion Picture Production Tax Credit (refundable)	2011 (effective 2011)	Individual and Corporate	4	7,176,474
§ 58.1-439.12:06	International Trade Facility Tax Credit	2011 (effective 2011)	Individual and Corporate	13	146,096
§ 58.1-439.12:08	Research and Development Expenses Tax Credit (Refundable)	2011 (effective 2011)	Individual and Corporate	317	4,210,012
§ 58.1-439.12:09	Barge and Rail Usage Tax Credit	2011 (effective 2011)	Individual, Corporate, Insurance and Bank	*	41,700
§ 58.1-439.12:10	Virginia Port Volume Increase Tax Credit	2011 (effective 2011)	Individual and Corporate	34	736,816
§ 58.1-439.12:07	Telework Expenses Tax Credit	2011 (effective 2012)	Individual and Corporate	10	112,843
§ 58.1-439.26	Education Improvement Scholarships Tax Credits	2012 (effective 2013)	Individual, Corporate, Insurance and Bank	347	1,613,525

Research & Development Credits

Research and Development Credits (Article 3F)

1. **Small Business R&D Credit**
Citation: G.S. 105-129.55(a)(1)
Description: A small business thas has qualified North Carolina research expenses for the taxable year is allowed a credit equal to 3.25% of the expenses. A small business is defined as a business whose annual receipts did not exceed $1 million. The amount of credit taken in any tax year cannot exceed 50% of the taxpayer's tax liability after other credits taken. Unused credits can be carried forward 15 years.
Enacting Legislation: S.L. 2004-124 - effective for business activities occurring on or after May 1, 2005
Sunset Date: Expires Jan. 1, 2016

Estimate (in millions): FY15-16........$0.3 FY16-17 .... $0.2

Data Source: Department of Revenue "Economic Incentive Reports"

2. **Low-Tier R&D Credit**
Citation: G.S. 105-129.55(a)(2)
Description: A taxpayer that performs research in a development tier one area is allowed a 3.25% credit for eligible expenses. The amount of credit taken in any tax year cannot exceed 50% of the taxpayer's tax liability after other credits taken. Unused credits can be carried forward 15 years.
Enacting Legislation: S.L. 2004-124 - effective for business activities occurring on or after May 1, 2005
Sunset Date: Expires Jan. 1, 2016

Estimate (in millions): FY15-16........$4.0 FY16-17 .... $2.2

Data Source: Department of Revenue "Economic Incentive Reports"

3. **University Research Credit**
Citation: G.S. 105-129.55(a)(2a)
Description: A taxpayer that has NC university research expenses for the taxable year is allowed a credit equal to 20% of the expenses. The amount of credit taken in any tax year cannot exceed 50% of the taxpayer's tax liability after other credits taken. Unused credits can be carried forward 15 years.
Enacting Legislation: S.L. 2004-124 - effective for business activities occurring on or after May 1, 2005
Sunset Date: Expires Jan. 1, 2016

Estimate (in millions): FY15-16........$0.5 FY16-17 .... $0.3

Data Source: Department of Revenue "Economic Incentive Reports"

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Research & Development Credits

4. **Eco-Industrial Park R&D Credit**
Citation: G.S. 105-129.55(a)(2b)
Description: A taxpayer that performs research in an Eco-Industrial Park certified under G.S. 143B-437.08 is allowed a 35% credit for eligible expenses. The amount of credit taken in any tax year cannot exceed 50% of the taxpayer's tax liability after other credits taken. Unused credits can be carried forward 15 years.
Enacting Legislation: S.L. 2010-147 - effective for taxable years beginning on or after Jan. 1, 2011
Sunset Date: Expires Jan. 1, 2016

Estimate (in millions): Unavailable

Data Source: Department of Revenue "Economic Incentive Reports"

Note: No credits have been taken through tax year 2012.

5. **Other R&D Credit**
Citation: G.S. 105-129.55(a)(3)
Description: A taxpayer that has qualified North Carolina research expenses not covered under another subdivision of this section is eligible for 1.25% credit on expenses up to $50 million; 2.25% of expenses between $50 million and $200 million; and 3.25% of expenses over $200 million. The amount of credit taken in any tax year cannot exceed 50% of the taxpayer's tax liability after other credits taken. Unused credits can be carried forward 15 years.
Enacting Legislation: S.L. 2004-124 - effective for business activities occurring on or after May 1, 2005
Sunset Date: Expires Jan. 1, 2016

Estimate (in millions): FY15-16........$44.0 FY16-17 .... $24.8

Data Source: Department of Revenue "Economic Incentive Reports"

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Notes: Above are two examples of source data for tax expenditures, the top from Virginia, and the bottom from North Carolina. This is just a snapshot of the tax expenditure report from both states.

Figure A.3: Examples of Budget Documents

VIRGINIA GENERAL ASSEMBLY / LIVE HELP / LIS HELP CENTER / LIS HOME

LIS

STATE BUDGET

Budget Bill ▾ Search

2015 Session ▾

• Budget Bill

2014 - 2016 Biennium

HB1400

› Introduced

› Enrolled

› Chapter 665

SB800

› Introduced

Budget Amendments

Committee Reports

2015 Session

Budget Bill - HB1400 (Chapter 665)

Bill Order » Office of Commerce and Trade » Item 101

← Item → Print PDF Email Item Lookup ex. 43, C-1, 3-3.01

Economic Development Incentive Payments

Item 101	First Year - FY2015	Second Year - FY2016
Economic Development Services (53400)	**~~$52,160,436~~** **$62,076,436**	**~~$67,863,444~~** **$79,363,444**
Financial Assistance for Economic Development (53410)	~~$52,160,436~~ *$62,076,436*	~~$67,863,444~~ *$79,363,444*
Fund Sources:		
General	~~$51,910,436~~ *$61,826,436*	~~$67,613,444~~ *$79,113,444*
Dedicated Special Revenue	$250,000	$250,000

Authority: Discretionary Inclusion.

A.1. Out of the amounts in this Item, ~~$10,000,000~~ *$19,916,000* the first year and ~~$10,000,000~~ *$20,750,000* the second year from the general fund shall be deposited to the ~~Governor's~~ *Commonwealth's* Development Opportunity Fund, as established in § 2.2-115, Code of Virginia. Such funds shall be used at the discretion of the Governor, subject to prior consultation with the Chairmen of the House Appropriations and Senate Finance Committees, to attract economic development prospects to locate or expand in Virginia. If the Governor, pursuant to the provisions of § 2.2-115, E.1., Code of Virginia, determines that a project is of regional or statewide interest and elects to waive the requirement for a local matching contribution, such action shall be included in the report on expenditures from the ~~Governor's~~ *Commonwealth's* Development Opportunity Fund required by § 2.2-115, F., Code

Summary by Purpose

24609 Commerce - Special Funds GF

CODE	DESCRIPTION	2011-2012 ACTUAL	2012-2013 CERTIFIED	2012-2013 AUTHORIZED	2013-2014 INCR/DECR	2013-2014 TOTAL	2014-2015 INCR/DECR	2014-2015 TOTAL
REQUIREMENTS								
2535	NC Green Business Fund	104,040	0	0	0	0	0	0
2536	GREEN BUS ENERGY SUB GNT	7,522,630	208,725	0	0	0	0	0
2537	ENERGY RESEARCH GRANTS	15,625	0	0	0	0	0	0
2560	ONE NORTH CAROLINA FUND	104,484,675	49,685,986	54,000,000	-45,000,000	9,000,000	-45,000,000	9,000,000
2562	ONE NC SMALL BUSINESS	529,013	0	0	0	0	0	0
2564	JDIG FEES	405,646	190,489	448,020	0	448,020	0	448,020
2565	JDIG SPECIAL REVENUE	19,951,815	19,000,000	15,000,000	0	15,000,000	0	15,000,000
2566	INDUSTRIAL DEVELOPMENT	790,000	1,141,800	1,141,800	0	1,141,800	0	1,141,800
2567	INDUSTRIAL DEV UTIL ACNT	3,451,510	3,023,074	3,750,000	0	3,750,000	0	3,750,000
2584	ECONOMIC DEVELOPMENT RES	0	811,493	49,688	0	49,688	0	49,688
2586	JOB MAINT & CAP DEV FND	5,745,079	0	0	0	0	0	0
TOTAL REQUIREMENTS		143,000,033	74,061,567	74,389,508	-45,000,000	29,389,508	-45,000,000	29,389,508
ESTIMATED RECEIPTS								
2536	GREEN BUS ENERGY SUB GNT	4,589,395	208,725	0	0	0	0	0
2560	ONE NORTH CAROLINA FUND	110,000,000	5,000,000	9,000,000	0	9,000,000	0	9,000,000
2562	ONE NC SMALL BUSINESS	12,621	0	0	0	0	0	0
2564	JDIG FEES	213,000	176,475	176,475	0	176,475	0	176,475
2565	JDIG SPECIAL REVENUE	20,169,879	19,000,000	15,000,000	0	15,000,000	0	15,000,000
2566	INDUSTRIAL DEVELOPMENT	40,000	821,693	821,693	0	821,693	0	821,693
2567	INDUSTRIAL DEV UTIL ACNT	4,694,826	3,023,074	3,750,000	0	3,750,000	0	3,750,000
2586	JOB MAINT & CAP DEV FND	6,000,000	0	0	0	0	0	0
TOTAL RECEIPTS		145,719,721	28,229,967	28,748,168	0	28,748,168	0	28,748,168
CHANGE IN FUND BALANCE		2,719,688	-45,831,600	-45,641,340	45,000,000	-641,340	45,000,000	-641,340

Notes: Above are two examples of source data for economic development program spending, the top from Virginia, and the bottom from North Carolina. This is just a snapshot of a relevant part of the budget document from both states.

A.1 Runner-up State Examples

Figure A.4: Sources for Identification of the Runner-up State

December, 2002

Incentives Deal of the Month

from *Site Selection*'s exclusive New Plant database

Oregon Incentives, Idle Plant Are 'Fab' for Microchip's Expansion Plans

by **JACK LYNE**, *Site Selection* Executive Editor of Interactive Publishing and **ADAM BRUNS**, *Site Selection* Managing Editor

At full capacity, the 826,500-sq.-ft. (76,782-sq.-m.) facility that Microchip purchased (pictured) will double the company's chip-production capacity.

GRESHAM, Ore. – Spurred by US$17.3 million in state incentives, Microchip Technology (www.microchip.com) has hired the first 60 of what may be as many as 688 employees at its newly acquired facility in Gresham, Ore. - a turnaround that one local official calls "a miracle."

Gresham had needed something like an economic miracle since late last year. That was when Fujitsu announced that is was shutting down its local flash-memory plant, laying off 670 employees. The 826,500-sq.-ft. (76,782-sq.-m.) facility - Fujitsu's first U.S. fab - had been sitting idle since early this year, edging dangerously close to white-elephant status. Razing had become a distinct possibility in the facility's future.

Enter Microchip Technology. The company, which makes microcontrollers embedded a wide array of commercial, industrial and consumer products, was no stranger to the Pacific Northwest. In 2000, Microchip bought an existing Matsushita fab in Puyallup, Wash., 155 miles (249 kilometers) north of Gresham. The Puyallup fab, which is also currently idle, was the clear frontrunner in Microchip's U.S. expansion plans - and even after the company first got wind of the Fujitsu plant's availability.

(a) *Site Selection* Magazine

Electrolux Home Products, Inc. ("EHPI")

In addition to North Carolina, EHPI management considered two other potential locations: South Carolina and Tennessee. South Carolina offered several desirable locations in York and Lancaster Counties. South Carolina submitted a formal proposal that included significant up-front cash incentives and cash grants valued at approximately $54 million. EHPI recently established a large manufacturing facility in Memphis, Tennessee. That facility was located there after extensive analysis of the incentives offered in Tennessee, Alabama, and North Carolina. Tennessee was chosen in large part due to its superb incentive package.

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(b) State of North Carolina Subsidy Report

- Nexteer Automotive (Steering Solutions Services Corporation) - The former steering division of Delphi Corporation, which operates in **Saginaw** under the Nexteer brand name, is the only global Tier One automotive supplier focused on advanced steering and driveline systems technology. The company plans to invest $413 million to actively pursue diverse new business opportunities. The project will retain 8,711 total jobs, including 2,400 directly by the company. The MEDC estimates the increased economic activity created by the project will retain an additional 6,311 indirect jobs. Based on the MEDC's recommendation, the MEGA board today approved a state tax credit valued at $70.7 million over 10 years to encourage the company to expand in Michigan over competing sites in Europe and China. Buena Vista Charter Township is considering an abatement in support of the project. http://www.nexteer.com/

(c) State of Michigan Press Release

Notes: This figure contains three examples of sources that I use to find information on the runner-up state in the subsidy competition. The source can be an article from a magazine or newspaper (a), state reports on discretionary subsidies (b), or state/company press releases (c).

A.2 Data Snapshot

Figure A.5: Subsidy Source Data

Subsidy Tracker Individual Entry

Company: Toyo Tire

Parent Company: Toyo Tire & Rubber

Subsidy Source: multiple

Location: Georgia

City: Cartersville

County: Bartow

Project Description:
Tire plant

Year: 2004

Major Industry of Parent: automotive parts

Specific Industry of Parent: automotive parts-tires

Subsidy Value: $71,000,000

Program Name: multiple

Awarding Agency: multiple

Type of Subsidy: MEGADEAL ?

Number of Jobs or Training Slots: 900

Wage Data: $15

Wage Data Type: estimated average hourly wage

Capital Investment: $392,000,000

Source of Data:
The outlines of the project and subsidy details were taken from: "Bartow County makes formal proposal for $392 million tire plant," The Associated Press State & Local Wire, June 4, 2004. The total subsidy amount and wage data were taken from: Christopher Quinn, "The cost of new jobs; Incentives for tire plant spark debate in Bartow," The Atlanta Journal-Constitution, August 23, 2004.

Notes:
The state of Georgia and Bartow County approved a subsidy deal for Toyo Tire to locate a tire plant in the county. Toyo Tire received $8 million in infrastructure and land, $1,750 in state tax credits for each job created (potentially 900 jobs total), tax abatements for five years (undisclosed amount), exemption from state and local sales taxes for equipment purchases, and possibly other incentives. The deal also had three phases of investment from the company: (1) $146 million and 350 workers, (2) $127 million and 300 workers, and (3) $119 million and 250 jobs. Overlap with main Subsidy Tracker data: none.

Source Notes: If an online information source is not working, check the Tracker inventory page for an updated link.

(a) Toyo Tire

Subsidy Tracker Individual Entry

Company: Microchip

Parent Company:

Subsidy Source: state

Location: Oregon

City: Gresham

Project Description:
Semiconductor fabrication

Year: 2002

Subsidy Value: $13,100,000

Program Name: Strategic Investment Program

Awarding Agency: Business Oregon

Type of Subsidy: property tax abatement

Source of Data:
Direct from Business Oregon; not on web

Notes:
Year is year of approval; subsidy value is cumulative amount of abatement through 2010

(b) Microchip

Notes: These are two examples of the information available in the *Good Jobs First* Subsidy Tracker. Each entry is a subsidy deal. Both entries include the company name, location, project description, year, size of the subsidy, and source of the subsidy funds.

A.3 Data Integrity

I do two checks to ensure the data integrity of the sample of subsidy deals from *Good Jobs First* (GJF) subsidy data.[75] I (1) compare subsidies for new establishments against establishment entry in Business Dynamics Statistics, and (2) compare subsidies for the state of Virginia with an administrative list from a contact at Virginia's Joint Legislative Audit & Review Commission (JLARC).

Table A.1 displays the results comparing establishment entry from the Census with the subsidy data. Note that 52 new manufacturing establishments with over 1000 employees entered the U.S. between 2008 and 2014, and I observe 52 manufacturing firms promising over 1000 jobs receiving discretionary subsidies in the GJF data over the same period. The numbers do not always line up at the annual level, as the GJF data sometimes uses the year the deal was made (before the establishment physically locates in the state), and other times the year the subsidy began to be disbursed (after the establishment locates). As the establishments get smaller they are less likely to receive a discretionary subsidy (50% of establishments creating 500-999 direct jobs are presumed to receive discretionary subsidies, and 6% of establishments creating 250-499 jobs), or the subsidy they do receive is too small to be picked up in my sample selection process. These data checks suggest that the GJF data has a fairly comprehensive list of large subsidies given for establishment location.

Table A.1: Manufacturing Entry vs. Manufacturing Subsidy Deals

	Establishment Entry			**Subsidy Data**		
Year	250-499	500-999	1000+	<500	500-999	1000+
2008	147	34	12	9	6	9
2009	123	27	7	3	11	11
2010	106	9	8	6	10	8
2011	94	23	4	3	12	5
2012	78	9	6	8	12	5
2013	89	12	7	14	7	6
2014	90	31	8	12	15	8
Total:	727	145	52	55	73	52

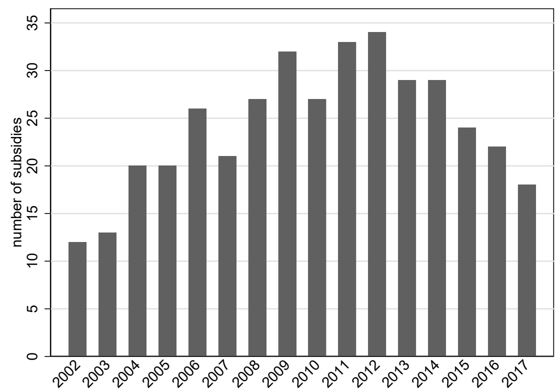
Notes: The left side of the table above lists the counts of manufacturing establishments entering U.S. states by year and size of establishment, according to the Census Business Dynamics Statistics. The right side of the table lists the counts of manufacturing establishments that received discretionary subsidies from states for entering or expanding, in my dataset of discretionary subsidy deals.

[75] Which I also supplement with the data from *Site Selection* magazine.

A.4 Extended Descriptive Statistics

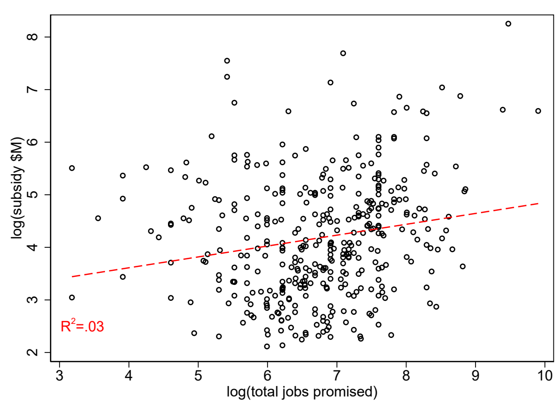
Figure A.6 shows the number of subsidies in the data, over time. Figure A.7 shows the size of the subsidy, in log terms, plotted against the total number of jobs promised, also in logs. This includes jobs retained, for subsidy deals that are expansions in the current location. When I restrict to job promises under 10,000 one additional job is correlated with about $18,000 more in subsidy. There are only 3 deals with job promises over 10,000 but this leads to a much larger correlation, at $60,000 per job.

Figure A.6: Subsidy-giving by Year, 2002-2017



Notes: This figure shows the number of subsidy deals in the sample in each year. Subsidy-giving increased from 2002, at just over 10 deals, to 2012, with almost 35 deals. Data collected by the author. The lower number of subsidy deals in the last 2 years of the sample is not necessarily representative. The data were collected in 2018 and it can take more than a year before all of the information about the subsidy deal that I need is public information.

Figure A.7: Total Jobs Promised vs. Subsidy Size



Notes: This figure plots the log number of jobs promised in a subsidy deal, with the log size of the subsidy the firm receives. Log jobs is on the x-axis, and subsidy size, in log($M), is on the y-axis. The red dashed line is the trend line, which has a R^2 of 0.03. An additional job is associated with an approximately $60,000 larger subsidy. However, when I drop the deals that promise over 10,000 jobs, which is the case for 3 deals (less than 1% of the sample), the correlation falls to about $18,000 per additional job. Data collected by the author.

Table A.2 shows how state-level economic and political characteristics correlate with per capita business incentive spending, within a state. Decreases in the employment to population ratio are correlated with large increases in per capita incentive spending. A state with 1% lower employment ratio spends 8.6% more on business incentives per capita. The same is true in differences; a state that experience a 1% decrease in the employment ratio in the previous year will increase per capita incentive spending by about $4 (or 7%). This is further descriptive evidence that heterogeneity in local labor markets may drive differences in subsidy spending, as states which struggle to create jobs have a higher valuation for the marginal job (Bartik, 1991; Bilal, 2023). The table also shows that when governors are term-limited they are likely to decrease per capita incentive spending.[76]

Table A.2: State Characteristics and Total Incentive Spending

	Per Capita Incentives ($)				Δ Per Capita Incentives ($)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP per capita ($1000)	0.75			1.95				
	(0.42)			(0.48)				
% Population Employed		-2.62		-4.74				
		(0.97)		(1.11)				
Corporate tax rate (%)			2.18	2.48				
			(1.26)	(1.24)				
Δ_{t-1} GDP per capita					-0.67			-0.40
					(0.78)			(0.78)
Δ_{t-1} % Pop. Employed						-3.96		-3.83
						(1.49)		(1.50)
Term-limited Governor							-7.87	-7.87
							(3.30)	(3.27)
Observations	384	384	384	384	336	336	336	336
R-squared	0.85	0.86	0.85	0.86	0.07	0.09	0.08	0.11
Dep. Var. Mean	54.76	54.76	54.76	54.76	0.09	0.09	0.09	0.09
Ind. Var. Mean	52.80	36.41	6.51		-0.02	-0.31	0.30	

Notes: This table presents the results of a linear regression of state characteristics on state per capita business incentive spending. The panel on the left regresses state characteristics on per capita incentives, and the means of each variable are recorded below the R^2. The panel on the right regresses changes in per capita incentives between $t-1$ and t on changes in state characteristics between $t-2$ and $t-1$, as well as whether the governor can run for re-election. Observations are at the state-year level, state and year FE are included in each specification, and the sample is 2007-2014. Standard errors reported in parentheses. Sources include the U.S. Bureau of Economic Analysis (1967-2017) (population, GDP), the Census Bureau County Business Patterns (1997-2017) (employment), National Institute on Money in Politics (2000-2018) (term limits), and the author (state business incentive spending). States' total business incentive spending is not limited to discretionary subsidies. Business incentive spending includes all tax credits and economic development programs, such as job training programs, that the state has available to new and expanding businesses. Descriptive statistics for the state level incentive spending data are presented in Slattery and Zidar (2020).

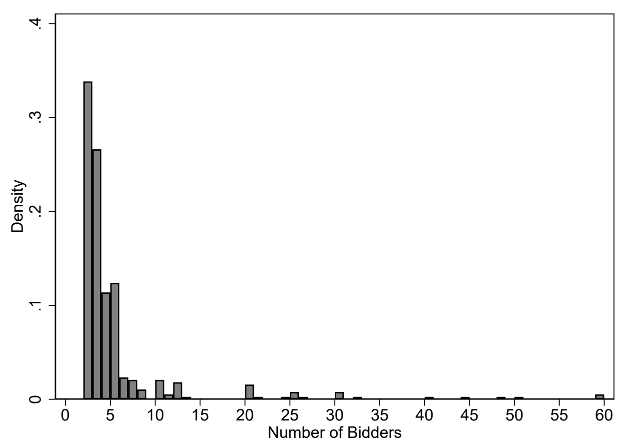
[76]Past literature in public economics has found evidence of political motivations for policy changes (Besley and Case, 1995; Poterba, 1994). It is also possible that these subsidies are driven by corruption—governors can use discretionary incentives to funnel money to their friends and political supporters. Industries that have greater political influence in a state, such as oil and gas in Louisiana and Texas, may use their political capital to ensure more financial support from the government. I will not be able to speak to these motivations in this paper, but it is a rich area for further work.

B Number of Bidders

Figure B.1 presents the data I have available on the number of competitors in each subsidy competition. I have information on the number of bidders for 95% subsidy deals. If I can only find the identity of the runner-up, and there is no suggestion that there were other sites in contention, the number of competitors is assumed to be 2. In many cases the number of competitors is reported to be "at least *N*", and I take the number of bidders in those cases to be *N*. Therefore, this might be a lower bound. I assign the average number of bidders (5) to any observations where the number of bidders is reported to be "multiple sites" or "numerous states," but an actual number is not specified.

This is roughly a measure of the number of sites a firm was considering in the subsidy competition (the number of locations on the shortlist). As I mention in the text, a usual concern in the estimation of English auctions is that the number of bids is a lower bound on the actual number of bidders (Haile and Tamer, 2003). However, this data on the number of bidders is not from bidding data, where this would be a concern. Instead, I collected this data from articles and press releases describing the site selection process. For example, an article about Wells Fargo's 2003 subsidy deal in Iowa from *Site Selection Magazine* mentions six total competitors: "Wells Fargo Mortgage earlier this year made it known that it was considering other states as well, including Arizona, California, Illinois, Minnesota and South Carolina." An example from North Carolina's annual incentive report lists the actual towns that Sid Tool Co was choosing between in 2012, totaling three competitors: "The town of Davidson was one of three locations under consideration for this project. Lexington, Kentucky and Fort Mill, South Carolina were alternative locations."

Figure B.1: Number of Reported Bidders



Notes: This is the distribution of number of locations competing in the subsidy competitions in the data, as described above. Data collected by the author; sources are available in the data appendix.

C Evidence for Assumption 1

Figure C.1 presents anecdotal evidence that states are aware of their competitors' subsidy offers. This is an excerpt from North Carolina's discretionary subsidy report (see Figure A.4(b) for another example from the same source). Therefore, the more demanding assumption is that states know the firm's profit in each state. Firms may not want to be truthful about where they have the highest profit, in order to extract a larger subsidy from the state.

Figure C.1: Evidence that states know competitors' subsidy offers

General Electric Company ("GE")

GE consists of eight primary business divisions: Oil & Gas, Energy Management, Power & Water, Healthcare, Transportation, Capital, Home & Business Solutions and Aviation. GE Aviation is a leading provider of commercial and military jet engines and components, as well as avionics, electric power, and mechanical systems for aircraft with an extensive global service network to support these products.

This project brings new manufacturing to North Carolina, including a facility for the production of advanced ceramic matrix composite (CMC) materials for aircraft and gas turbine engines. CMC components are lighter weight than existing materials used in engine production and allow for higher temperatures, increasing engine efficiency.

Nine states including North Carolina were considered for the project. South Carolina's incentive package was valued at $14.8 million while Virginia's totaled $11 million.

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Additionally, South Carolina had several local incentive packages worth over $30 million over a 10-year period.

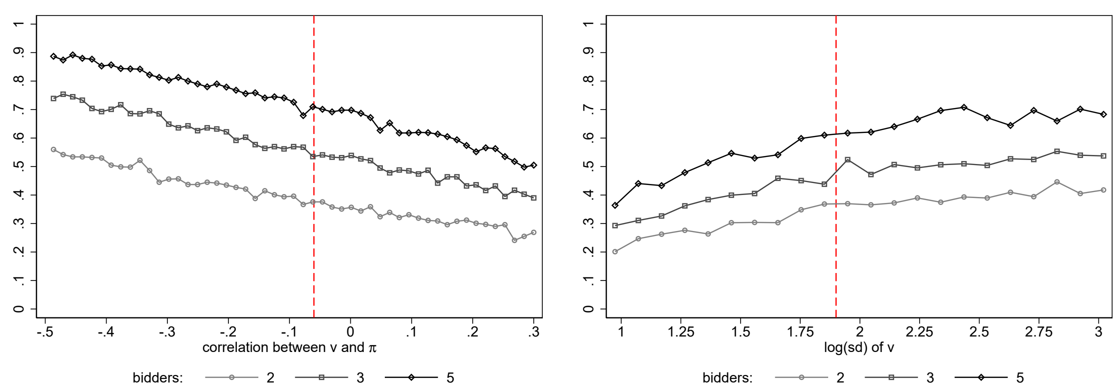
Notes: This is an excerpt from North Carolina's 2013 Job Development Investment Grant Report. For each firm that receives a discretionary subsidy from the program, there is a description of the firm and the competition. As detailed above, North Carolina is aware of the value of the incentive offers in runner-up states.

D Simulation Exercise: Model Predictions

In Figures D.1 though D.3 I present the results of model simulations. I take the distribution of profits and valuation for an average manufacturing subsidy deal—where $\pi \sim N(223, 115)$ and $v \sim logN(3.74, 1.94)$.[77] Given 1,000 draws of v and π, I simulate the results of the subsidy competition game. I then repeat the exercise changing the covariance π and v, and changing the variance of v.

Figure D.1 shows how the share of simulated deals with a positive welfare gain (e.g. the share of cases where allowing competition induced the firm to choose a higher welfare location) changes with the covariance of v and π (left panel) and the variance of v (right panel). I show the results of the simulation for 2, 3, and 5 bidders—80% of the competitions in the sample have 5 or fewer bidders, where 5 is the mean and 3 is the median. The dashed vertical red line shows the baseline ("data"): the correlation in the manufacturing subsample is -0.07, and $v \sim logN(3.74, 1.94)$. This baseline represents the average relocation rate for manufacturing in the counterfactual: 53% of the subsidy-winning establishments in the manufacturing subsample would stay in the same location in the absence of a subsidy deal, implying 47% would relocate (Table I.3). These figures show an average relocation rate of about 50%, taking the weighted average over the number of bidders in the data.

Figure D.1: Share of Deals with Strictly Positive Welfare Gain



Notes: Figure D.1 shows how the share of simulated deals with a positive welfare gain (e.g. the share of cases where allowing competition induced the firm to choose a higher welfare location) changes with the covariance of v and π (left panel) and the variance of v (right panel). The baseline represents the correlation or standard deviation in the data.

The left panel in Figure D.1 shows that as the covariance between v and π grows, the highest profit place is more likely to be the highest welfare place, decreasing the share of deals that induce firms to choose a different location. However, this is not the only thing that matters for location choice. Importantly, given the baseline level of heterogeneity in profits and valuations, the model would predict that competition changes firms' locations even under a positive correlation between v and π. The right panel in Figure D.1 shows that the share of deals with a strictly positive welfare gain is increasing in the variance of v—though this is a slightly weaker pattern than shown for the covariance.

[77] This is the distribution of π and v I recover in Section 5, for a manufacturing subsidy deal with 870 jobs and \$890 million in investment.

Figure D.2 shows the welfare gain from competition—normalizing by welfare in the baseline ("data"). As the correlation between v and π increases, the relative welfare gain decreases, partly mechanically, as less firms relocate due to competition. However, the variance of v shows a dramatic increase in welfare arising from an increase in heterogeneity in the valuations. This is due to the growing difference between the valuation in the winning location and the location with the highest profit that would have been chosen in the absence of subsidy competition.

Finally, Figure D.3 shows the change in the firm's share of total welfare due to subsidy competition. The correlation between v and π has no effect on the firm's share of the welfare gain. However, the firm's share of welfare decreases rapidly with the variance of v, before flattening. As the variance of the valuation decreases, there will be a smaller difference between the valuation in the winning and runner-up location, leading the states to compete away most, if not all, of the welfare gain.

The results of this simulation exercise highlight the importance of the heterogeneity of valuations, as opposed to the correlation between v and π, for the welfare results.

Figure D.2: Relative Change in Welfare

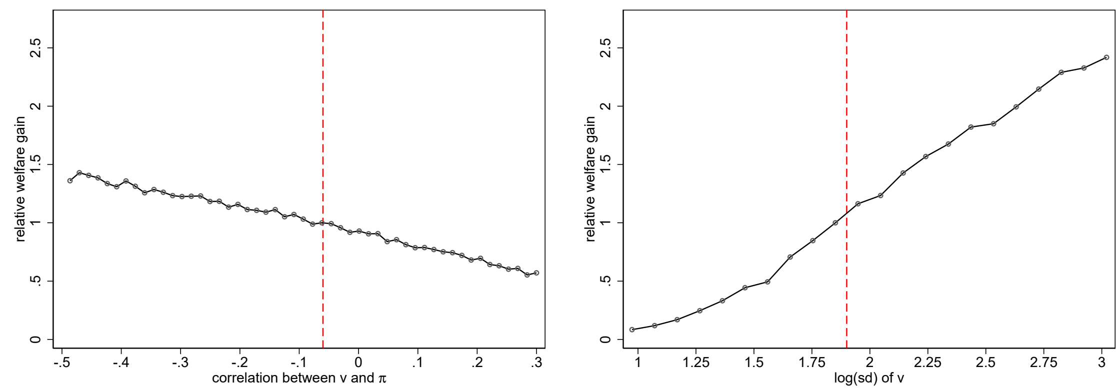
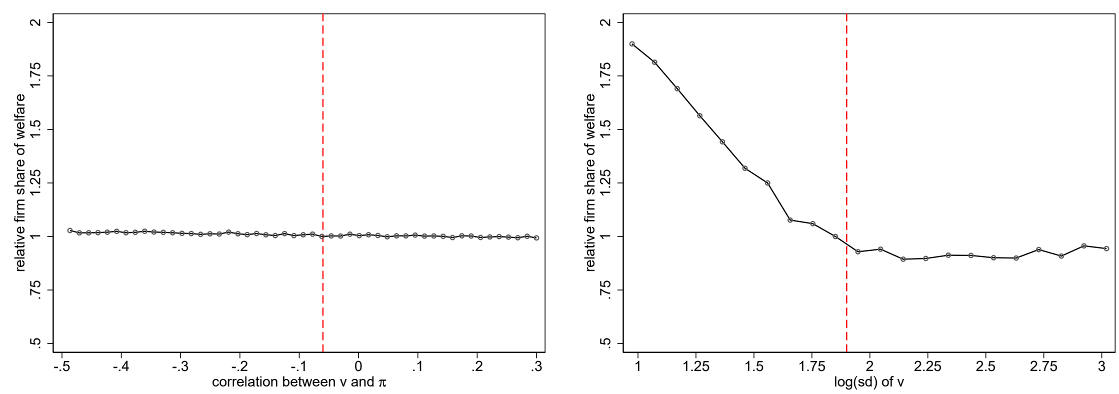


Figure D.3: Relative Change in Firm Share of Surplus



Notes: Figures D.2 and D.3 show the relative change in welfare and change in the firms' share of welfare, respectively, as a result of the simulation described in Appendix Section D. The welfare analysis in the simulation is relative to a baseline welfare gain, so at the red dashed line the change is equal to 1. The baseline represents the correlation and the standard deviation in the data, for the left and right figures, respectively.

E The Site Selection Process

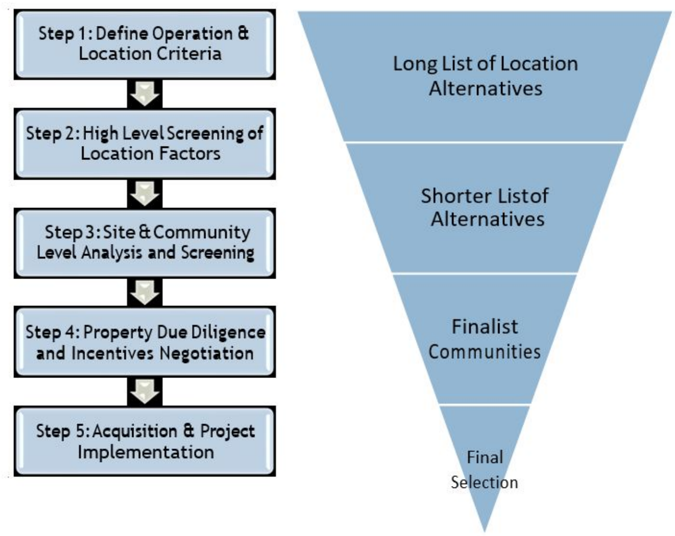
In the text I refer to the in-depth interview of the Volkswagen 2008 site selection process to motivate the model. Reproduced from page 25: "A team of 25 people with Staubach worked on the project, helping VW consider an initial pool of more than 100 candidate sites, all located in the central or eastern U.S. because of time-zone proximity to Germany. 'What you look for is mostly problems sites have—readiness, labor, logistics infrastructure,' says Greg Lubar, project leader and senior vice president at Staubach. VW said it short-listed 25 sites. 'It was then a dozen or so we were in discussions with until the three finalists,' says Lubar." (Bruns, September 2008). Greg Lubar looks for JLL, a real estate firm that also works in project management and site selection consulting.

This strategy is not specific to JLL or Volkswagen. Biggins Lacy Shapiro & Company (BLS & Co.) is a consulting firm that specializes in site selection. They claim: "Our team can help you identify, evaluate, and select the optimal location for your operation and secure meaningful state and local tax credits and other business incentives to optimize the financial performance of that choice." Clients mentioned on their website include many that are in my own data set of subsidy deals, including Nestle, Subaru, Citi, RBS, Roche, and Bristol-Myers Squibb.

Figure E.1 shows how BLS describes the site selection process, from an article titled "Selecting the Best Location for your U.S. Manufacturing Plant." The first step is to define the operational requirements of the proposed facility, in order to determine the set of "must-haves" for the site. Once these requirements are defined, Step 2 is a high level screening of location factors. It is in this step that the firm, with the help of the consultant, will go from a long list of potential locations, to a much shorter list. Figure E.1(b) lists typical factors that are reviewed at this stage, which are consistent with the location factors I lay out in Appendix F and try to control for in the firm's location choice problem.

Step 3 is the site and community level analysis and screening, which, according to BLS, focus on a small (3-10) list of potential regions. Here, it is where issues like zoning, the local economy, labor force, and incentives come in. In Step 4, the finalist locations are selected and the firm should do due diligence on each site and negotiate incentives with the state and local governments. From the BLS & Co. article: "As finalist locations, both options should be able to meet your operational needs, so at this step, you will want to prepare a detailed financial analysis for each finalist site and negotiate incentive programs that will help 'close the deal' by providing upfront and/or ongoing cost savings and risk management." This motivates the model. First, firms select a short list of locations where they will be profitable, and then they compete on incentives.

Figure E.1: Site Selection Process



(a) Overview

HIGH LEVEL SITE SELECTION SCREENING FACTORS	
Transportation and Logistics	☑ Inbound transportation costs to ship raw materials into the plant ☑ Outbound transportation costs to ship finished products to customers ☑ Transportation Service and Infrastructure Availability ☑ Airport Accessibility
Labor	☑ Labor Costs ☑ Labor / Management Relations ☑ Mandated Benefits ☑ Population/Demographics ☑ Concentration of Specified Labor Skills ☑ Labor Training Programs
Utilities	☑ Electric Power - availability and cost ☑ Natural Gas - availability and cost ☑ Water - availability and cost ☑ Wastewater - availability and cost ☑ Telecommunications - availability and cost
Taxes	☑ State Corporate Taxes ☑ Property Taxes - Real and Personal ☑ Inventory Taxes
Real Estate	☑ Availability of Sites and/or Buildings ☑ Cost of Real Estate
Regulatory Environment	☑ Business Climate ☑ State Regulations ☑ Environmental Regulations

(b) Location Factors

Notes: These figures give an overview of the site selection process, according to one prominent site selection firm. The source is an article from their website (https://www.blsstrategies.com/insights-press/selecting-the-best-location-for-your-u-s-manufacturing-plant), titled "Selecting the Best Location for Your U.S. Manufacturing Plant."

F Variable Selection

F.1 Profit Function

I rely on existing research on firm location decisions and interviews with consultants published in *Site Selection Magazine* to specify the firm profit function. Martin (2000*a*) summarizes the factors that firms consider when choosing locations: "Firm costs differ across locations due to differences in regulation, wages, transportation costs, quality and quantity of public infrastructure, access to airports and interstate highways, proximity to research centers and universities, amenities valued by employees, and differences in tax structures." Porter and Rivkin (2012) agree, adding, "Many factors affect the profitability of operating in a certain locale: wage levels, skills availability, utility rates, taxes, subsidies, shipping costs and reliability, local productivity, supervision costs, and many more."

Appendix F.4 verifies that these are all relevant site selection components, with a handful of excerpts from interviews and news articles on these firm location searches. Differences between manufacturing and high-skilled services are pronounced from these articles. Projects like automobile assembly plants and steel mills list "readiness, labor, logistics" and "raw material" and "power". Meanwhile projects like medical device R&D centers and automobile headquarters cite "employee quality of life, availability of skilled labor, local costs and business environment" and "work-life balance and cost-of-living considerations for our employee team."[78] I will specify two separate profit functions—one for manufacturing and the other for trade and services.

I take the categories listed by Martin (2000*a*), and add four more that are cited in the site selection articles and supporting research. In each category I list the relevant data I have collected, and the source.

- **Regulation**: Right-to-work status, local zoning[79] (National Conference of State Legislatures, 2019; Gyourko, Hartley and Krimmel, 2021)
- **Wages**: Industry wages (County Business Patterns, 1997-2017)
- **Quality/Quantity of Infrastructure**: Bridge quality, freight miles (Bureau of Transportation Statistics, 2022)
- **Access to Airports and Highways**: Airport dummy, highway network (Federal Aviation Administration, 2019; Environmental Protection Agency, 2021)
- **Proximity to Research Centers and Universities**: Number of top research universities (National Science Foundation, 2000-2017)
- **Amenities/Cost of Living**: Housing prices, income tax (Zillow, 1996-2020; CSG Book of the States, 1950-2018)
- **Differences in Tax Structure**: Corporate tax, sales tax, property tax (CSG Book of the States, 1950-2018; Ruggles, Flood, Goeken, Grover, Meyer, Pacas and Sobek, 2019)

[78] See Appendix F.4 for the full quotations and more examples.

[79] The Wharton Land Use Regulation Survey asks "How do you perceive the supply of land zoned for industrial use compared to the demand for it in your community?", on a scale from 1-6. I rescale the variable to 0-1.

- **Skilled Labor**: Education, employment in relevant occupations[80] (Ruggles, Flood, Goeken, Grover, Meyer, Pacas and Sobek, 2019; Bureau of Labor Statistics, 2021)
- **Proximity to Suppliers**: Industry establishment share (County Business Patterns, 1997-2017)
- **Utility Rates**: Industrial and commercial electrical prices (U.S. Energy Information Administration, 2000-2017)
- **Natural Resources/Raw Materials**: Here I do not have any data. I assume that this is a first order consideration of the firm, therefore there are no locations on the short list that do not have the natural resources/raw materials necessary to operate the plant.

Table F.1: Winning and Runner-up Places

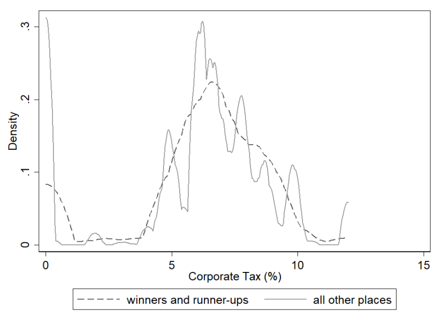
	Winners			Runner-ups			All U.S.		
	Mean	Med.	SD	Mean	Med.	SD	Mean	Med.	SD
State-level:									
Corporate Tax (%)	6.39	6.90	2.58	5.97	6.50	2.87	5.92	6.50	3.06
Income Tax (%)	5.52	6.00	2.82	5.16	5.90	3.23	4.91	5.64	3.01
Sales Tax (%)	5.46	6.00	1.31	5.48	6.00	1.34	5.18	5.95	1.66
Right-to-Work	0.59	1.00	0.49	0.56	1.00	0.50	0.58	1.00	0.49
Industrial Electricity Price (c/KwH)	7.56	6.73	2.25	7.48	6.73	2.10	6.96	6.64	1.58
Commercial Electricity Price (c/KwH)	9.38	8.89	2.29	9.50	9.06	2.34	8.75	8.55	1.86
Term-limited Gov.	0.32	0.00	0.47	0.30	0.00	0.46	0.31	0.00	0.46
State-CZ-level:									
Property Tax (%)	1.32	1.17	0.63	1.33	1.17	0.65	1.64	1.43	0.93
Housing Prices ($1,000)	208.38	177.38	102.17	226.69	187.47	121.04	149.83	130.25	80.01
Perceived Industrial Land Supply	0.64	0.66	0.10	0.64	0.66	0.11	0.58	0.51	0.13
Poor Condition Bridges (%)	6.68	6.92	4.12	6.17	5.64	4.74	7.07	6.12	5.51
Auto Network Density	0.96	0.90	0.35	1.00	0.94	0.43	0.54	0.46	0.35
Major Airport	0.52	1.00	0.50	0.54	1.00	0.50	0.09	0.00	0.29
Freight Rail Density	0.10	0.09	0.06	0.10	0.09	0.07	0.06	0.05	0.04
Population with BA+ (%)	20.92	21.17	6.14	21.12	21.20	6.01	15.96	15.04	4.98
Research University	0.25	0.00	0.50	0.32	0.00	0.55	0.04	0.00	0.21
ln(Per Cap Income, $1000)	3.81	3.80	0.20	3.82	3.81	0.20	3.65	3.64	0.19
Unemployment Rate (%)	6.72	6.28	2.34	6.57	6.03	2.27	6.44	5.92	2.67
Density (1,000 Persons/Mile^2)	0.92	0.69	0.77	0.96	0.69	0.83	0.20	0.06	0.40
Distance to State Border	32.48	9.50	56.04	37.97	10.50	56.08	38.76	17.10	50.51
State-CZ × Industry-level:									
Industry Wage ($1,000)	70.63	63.15	30.53	72.34	63.14	33.02	45.25	41.07	20.05
Relevant Occupation Wage ($1,000)	46.02	41.68	17.51	46.22	41.47	17.65	39.60	36.49	15.26
Share Industry Establishments	0.39	0.13	0.55	0.37	0.11	0.55	0.22	0.03	0.41
Population in Relevant Occupations (1,000)	13.61	7.70	13.98	14.45	7.61	15.09	2.45	0.50	6.16
Population in Relevant Occupations (%)	0.01	0.01	0.01	0.01	0.01	0.05	0.01	0.01	0.03

Notes: This table includes descriptive statistics for the places that win subsidy deals, are runner-ups in subsidy deals, and the entire United States. The observation level is at the commuting zone-industry-year, and the sample is 2002-2017. Sources are listed with the variable descriptions in Appendix Section F.

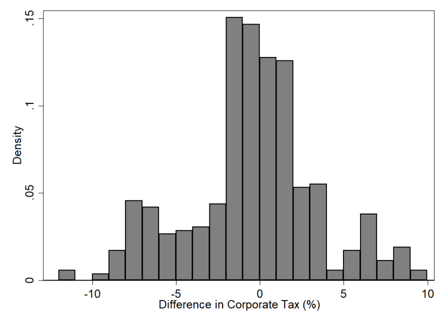
[80] This measures local employment in occupations that the firm likely wants to hire in, but does not restrict that employment to the same industry of the firm. For example, if the firm is an auto assembly plant, I first take the five occupations in the broader transportation manufacturing industry. Then, the relevant occupation count for auto assembly plants in each location is the total count of employment in these five occupation codes, regardless of industry.

Table F.1 presents the descriptive statistics for each of the variables listed above for the winning commuting zones, the runner-up commuting zones, and the entire United States. Winning locations have slightly higher state tax rates than the runner-ups, and are more likely to be right-to-work than the runner-up or average state. The industry-CZ specific variables also highlight a striking difference between winners, runner-ups and the average CZ—the industry of the firm has a much larger footprint (as measured by industry establishments) in the winner and the runner-up than the average. Also, industry wages are higher in both winning and runner-up locations. Figures F.1 and F.2 show this variation in graphical form, along with the distribution of the *differences* in the runner-up and winner's characteristic.

Figure F.1: Variation in the Data: Taxes

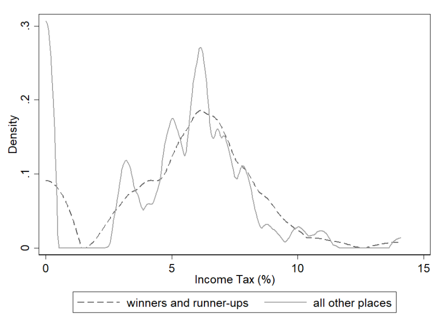


(a) Top 2 vs All Locations

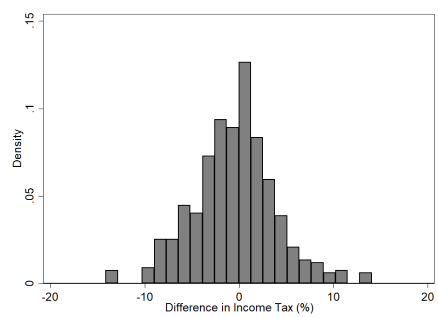


(b) Difference in Runner-up and Winner

Corporate Tax

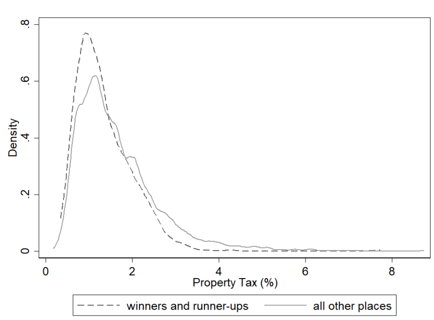


(c) Top 2 vs All Locations

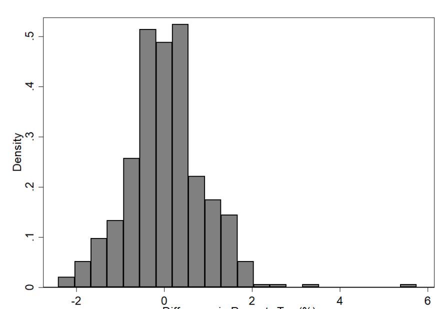


(d) Difference in Runner-up and Winner

Income Tax



(e) Top 2 vs All Locations

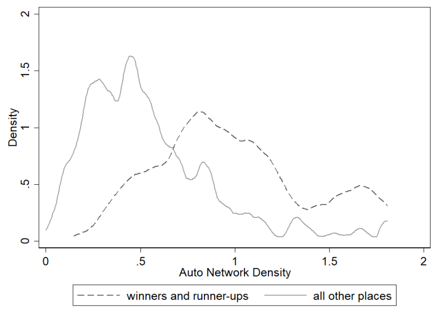


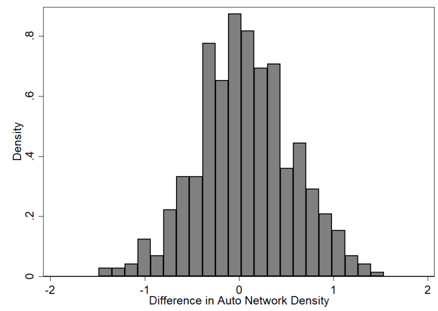
(f) Difference in Runner-up and Winner

Property Tax

Notes: The figures on the left show the distribution of tax rates for the winning and runner-up locations, and for the rest of the United States. The figures on the right show the distribution of differences between the runner-up and winner.

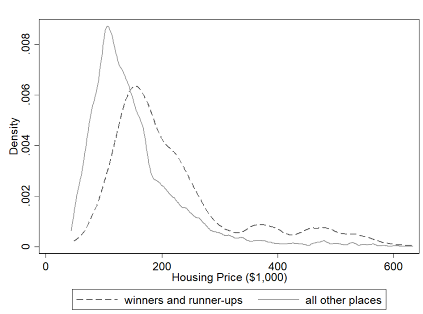
Figure F.2: Variation in the Data: Other Location Characteristics

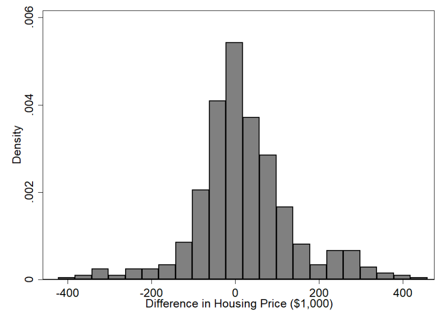




(a) Top 2 vs All Locations (b) Difference in Runner-up and Winner

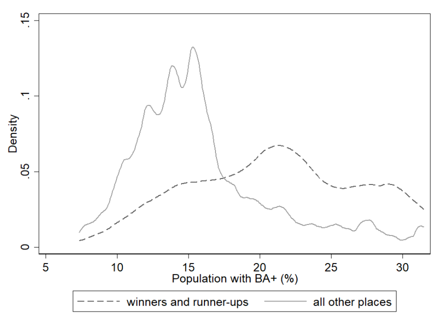
Auto Network Density

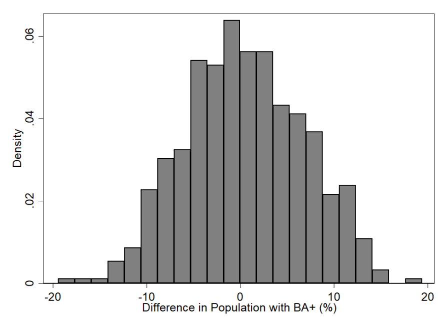




(c) Top 2 vs All Locations (d) Difference in Runner-up and Winner

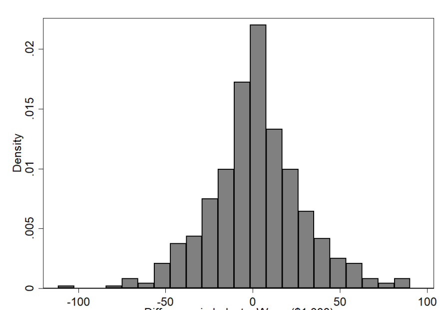
Housing Prices





(e) Top 2 vs All Locations (f) Difference in Runner-up and Winner

Education



(g) Top 2 vs All Locations (h) Difference in Runner-up and Winner

Industry Wages

Notes: The figures on the left show the distribution of a set of location characteristics for the winning and runner-up locations, and for the rest of the United States. The figures on the right show the distribution of differences between the runner-up and winner.

The preferences of manufacturing and trade/services firms differ when asked about location decisions. For example, the services firms are more likely to mention proximity to an airport, while manufacturing firms focus on the price of utilities. Therefore, I make the following distinctions and focus on a *slightly* different set of variables for the two types of firms.

- **Manufacturing:** Right-to-work status, local zoning, industry wages, road quality, freight miles, highway network, corporate tax, sales tax, property tax, education of population, employment in relevant occupations, industry concentration, industrial electrical prices
- **Trade and Services:** Right-to-work status, local zoning, industry wages, airport dummy, highway network, research universities, housing prices, weather, income tax, corporate tax, sales tax, property tax, education of population, employment in relevant occupations

Even within sector (manufacturing or services/trade) there is a significant amount of heterogeneity in industry. There are both pharmaceutical manufacturing and paper mills in the manufacturing sector, and warehouses and tech firm headquarters in the services/trade sector. The profit function should be able to account for this. Therefore, I allow for interactions in the following dimensions:

- Size of the project:
  - Number of jobs promised, investment planned
- Industry of the subsidized establishment:
  - High-skill manufacturing
    - NAICS 3254, 3341, 3342, 3344, 3345, 3364: Pharmaceutical and Medicine, Computer and Peripheral Equipment, Communication Equipment, Semiconductor and Electronic Component, Navigational, Measuring, Electromedical, Control Instrument, and Aerospace Product and Parts Manufacturing
  - High-skill services
    - NAICS 5112, 5173, 523, 541, 5511: Software Publishers, Wireless Telecommunications Carriers, Securities and Commodity Contracts Intermediation and Brokerage, Professional, Scientific, and Technical Services, Management of Companies and Enterprises
  - Trade vs Services
    - NAICS 42, 44-45, 48-49: Wholesale Trade, Retail Trade, Transportation and Warehousing
    - NAICS 51, 52, 53, 54, 55, 56, 62, 72: Information, Finance and Insurance, Real Estate, Professional, Scientific, and Technical Services, Management of Companies and Enterprises, Administrative and Support and Waste Management and Remediation Services, Health Care and Social Assistance, Accommodation and Food Services

I also allow for random coefficients in the profit function in order to capture unobserved differences across firms. Before moving to estimation of the profit parameters, I need to discuss the location characteristics that may affect the valuation of the runner-up.

F.2 Valuation Function

The factors that locations reportedly value when bidding for firms are more uniform, and almost always include the jobs promised, the indirect jobs projected, and the tax revenue projected. Examples are listed in Appendix F.5. These can be captured by observables on the number of jobs promised, investment planned, industry multiplier, unemployment, industry wages, and the tax rates. However, we have anecdotal evidence that there is a role for politics in the process as well (Swaine, 2014; Corasaniti and Haag, 2019; Patel and Madden, May 2013), and how politically popular or important a deal might be would be left to the unobservables. I can control for whether the governor is running for re-election, but this does not include the importance of job creation to the election, local politics, union strength, and the strength of other interest groups in the region. Also left to unobservables are many local tax variables, such as commercial/industrial property taxes and franchise taxes, which would affect the local government's willingness-to-pay for a given firm. Lastly, an important and related factor is the cost of raising funds for the state. It can be costly to put together one of these deals, both in terms of financing the deal and the opportunity cost of spending time on the deal instead of another governmental priority.

I also include variables on congestion (density), potential spillovers to other states (distance to border), and whether or not the location is competing to *retain* or expand the firm instead of win a new plant (retention). Therefore, the list of potential variables that enter willingness to pay includes:

- Jobs Promised, Industry Multiplier, Investment planned, Tax rates (Corporate, Income, Sales, Property), Re-election dummy, Income per capita, Unemployment, Distance to border, Wages, Retention dummy, Density

Data on jobs promised, investment planned, and retention are hand-collected, as described in Appendix Section 2.2. Sources for characteristics that were not already described in the previous section include the Economic Policy Institute (2019) (industry multiplier), National Institute on Money in Politics (2000-2018) (term limits), U.S. Bureau of Economic Analysis (1967-2017) (per capita income), Bureau of Labor Statistics (1990-2017) (unemployment), Ruggles, Flood, Goeken, Grover, Meyer, Pacas and Sobek (2019) (density), and Holmes (1998*b*) (distance to border).

Table F.1 includes the location characteristics that enter the valuation. Winning and runner-up locations are wealthier, more expensive, and dense, than the average commuting zone. This is important from a policy perspective. In Slattery and Zidar (2020) we document that within winning locations poorer places pay more per job when they give a discretionary subsidy, but the poorest places are never the winner in the subsidy competition. The equity gains from using subsidies as a place based policy may be limited if the most distressed places still are not able to win firms, either because the subsidy offer does not overcome the fundamentals, or because they are budget constrained.[81]

[81] I discuss this at greater length in Section K.

F.3 Arriving at a final specification

The sample size is limited so it is not possible to include each interaction and a random coefficient on each variable in the profit function. I also do not include all of the variables I set out to include in the profit or valuation function, because in estimation, some variables do not explain any of the variation in subsidy size. This could be due to a variety of reasons, including selection on that variable and measurement error in the data. For example, for the majority of subsidy deals in the manufacturing sub-sample, both the winner and the runner-up located in a right-to-work state. This suggests that the firms select on right-to-work states, and limits my ability to estimate their preference for this regulation, given the lack of variation.

I start with all of the potential variables, as listed in the preceding sections, adding interactions to variables where there would be a reason for firms to have a different preference by industry or by size. Then, I remove variables that do not have any explanatory power, and add the random coefficients on the profit variables. The coefficient estimates and standard errors for each specification are listed in Appendix Tables F.2 and F.3 (for manufacturing and trade/services, respectively). The exercise of course involves a fair amount of researcher discretion. I try to be transparent, while remaining parsimonious, given the relatively small number of observations.

Table F.2 shows that corporate tax, income tax, property tax, industry wage, electricity prices, perceived industrial land supply, auto network density, large airport, population in relevant occupations, population with a BA, and industry establishment share all remain in the manufacturing profit function by specification (3), but many of these variables are interacted with firm characteristics or industry type. One important absence is the right-to-work status of the state, due, as discussed above, to a lack of variation in the *difference* in right-to-work status between the winner and runner-ups.

Two unexpected signs come from the income tax rate and the industrial electricity price. Both are positively associated with profits, likely for different reasons. My hypothesis for the positive income tax coefficient is that income taxes are correlated with amenities that are attractive to firms but I am not measuring, such as higher quality public services. My hypothesis for the positive electricity price coefficient is that list prices, especially for a large investment project, are not the relevant price for the firm, and the firm can actually negotiate it's own price quite easily. Therefore, the state level industrial electricity price is not a good estimate of the price the firm is paying for these projects, and, in fact, a higher list price may indicate a greater willingness to negotiate.

For the runner-up valuation, there are not many surprises. Sales tax, population density, distance to the state border, and the firm presence have no explanatory power, and therefore I do not include them when I move to the random coefficients specification.

Table F.3 shows that many of the same characteristics enter the trade/services profit function, although with different magnitudes and interactions. Notably, population with a BA does not have any explanatory power in the trade/services profit function. This may be due to less variation as well as a correlation with the research university dummy. Perceived industrial land supply is not included in trade/services profits, which is logical, as these projects are much smaller than the manufacturing sample.

The valuation function for trade/services differs from manufacturing in a few important ways. First, jobs promised is not as important. One thousand manufacturing jobs are associated with over \$100 million in runner-up valuation, and is an order of magnitude smaller, at \$10 million, for trade/services. There does not seem to be a political cycle for trade/services firms; term-limited governors do not spend less than their counterparts. Lastly, poorer places have higher valuation for firms, but unlike in manufacturing, unemployment is not associated with willingness to pay.

I take the set of variables in specification (3) to the random coefficients model. The results are shown in Tables 3 and 4 in the main text. In the manufacturing sample, the only difference from the OLS specification is the absence of the large airport variable, which loses all explanatory power when estimated in the random coefficient model. In the trade/services sample this is the case for the relevant occupation and industry concentration variables.

Table F.2: Variable Selection for Manufacturing Sample

	(1)	(2)	(3)
Profit Function:			
Δ Corporate Tax (%)	-10.30** (3.88)	-10.10* (4.20)	-8.11* (3.56)
× Investment Planned ($ B)		-3.50* (1.40)	-3.76*** (1.09)
Δ Income Tax (%)	5.13 (3.95)	9.20 (5.82)	5.72 (3.43)
× Jobs Promised (1,000)		-2.55 (3.69)	
Δ Property Tax (%)	-13.16 (14.02)	-18.88 (14.48)	-14.42 (9.96)
× Investment Planned ($ B)		1.10 (7.20)	
Δ Sales Tax (%)	7.82 (5.37)	1.09 (5.31)	
Δ Industry Wage ($1,000)	-0.13 (0.39)	-0.90 (0.65)	-0.83* (0.35)
× Jobs Promised (1,000)		0.38 (0.61)	
Δ Industrial Electricity Price (c/KwH)	-0.93 (5.17)	1.87 (5.30)	
× Investment Planned ($ B)		4.34 (2.25)	4.76** (1.67)
Δ Housing Price ($1,000)	0.28 (0.16)		
× High-Tech Manufacturing		-0.02 (0.18)	
× Traditional Manufacturing		0.07 (0.17)	
Δ Right-to-Work State	-0.50 (17.70)		
× High-Tech Manufacturing		-12.85 (25.24)	
× Traditional Manufacturing		17.59 (19.18)	
Δ Perceived Industrial Land Supply	84.73 (61.48)	-30.72 (68.29)	
× Investment Planned ($ B)		112.76** (34.22)	122.08*** (26.06)
Δ Auto Network Density	58.92** (21.12)		
× High-Tech Manufacturing		27.55 (33.96)	
× Traditional Manufacturing		82.23** (26.00)	73.35*** (20.03)
Δ Poor Condition Bridges (%)	-0.15 (1.46)		
Δ Freight Rail Density	-127.40 (124.01)		
× High-Tech Manufacturing		-192.97 (175.16)	
× Traditional Manufacturing		-22.17 (157.15)	
Δ Large Airport	2.96 (15.21)		
× High-Tech Manufacturing		34.14 (19.80)	37.56 (20.12)
× Traditional Manufacturing		-5.26 (17.79)	
Δ Population in Relevant Occupations (1,000)	-1.39 (1.07)	-3.12 (1.68)	-3.15* (1.51)
× Jobs Promised (1,000)		2.30 (1.24)	2.62* (1.18)
Δ Population with BA+ (%)	-3.88* (1.74)		
× High-Tech Manufacturing		4.32 (2.62)	5.07** (1.91)
× Traditional Manufacturing		-4.69* (2.26)	-3.99* (1.77)
Δ Industry Establishment Share (%)	79.03* (38.71)		
× High-Tech Manufacturing		238.73** (82.95)	273.62*** (70.80)
× Traditional Manufacturing		11.74 (48.91)	
Runner-up Valuation:			
Jobs Promised (1,000)	142.34** (54.40)	136.76** (48.13)	128.27*** (36.79)
Investment Planned ($ B)	50.17*** (7.55)	59.46*** (7.11)	58.84*** (6.39)
Indirect Jobs (Jobs × Multiplier)	1.88*** (0.25)	1.80*** (0.32)	1.94*** (0.27)
Income Tax (%)	-11.09* (4.85)	-9.87 (5.25)	-8.03* (4.00)
Corporate Tax (%)	9.24 (4.72)	7.57 (4.57)	5.98 (4.12)
Sales Tax (%)	-8.54 (10.06)	-3.63 (9.04)	
Property Tax (%)	19.85 (16.75)	19.69 (16.68)	10.94 (14.35)
Log(Personal Income per Capita)	-4.13 (23.01)	1.51 (23.53)	
Relevant Occupation Wage ($1,000)	12.46 (6.57)	8.04 (6.31)	7.65* (3.80)
× Log(Personal Income per Capita)	-3.19 (1.67)	-2.29 (1.61)	-2.17* (0.94)
Unemployment Rate (%)	9.98 (8.00)	8.49 (7.89)	7.06 (5.89)
× Jobs Promised (1,000)	-10.81 (8.52)	-11.54 (7.66)	-10.59 (6.21)
Term-limited Governor	-38.09* (17.08)	-27.54 (16.62)	-31.14 (16.07)
Distance to State Border	-0.36 (0.20)	-0.23 (0.20)	
Firm Presence in Runner-up Location	-8.25 (16.08)	-10.32 (16.75)	
Population (1,000) per Mile	-1.79 (15.84)	7.50 (16.38)	
Observations	200	200	200
R-squared	0.770	0.811	0.802

Notes: Table F.2 displays the profit parameter estimates, $\hat{\beta}$, and runner-up valuation correlates, $\hat{\alpha}$, for the manufacturing sample. This is the result of estimating Equation 6 via OLS, and without any random coefficient terms. Descriptive statistics for the location characteristics included in these specifications can be found in Appendix Table F.1. The mean subsidy size for this sample is $144 million, and the median is $83 million.

Table F.3: Variable Selection for Trade/Services Sample

	(1)	(2)	(3)
Profit Function:			
Δ Corporate Tax (%)	-5.39** (2.05)	-4.76 (2.52)	-4.94** (1.90)
× Investment Planned ($ B)		-0.26 (3.13)	
Δ Income Tax (%)	5.11** (1.91)	7.91*** (2.26)	7.64*** (2.25)
× Jobs Promised (1,000)		-3.03** (1.00)	-2.99** (0.97)
Δ Property Tax (%)	-11.56 (13.77)	-10.43 (14.91)	-20.51* (10.22)
× Investment Planned ($ B)		-17.36 (21.30)	
Δ Sales Tax (%)	-1.83 (4.01)	-1.43 (3.74)	
Δ Industry Wage ($1,000)	-0.50 (0.52)		
× High-Skill Services		0.00 (0.49)	0.01 (0.42)
× Trade and Other Services		-2.04* (0.99)	-1.87* (0.91)
Δ Commercial Electricity Price (c/KwH)	-3.41 (2.80)	-5.14 (2.89)	-3.48 (2.22)
× Investment Planned ($ B)		2.09 (7.37)	
Δ Housing Price ($1,000)	0.05 (0.07)	0.08 (0.07)	0.02 (0.06)
× Investment Planned ($ B)		-0.07 (0.12)	-0.05 (0.03)
Δ Right-to-Work State	11.97 (8.60)	13.00 (8.35)	8.64 (8.68)
Δ Perceived Industrial Land Supply	-26.81 (40.44)	10.11 (51.12)	
× Investment Planned ($ B)		-213.29 (145.60)	
Δ Auto Network Density	18.04 (12.47)	19.12 (12.68)	22.43* (10.49)
Δ Large Airport	12.55 (11.72)		
× Trade		51.88 (27.49)	48.88** (17.10)
× Services		3.93 (11.07)	
Δ Population in Relevant Occupations (%)	-1.27 (5.74)		
× Trade		-0.70 (8.54)	
× Services		9.68 (10.82)	5.94 (11.36)
Δ Research University	4.29 (8.04)		
× Trade		-30.88 (18.55)	-27.76 (17.91)
× Services		6.97 (7.39)	5.32 (5.34)
Δ Population with BA+ (%)	-0.88 (1.10)		
× High-Skill Services		-1.77 (1.26)	
× Trade and Other Services		-0.10 (1.38)	
Δ Industry Establishment Share (%)	6.21 (9.89)		0.98 (9.44)
× High-Skill Services		8.77 (10.28)	
× Trade and Other Services		-18.05 (22.29)	
Runner-up Valuation:			
Jobs Promised (1,000)	-3.84 (15.91)	-4.96 (13.04)	10.76* (5.38)
Industry Multiplier	3.96 (2.35)	2.77 (2.18)	2.95 (2.06)
Investment Planned ($ B)	32.73*** (8.68)	43.98*** (8.36)	48.70*** (8.52)
Income Tax (%)	-3.68 (2.65)	-4.34 (2.95)	-4.71 (2.68)
Corporate Tax (%)	8.76*** (2.43)	7.68** (2.60)	7.60*** (2.14)
Sales Tax (%)	5.06 (5.74)	5.39 (5.29)	4.78 (2.72)
Property Tax (%)	34.45** (13.10)	37.65** (12.01)	35.46*** (10.51)
Term-limited Governor	0.19 (9.67)	10.28 (9.06)	10.79 (8.50)
Unemployment Rate (%)	0.01 (3.30)	-0.98 (3.08)	1.97 (2.33)
× Jobs Promised (1,000)	1.43 (2.83)	2.58 (2.43)	
Log(Personal Income per Capita)	-19.65 (12.27)	-22.05 (12.04)	-24.39** (8.73)
Relevant Occupation Wage ($1,000)	1.52 (2.10)	1.11 (2.23)	0.36 (0.22)
× Log(Personal Income per Capita)	-0.31 (0.51)	-0.17 (0.54)	
Distance to State Border	-0.02 (0.10)	0.01 (0.09)	
Firm Presence in Runner-up Location	-6.26 (8.78)	-7.75 (8.56)	
Population (1,000) per Mile	-2.80 (7.86)	0.57 (6.94)	
Observations	177	177	177
R-squared	0.665	0.719	0.698

Notes: Table F.3 displays the profit parameter estimates, $\hat{\beta}$, and runner-up valuation correlates, $\hat{\alpha}$, for the trade/services sample. This is the result of estimating Equation 6 via OLS, and without any random coefficient terms. Descriptive statistics for the location characteristics included in these specifications can be found in Appendix Table F.1. The mean subsidy size for this subsample is $78 million, and the median is $45 million.

F.4 What factors affect firm location choice?

Services sector examples from an auto HQ, medical device facility, and information services firm:

- Mitsubishi HQ (Source: "Tennessee Two-Step: How a global auto giant and a Bay Area fintech firm fell in love with the Nashville region," *Site Selection*)

  > A variety of factors sealed the deal for Tennessee, he says. "**The combination of the cost of doing business, cost of living, lifestyle, climate and all the things that will make our current employee team want to move, as well as the business climate** the city of Franklin and the state of Tennessee offer" were pivotal.

- Reed Elsevier (Source: "Job Development Investment Grant: 2012 Annual Report," *North Carolina Department of Commerce*)

  > The company evaluated the 10 locations where it had existing operations that were feasible sites for consolidation as well as an additional 20 locations with no company presence. Key factors that were evaluated and that influenced the final decision included the **availability of skilled labor force, labor costs, corporate income tax and other taxes, quality of life** and the availability of incentives to offset operating, and implementation costs. Through this process the company narrowed the search to three sites: Charlottesville, Virginia, metropolitan Chicago, Illinois, and Cary, North Carolina.

- Medtronic (Source: "Site Selection Top Deals of 2009," *Site Selection*)

  > "The final decision to choose San Antonio resulted from an evaluation of more than 930 locations across all 50 states," the company said. "Medtronic assessed several criteria including **employee quality of life, availability of skilled labor, local costs and business environment**."

Manufacturing sector examples from a dairy plant, a steel plant, and an EV manufacturing facility:

- Chobani (Source: "Chobani Picks Twin Falls for Its Next U.S. Plant," *Site Selection*)

  > It was a hard decision to make, but in the end we chose Twin Falls due to its **abundant milk supply, skilled labor force and tight-knit local community**.

- Big River Steel (Source: "Faith, Fire and Falcons: Arkansas is a lot more than ground zero for everyday low prices. Three companies explain why," *Site Selection*)

  > "First is **access to my market**, my customers. Arkansas has a lot to offer. It is almost smack dab in the center of the U.S. Second is **access to raw material**... Third is **power**."... Other crucial location factors, according to Correnti, included **natural gas costs, rail and highway access, and the availability of a qualified work force.**

- Faraday Future (Source: "Whole New World: Faraday Future's Billion-Dollar Bet," *Site Selection*)

> The team worked with Faraday to evaluate over 100 properties, both brownfield and greenfield, in 10 US states and portions of Mexico, **weighing human resources costs and labor availability, access to supplier and customer markets, real estate and infrastructure suitability** and incentives. The 10 states in the running: Arizona, Texas, Louisiana, Mississippi, Alabama, Tennessee, South Carolina, Georgia, California and Nevada ... The short list was down to eight sites that were featured on a tour of Louisiana, parts of Georgia, Texas, Arizona, Nevada and California. Labor market evaluation and employer interviews followed, along with detailed cost comparisons, "and incentives were kicked into high gear at that point," he said.

F.5 What factors affect locations' willingness to pay?

Manufacturing examples from an auto assembly plant, a steel plant, and a pulp plant:

- General Motors (Source: "GM rolls out Wentzville plant's future," *St Louis Post-Dispatch* Nov 4, 2011)

  > **The biggest economic impact would come from the 1,260 new workers spending money in the community, Lambi said. Every automobile manufacturing job creates nine additional jobs in the local economy**, according to a 2010 report by the Center for Automotive Research. Lambi said the **economic growth could push the city's population from its current 30,000 to 60,000 in 10 years, necessitating greater investment in infrastructure and education. The plant expansion would provide the revenue stream to pay for these improvements**, Lambi said.

- Benteler Steel (Source: "Benteler Steel Announces 675-Job Manufacturing Plant At The Port Of Caddo-Bossier," *Louisiana Economic Development News Release* Oct 26, 2012)

  > Specifically, LSU estimates that **the 675-job project will lead to the creation of approximately 1,540 new indirect jobs,** resulting in a total of more than 2,200 new, permanent jobs in the area as a result of the project. Additionally, during the term of Benteler's contract with LED, which runs through 2035, LSU estimates that **the project will result in total new earnings of $2.7 billion (approximately $150 million per year at full employment) in Northwest Louisiana and a total, cumulative economic impact of $16.2 billion in the region.**

- Shandong Sun Paper (Source: "$1B pulp plant to employ 250 in state's south: Impact to top $100M a year," *Arkansas Democrat-Gazette* Apr 27, 2016)

  > **In addition to the 250 mill jobs, which will each pay about $52,000 annually, the mill is expected to provide another 1,000 jobs in the logging industry, and 2,000 to 2,400 more jobs during the plant's 2.5 years of construction. Arkansas landowners will receive timber revenue of about $28 million a year**, said state Sen. Bruce Maloch, D-Magnolia

Services examples from a data center, a medical R&D center, and a web hosting HQ:

- Microsoft (Source: "West Des Moines' data center incentives praised," *Des Moines Register* May 4, 2014)

A simple calculation shows that Microsoft at full build out will produce **more than $87 million of tax revenue** in less than 11 years, allowing the city to release the TIF money into the traditional tax stream as soon as that happens.

- Scripps Research Institute (Source: "Funding New Biomedical Research Center is an Ideal Use of Florida's Federal Economic Development Funds," *Florida Tax Watch* Oct 17, 2003)

  According to a study commissioned by the State by the Washington Economics Group, this initiative will **create 6,500 jobs, generate $1.6 billion in additional Florida personal income and boost the state's gross domestic product by $3.2 billion in the next 15 years.** In addition, as Florida's biomedical industry grows and "clusters" around the Scripps facility, **an additional 40,000 jobs will be created. Directly, Scripps plans to employ 545 at the facility within seven years, and Florida expects employment there to grow to 2,800.**

- Rackspace (Source: "Gov. Perry announces $22 million to Rackspace Managed Hosting," *US States News* Aug 2, 2007)

  Gov. Rick Perry today announced a $22 million Texas Enterprise Fund (TEF) grant to Rackspace Managed Hosting as part of the state and local efforts to secure the company's expansion to a new facility in the Windcrest/San Antonio area. **This investment is projected to generate more than $100 million in capital investment and will create approximately 4,000 new jobs during the next five years**

G Relevant Unobservables

There are factors that potentially enter the firm profit function and I do not include due to lack of data. Unfortunately, I do not have enough data to estimate a firm-location specific match value.[82] Instead, I incorporate heterogeneity in the profit function by allowing firm preferences to vary over a given observed location characteristic. Then, in the runner-up valuation, I allow for an unobservable location-firm valuation match. Given the anecdotal evidence I have about the site selection process, most of the location characteristics that would be left to the unobservable productivity match are selected on in the first stage, when the firm researches the most profitable locations. Therefore, the unobservable factors that affect location willingness-to-pay are a larger concern.

Appendices E and F introduce the relevant location characteristics for firms. I can capture many of these factors in the data, as I discussed in Appendix F. However, the variables that are left to the unobservables include specifics on the local infrastructure, specifics about the site that the firm is planning to build on, the supplier network and natural resources. Examples from Appendix F.4 include "rail and highway access" and "abundant milk supply" (for the Big River Steel plant in Arkansas and a Chobani plant in Idaho, respectively). These are factors that the firm likely selects on when it assembles the shortlist.[83] Meanwhile, there are many unobservables that can possibly affect the location's valuation for a firm, which are listed below.

1. Location unobservables that affect profits:
    - Ready to build land
    - Natural resources (relevant for some plants: oil, steel, dairy)
    - Supplier network
2. Unobservables in the state/local government valuation, ε:
    - Union strength (in relevant industry)
    - Politics/appetite for new jobs that is not captured by re-election indicator
    - Governor planning to run on jobs platform
    - Local politics (mayoral race, city council interests)
    - Cost of raising funds
    - Interest groups in the region
    - Local franchise taxes

[82] One possibility would be to estimate establishment profits for a larger sample of firms, outside the model, and use those parameters as the profit parameters. However, firm location decisions are very complicated; in reality firms have a network of establishments and relationships across space, and are optimizing with respect to that network. There may be benefits to density (Holmes, 2011) and reducing transportation costs (Houde, Newberry and Seim, 2023); in general there are many potential decision factors that will always be unobserved to the researcher. I am studying a select sample of large, profitable, and mostly multinational firms across many industries; the location choices of the average establishment may not reflect the same preferences as the establishments in my sample. Also, if I were to estimate the location decision of establishments and ignore the expected subsidies, I would introduce a different source of bias in the profit parameters.

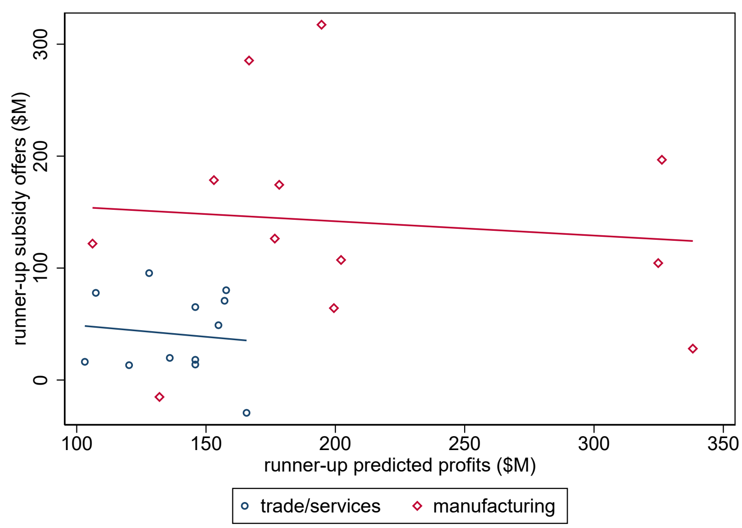
[83] This is also supported by Czohara, Melkers and Dagawa (2004), in a policy report on firm location: "Overall, location factors are a complex mix that includes primary factors, such as location in relation to markets, material sources, transportation cost and services, availability and cost of utilities, and availability and cost of labor. Secondary factors include items such as availability and cost of materials, the supply and cost of labor, state and local tax structure, legislation affecting industry, business climate, weather, availability of financial assistance, location relative to competitors or to other facilities of the company."

H Robustness of Negative Correlation between π and v

In this section, I use an additional moment condition to verify the correlation between profits and valuations. Instead of using the runner-up valuations predicted from the model, $\hat{v}_2$, I use the runner-up subsidy offers I have in the data. I have data on subsidy offers in the runner-up location in 25 subsidy competitions, 13 of which are manufacturing firms and 12 are trade/services firms. Figure H.1 shows the correlation between predicted runner-up profits, $\hat{\pi}_2$, and the runner-up subsidy offers. The runner-up subsidy offer should represent their valuation, as they would bid up to their willingness to pay.

In order to calculate the correlations I condition on firm characteristics. I use the average project size in each sample: 870 jobs and \$900 million in investment for manufacturing and 940 jobs and \$250 million in investment for trade/services.[84] The correlation coefficients are very similar to the coefficients I find when I use both profits and valuations predicted from the model. The correlation coefficient for trade/services is -0.11 and the correlation coefficient for manufacturing is -0.10. In the main text (Figure 5) the correlation coefficient for trade/services is -0.28 and the correlation coefficient for manufacturing is -0.08.

Figure H.1: Robustness Check: Predicted Profits and Runner-up Offers



Notes: This figure is the scatter plot of predicted runner-up profits and the runner-up location subsidy offers, which reflect runner-up valuations. I condition on average firm characteristics for each sub-sample. Though this is for a much smaller sample, the results are consistent with the exercise conducted in Figure 5.

[84] For the runner-up subsidy offers I regress the offer on jobs and investment, and then use those coefficients to adjust to the average sized deal.

I Estimation: Supplementary Analysis

In this section I provide details and supplemental figures and tables that complement the analysis in the main text (Section 5).

I.1 Negative Profits

There is one issue in estimating profits off of the difference in location characteristics. All locations on the shortlist have a set of similar characteristics that make them profitable, but I do not have sufficient variation on the *difference* for some of these characteristics, because they are similar.

One can think of an example where the runner-up and winner are both right-to-work states and is why the firm put them on its' short list. However, they have different corporate tax rates, which the firm also cares about. Then, the profit of firm i in state s is :

$$\pi_{is} = \beta_{r2w}\text{Right-to-Work}_{is} + \beta_{tax}\text{Corporate Tax}_{is}.$$

However, when I go to estimate the β, I have the following equation:

$$\text{subsidy}_{i1} = \beta_{tax}\Delta\text{Corporate Tax} + v_2$$

because ΔRight-to-Work $= 0$.

Therefore, when I use $\hat{\beta}$ to predict profits in runner-up and winning locations, I predict profits that are too low. Therefore, I make the following assumption: Winning and Runner-up locations must have weakly positive profits. This is Assumption 7, on page 38. In order to implement this I make a simple adjustment, and shift all estimated profits by the minimum predicted profit in the sample. Therefore, the lowest predicted profit resulting from model is 0.

One might also be concerned that 0 is too low, but I will note that the majority of deals for which I originally predict negative profits in the winning locations were retention or expansion deals. In fact, for the deals with negative predicted profits, over 80% fall into one or more of these categories:

- Retention
- Shut-down soon after receiving the subsidy, or project never materialized
- Start-ups
- Food Manufacturing[85]

Retentions are the most common category. Of the 20 deals with the most negative predicted profits, 15 were subsidies to retain the plant in the current location. When a firm receives a subsidy for retention in a given location, it is usually planning to relocate or expand elsewhere due to rising costs in the current location. Therefore, it seems like the model is doing a decent job of predicting low profit places.

[85] I have a pork, yogurt, poultry, and milk processing plant on my list of projects that choose negative profit locations. There are two potential factors at play. First, the model does not do a good job of predicting profitability in this industry due to unobservables. Second, these are very low profit projects, compared to the projects in other industries in my sample. This may be the case, as in some areas of food manufacturing, such as dairy, the government sets minimum prices that manufacturers must pay farmers (USDA, 2022).

I.2 Estimation Step 3

Following the identification strategy in Section 4.3, H_V can be estimated by simulating draws of π_t from the copula $\hat{C}(\pi|v<t,z)$ and calculating the sample average:

$$H_V^M(t|z) = \frac{1}{M}\sum_{m=1}^{M}\hat{F}(t+\pi_t|z). \tag{13}$$

The procedure follows:

1. For each possible valuation, t, I create a grid of guesses for $H_V(t|z)$: $H_V^g(t|z) \in [0,1]$.
2. For each guess $H_V^g(t|z)$, I draw π_t from $\hat{C}(H_\Pi(\pi|z)|H_V^g(t|z))$, M times.
3. I solve for $H_V^M(t|z)$, given π_t: $H_V^M(t|z) = \frac{1}{M}\sum_{m=1}^{M}\hat{F}(t+\pi_t|z)$.
4. For each t, $\hat{H}_V(t|z)$ is the guess, H_V^g, that minimizes $|H_V^g(t|z) - H_V^M(t|z)|$.

I.2.1 Copula Parameterization

In order to achieve identification I will employ a copula, which allows the representation of the joint distribution, $H(\pi,v|z)$, as a function of the two marginal distributions and a dependence parameter. I can rewrite $H(\pi,v|z)$ as $C(H_\Pi,H_V|z)$, where C represents the dependence structure between the two marginals, H_Π and H_V. Then, the distribution of welfare is just the convolution of the marginal distributions of profits and valuations:

$$\begin{aligned} H_V(t|z) = \Pr(v<t|z) &= \Pr(w-\pi<t|z)\\ &= \Pr(w<t+\pi|z)\\ &= \int F(t+\pi|z)h(\pi|t,z)d\pi, \end{aligned}$$

and I can represent the conditional density of profits, $h(\pi|v)$ using the copula (suppressing the firm characteristics, z, for clarity):

$$h(\pi|v) = \frac{h(v,\pi)}{h_V(v)} = c(H_V,H_\Pi)h_\Pi(\pi).$$

Here I have to make an assumption on the specific parametric copula to employ, and I use the Ali–Mikhail–Haq (AMH) copula, which is from the Archimedian family. The AMH copula has one parameter that governs the dependence structure and allows for that parameter to be negative:

$$c(H_V,H_\Pi) = \frac{1+\psi[(1+H_V)(1+H_\Pi)-3]+\psi^2(1-H_v)(1-H_\Pi)}{[1-\psi(1-H_V)(1-H_\Pi)]^3},$$

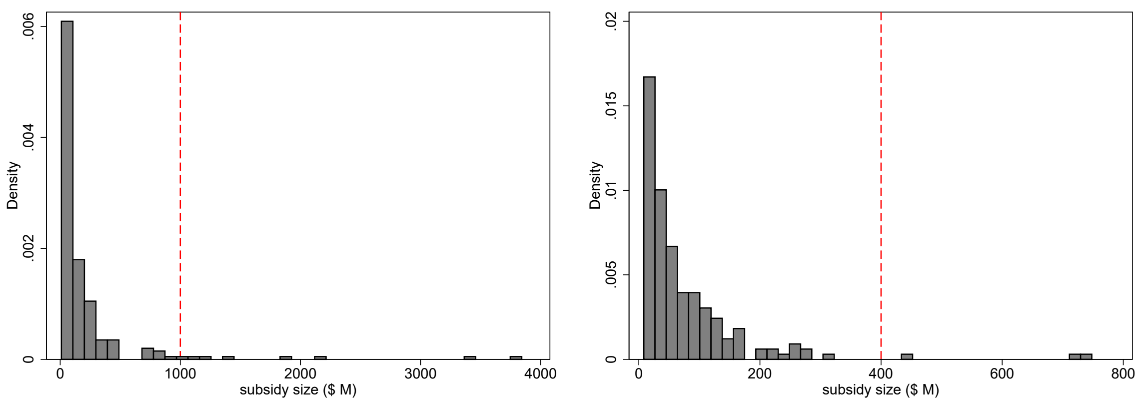
where ψ is the dependence parameter. Another advantage of the AMH copula is that there is a close relationship between the dependence parameter, ψ, and the correlation measures Kendall's τ and Spearman's ρ (Kumar, 2010).[86]

[86] Kendall's $\tau = \frac{3\psi-2}{3\psi} - \frac{2(1-\psi)^2\ln(1-\psi)}{3\psi^2}$ and Spearman's $\rho = \frac{12(1+\psi)di\log(1-\psi)-24(1-\psi)\ln(1-\psi)}{\psi^2} - \frac{3(\psi+12)}{\psi}$, see Kumar (2010) for derivation.

I.3 Primitives

Figure I.1 shows the distribution of subsidy size in the manufacturing and trade/services samples. The vertical dashed line in each figure shows the sample restriction. The analysis restricts to subsidy deals that are worth less than \$1 billion in the manufacturing sample, and less than \$400 million in the trade/services sample. This reduces the total sample by 10 observations, from 387 subsidy deals to 377.

Figure I.1: Observed Subsidies

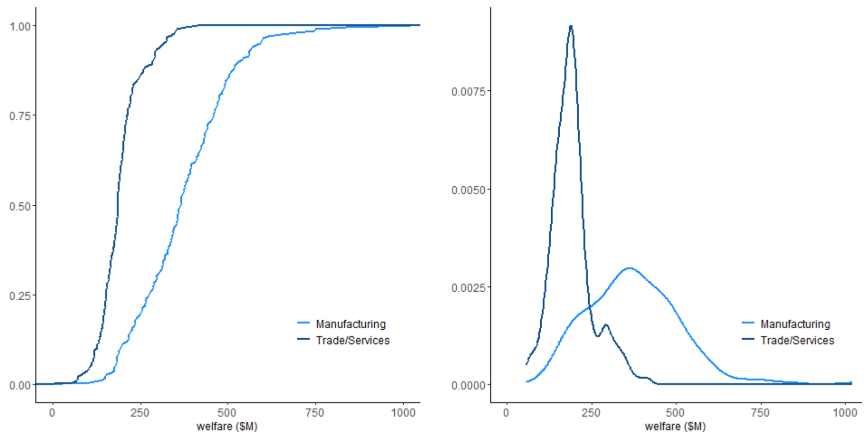


(a) Manufacturing (b) Trade and Services

Notes: This figure shows the distribution of winning subsidies for the manufacturing and trade/services samples. In estimation, I restrict to subsidies less than \$1 billion for manufacturing, and less than \$400 million for trade/services, so that outliers do not drive the coefficient estimates. The restrictions are based on the sample distribution—2% of all subsidy deals are greater than \$1 billion in value. Due to the significantly smaller deals in the trade/services sample, I take out the top 2% (over \$400 million) here as well.

Figure I.2 shows the empirical distribution and density of welfare in the runner-up location, calculated in Step (2) of Section 5. As a reminder, welfare is the measure of the total payoff created if the firm were to locate in that location: the sum of firm profits and the state valuation. The distribution is shown separately for manufacturing and trade/services, as the profit parameters are estimated separately in Step (1). The distribution is for the average site selection project in each sample—for manufacturing this is 870 jobs promised and \$900 million in investment. For trade/services this is 940 jobs promised and \$250 million in investment.

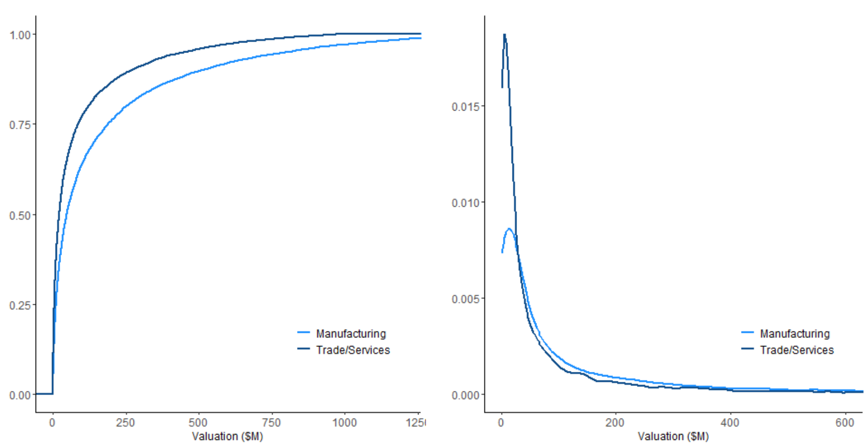
Figure I.2: Total Welfare in the Runner-Up Location (Step 2)



(a) Distribution (b) Density

Notes: The figure shows the empirical distribution and density of welfare in the runner-up location, calculated in Step (2) of Section 5. The distribution is shown separately for manufacturing and trade/services, as the profit parameters are estimated separately in Step (1). The distribution is for the average site selection project in each sample—for manufacturing this is 870 jobs promised and $900 million in investment. For trade/services this is 940 jobs promised and $250 million in investment.

Figure I.3: State and Local Government Valuations for Firms (Step 3)



(a) Distribution (b) Density

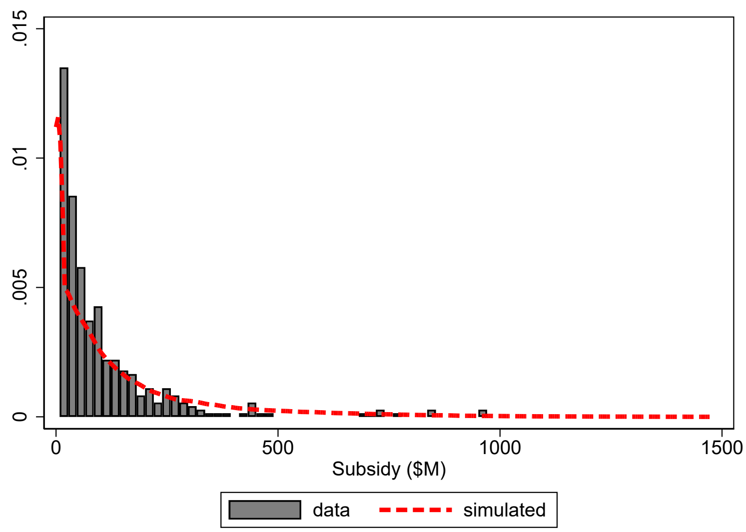
Notes: These figures display the marginal distribution of state and local governments' valuation for firms for an average firm location project in each sub-sample (the results of Step (3) of the estimation procedure). For manufacturing, this is 870 jobs promised and $900 million in investment. For the trade/services sectors, this is 940 jobs promised and $250 million in investment.

I.4 Model Fit

Figure I.4 supplements Figure 6 in the main text, by showing the over the distribution of *all* simulated subsidies. In Figure 6 I aggregate over subsidy deals by taking the median/mean over simulations. This shows the underlying distribution.

The simulated subsidy game is played 1,000 times, and the resulting subsidy is the difference between the profit in the winning location and the profit and valuation in the second highest payoff location. I enforce the restriction that predicted subsidies must be weakly positive. Here, the dashed red line shows the results of the subsidy game when the valuations are fit to the log-normal distribution.

Figure I.4: Model Fit



Winning Subsidy ($M)

Pctile	Data	Simulated
25^{th}	26.98	6.70
50^{th}	57.21	61.70
75^{th}	128.48	168.54
90^{th}	250.64	356.95
Mean	108.38	129.92
SD	143.09	185.06

Notes: The figure on the left and table on the right show the distribution of subsidies in the data, and the size of subsidies predicted by the model. These simulated wins are the result of playing the subsidy game by simulating profits and valuations for each firm in the data. The simulated subsidy game is played 1,000 times, and the resulting subsidy is the difference between the profit in the winning location and the profit + valuation in the second highest payoff location. In Figure 6 I aggregate simulations by taking the median for each subsidy deal.

Table I.1 shows the model fit in terms of the predicted locations. In each simulated subsidy game, the model may predict that the firm chooses a different location than it chose in the data. This table shows the distribution of states chosen in the model and in the data.

Table I.1: Model Fit: Winning Locations

	Manufacturing		Services	
State	Data (%)	Simulated (%)	Data (%)	Simulated (%)
AL	5.5	4.0	1.1	0.6
AR	4.0	2.7	0.0	0.3
AZ	2.0	1.4	0.0	1.5
CA	2.0	4.4	2.3	4.9
CO	0.0	0.3	0.0	0.7
CT	1.0	0.7	8.5	3.7
DE	1.5	0.8	1.7	1.1
FL	1.0	2.7	4.5	5.8
GA	3.5	4.5	1.7	3.0
IA	1.5	1.7	3.4	1.4
ID	1.0	0.7	0.0	0.1
IL	0.5	1.4	1.7	1.5
IN	2.5	2.3	1.7	1.4
KS	2.0	1.7	1.1	2.2
KY	4.0	1.8	3.4	2.2
LA	7.5	4.8	2.8	1.5
MA	1.0	1.1	1.1	1.4
MD	0.0	0.2	1.1	1.2
ME	0.0	0.0	0.0	0.0
MI	6.5	5.3	2.8	2.0
MN	0.0	0.3	0.6	1.0
MO	2.0	1.8	3.4	3.0
MS	5.5	3.0	0.0	0.4
MT	0.0	0.0	0.0	0.0
NC	11.5	8.1	18.6	11.5
ND	0.0	0.1	0.0	0.3
NE	0.5	0.4	0.0	0.3
NH	0.0	0.0	0.0	0.3
NJ	2.5	2.2	10.7	7.4
NM	0.5	0.4	0.0	0.2
NV	1.0	1.1	1.1	1.6
NY	2.5	3.4	3.4	7.9
OH	5.0	6.6	5.6	5.6
OK	0.5	1.1	0.6	1.0
OR	1.5	1.2	0.0	1.2
PA	0.5	2.2	0.6	1.8
RI	0.0	0.3	0.6	0.5
SC	6.0	5.8	0.0	2.0
SD	0.0	0.0	0.0	0.0
TN	3.0	3.5	1.7	1.7
TX	6.0	9.1	6.2	7.2
UT	0.5	0.8	4.5	3.4
VA	2.0	2.0	2.3	3.2
VT	0.0	0.2	0.0	0.2
WA	0.0	1.4	0.0	0.9
WI	1.0	1.6	0.6	0.6
WV	1.0	0.8	0.6	0.4

Notes: This table shows the percentage of subsidy deals won by each state in the data and in the simulation. The percentages are shown separately for manufacturing and trade/services firms. These simulated wins are the result of playing the subsidy game by simulating profits and valuations for each firm in the data, as described in Section 5.4. The simulated subsidy game is played 1,000 times. See Figure 6 for the model fit in terms of simulated and realized subsidy size.

I.5 Shortlist

In order to run the counterfactual I need to know the set of locations a firm is choosing between—I need to make an assumption on the set of locations on the shortlist, S^n.[87] I create the potential shortlist in the following steps:

1. Drop the smallest population CZs; these are never chosen as winners or runner-ups.
    - The population cut-off is 200,000. This results in dropping 65% of potential locations across the sample.
2. Then, I select on the population in the CZ that is in the top two relevant occupations for the industry of the deal. Therefore, if the firm is an auto assembly plant, I am looking for locations that have population in "Assemblers and fabricators" and "First-line supervisors of production and operating workers." I drop locations with less than 1,000 employees in these relevant occupations.
    - This further decreases the sample of potential firms by 21% for manufacturing and 14% for trade/services
3. Then, I sort locations by the percent of establishments in the industry of the deal.
    - For manufacturing firms, I drop any location that is not in the top 100 in terms of industry concentration, is not in the top 60 in terms of industry concentration or is not a right to work location, and is not in the top 40 in terms of industry concentration or does not have a major airport. This further decreases the sample of potential firms by 42%.
    - For trade/services firms, I drop any location that is not in the top 50 in terms of industry concentration or does not have a major airport.This further decreases the sample of potential firms by 59%.

At the end of the exercise, I have dropped about 90% of the sample of potential locations (starting with all CZs in the U.S.) for both manufacturing and trade/services firms. Each firm goes from almost 700 potential locations to a set of 60-80. Table I.2 shows that these "potential shortlist" locations are close to observed winners and runner-ups on observables.

[87] For 49% of the sample, when the number of bidders is small, I know all of the locations on the shortlist and I do not need to do this procedure.

Table I.2: Creating the Shortlist

	Manufacturing					
	Potential Shortlist		Runners-up		Winners	
	Mean	Med.	Mean	Med.	Mean	Med.
Population (1,000,000)	1.24	0.66	2.11	1.06	1.47	0.71
Industry Wage ($1,000)	52.65	48.74	60.09	53.56	59.60	53.34
Auto Network Density	0.88	0.81	0.94	0.85	0.88	0.83
Large Airport	0.34	0.00	0.46	0.00	0.38	0.00
Right-to-Work	0.65	1.00	0.64	1.00	0.67	1.00
Employment in Relevant Occupations (1,000)	6.00	3.50	9.55	4.54	7.22	3.76
Population with BA+ (%)	18.51	18.03	19.62	19.73	18.95	18.74
Share Industry Establishments	0.05	0.03	0.06	0.03	0.07	0.03

	Trade/Services					
	Potential Shortlist		Runners-up		Winners	
	Mean	Med.	Mean	Med.	Mean	Med.
Population (1,000,000)	1.98	1.25	3.21	2.07	2.42	1.94
Industry Wage ($1,000)	75.36	74.66	85.23	86.69	83.18	85.77
Auto Network Density	1.04	0.96	1.10	1.10	1.05	0.97
Large Airport	0.67	1.00	0.67	1.00	0.69	1.00
Right-to-Work	0.52	1.00	0.49	0.00	0.50	1.00
Employment in Relevant Occupations (1,000)	17.95	11.47	22.07	18.59	21.08	18.25
Population with BA+ (%)	21.59	21.67	23.27	22.88	23.27	23.31
Share Industry Establishments	0.80	0.64	0.72	0.55	0.75	0.61

Notes: Table I.2 compares the characteristics of the shortlisted locations with the winning and runner-up locations. The process of creating the "potential shortlist" is described in Appendix Section I.6. In short, the sample is selected on population, employment in relevant occupations, and industry concentration. However, the shortlist sample is similar to the runner-ups and winners in many characteristics (especially compared to the average CZ, as shown in Table F.1.)

I.6 Counterfactual

In the rest of the section I show the results from the counterfactual. Here I predict profis across iterations of the subsidy game/location choice problem. For a given firm in the data set, I simulate shortlisted location S^n, sampling from the potential shortlist as defined in Section I.5. Then, for each simulation of the shortlist, I simulate the firm's unobservable characteristic, η. I simulate S^n and η 33 times each, for a total of just over 1,000 simulations (1,089). Then, I calculate the firm profit in each shortlist location, and draw v given that profit, from $\hat{H}(v|\pi)$. For the subsidy competition, the winning location is the location with the highest welfare ($\pi + v$). For the subsidy ban, the winning location is the location with the higest profit.[88]

Table I.3 complements Table 5 in the main text, by showing the welfare analysis separately for the manufacturing and trade/services samples. While, on average, welfare gain increases by 4.3% over the full sample, the prediction is slightly lower, at 3.6% for manufacturing, and slightly higher, at 6.1% for trade/services.

Table I.3: Welfare Analysis

	Policy	Simulated v (\$B)	Simulated π (\$B)	Sub (\$B)	Payoffs (\$B) States	Payoffs (\$B) Firms	Total Welfare
Manufacturing:	Subsidy Ban	35.1	57.0	0.0	35.1	57.0	92.1
	Competition	44.9	50.5	28.8	16.1	79.3	95.4
				Δ *welfare from competition:*	-54.1%	39.0%	3.6%
Trade/Services:	Subsidy Ban	13.3	27.6	0.0	13.3	27.6	40.9
	Competition	16.4	27.0	12.1	4.3	39.1	43.4
				Δ *welfare from competition:*	-67.9%	41.7%	6.1%

Notes: Table I.3 displays the results of the counterfactual welfare analysis by sector (Table 5 shows the summary). For the "competition" policy, locations are observed, and I calculate profits using $\hat{\beta}$ and $\hat{\sigma}$ (Tables 3 and 4) and then simulate the valuations of the winning locations from $\hat{H}_V(v|\pi)$. For the "subsidy ban" policy, locations are predicted, as depicted and described in Figure 7.

Table I.4 shows the welfare analysis when I specify profits without random coefficients. This takes the profit parameters from Appendix Tables F.2 and F.3, and then repeats all of the steps of Section 5 in order to recover a new marginal distribution of valuations. Here there are a few important takeaways:

- There are many more movers. Over 60% of firms would choose alternate locations due to subsidy competition (compared to 50% in the original model).
- The difference in valuations is significantly larger than the difference in profits, unlike in the baseline. This is because there is less heterogeneity in profits in the absence of the random coefficients (Appendix Figure I.5). Because there is relatively more heterogeneity in valuations, this leads to more movers and a much larger welfare gain even conditional on the same moving rate, due to the fact that the winner does not need to offer a subsidy so close to their valuation.

[88] Winning locations, (the places I observe firms locating, with subsidies, in the data) are treated differently in two ways—I constrain predicted profits to be weakly positive in these locations, and I constrain simulated valuations to be at least 75% of the observed subsidy.

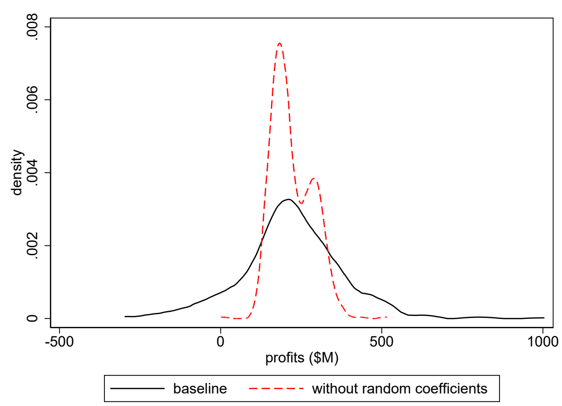
- This is only partly due to a difference in the correlations between valuations and profits—with this specification the correlation coefficients are similar to manufacturing at the baseline, but more negatively correlated for trade/services: -0.11 for manufacturing and -0.45 for trade/services.

Table I.4: Welfare Analysis: No Random Coefficients

Policy	Movers	Simulated v (\$B)	Simulated π (\$B)	Sub (\$B)	Payoffs (\$B) States	Payoffs (\$B) Firms	Total Welfare
Subsidy Ban	-	60.4	102.6	0.0	60.4	102.6	163.0
Competition	62.3%	108.9	92.6	40.9	68.0	133.5	201.5
				Δ welfare from competition:	12.6%	30.1%	23.6%

Notes: Table I.4 displays the results of the counterfactual welfare analysis for the specification without random coefficients. For the "competition" policy, locations are observed, and I calculate profits using $\hat{\beta}$ (from Spec (3) in Appendix Tables F.2 and F.3). Then I simulate the valuations of the winning locations from $\hat{H}_V(v|\pi)$.The first column shows the % of firms that "move" (choose an alternate location) due to the subsidy competition. The second column shows the sum of the simulated valuations. The third column shows the sum of simulated profits.

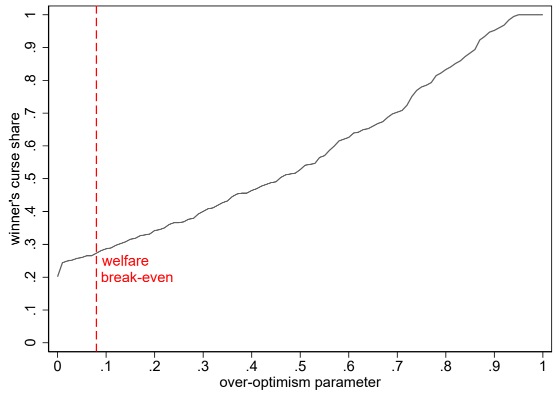
Figure I.5: Heterogeneity in Predicted Profits



Notes: Figure I.5 shows the distribution of predicted profits with and without random coefficients. The baseline uses the random coefficient specification, the dashed red line does not (this dashed red line is what is used for the counterfactual exercise shown in Table I.4). There is *much* less heterogeneity in profits in the specification without random coefficients. These profits are predicted for the average manufacturing project in the winning and runner-up locations.

Figure I.6 shows an extension of the counterfactual which assumes all bidders are over-optimistic about the value a firm will create in their jurisdiction. I simulate the valuation for winning locations in the standard counterfactual, but assume this simulated valuation is a function of the true valuation state s has for winning firm i, v^*_{is}. What I observe is $v_{is} = (1+oo)v^*_{is}$, where the true valuation is scaled by an "over-optimism" parameter, oo. The y-axis shows the share of locations that offer a subsidy that is larger than the "true" valuation, v^*, under the assumption on "over-optimism." The figure shows that at a very small level of over-optimism (8%), all of the welfare gains from subsidy competition, in the aggregate, disappear. At a higher level of optimism (33%), all of the gains to states disappear.

Figure I.6: Optimistic Bidders



Notes: I simulate the valuation for firm i (v_{is}) for winning locations s in the standard counterfactual, but assume that all states are optimistic, and the true valuations is v^*, where $v_{is} = (1+oo)v^*_{is}$. The x-axis shows the level of bidder "over-optimism," oo. The y-axis shows the share of locations which have an observed subsidy (in the data) that is larger than the adjusted valuation, v^*. The two red dashed lines show break-even points. At the "welfare break-even", an over-optimism parameter of 0.08, the total welfare gain from subsidy competition is 0. At the "valuation break-even," at a over-optimism parameter of 0.33, the benefit created from subsidy competition in the form of firms locating in higher valuation locations, is smaller than the size of the total subsidies offered.

J Alternate Models

J.1 Alternate Model 1: "Fake" Runner-ups

One potential concern with the way I have specified the model is that firms are not necessarily selecting locations for the shortlist on profits alone. Instead, a firm might add a location to its shortlist based on its expected valuation. Adding a relatively low profit but high valuation location to the competition can drive up subsidies in the higher profit locations, especially if there is some uncertainty over the firm's preferences over location characteristics. This happened in 1992, when BMW added a last minute location in Nebraska to compete with it's preferred location in South Carolina (Patrick, 2016). A similar scenario occurred in 1990, when cities were bidding for a new United Airlines facility (Martin, 2000*a*).

My discussions with economic development professionals suggest that these high profile cases actually served to discipline the firms. Governments have become more wary of misconduct, and therefore require firms to provide evidence of lower costs or higher productivity features in other locations. However, that is not to say this never occurs, and in this section I estimate the model under the assumption that the winning bidder bids up to their valuation. The observed subsidy, therefore, can be used as an estimate of the winning location's valuation.[89]

I use the winning bids to recover the correlations between location characteristics and willingness to pay, $\hat{\alpha}$, under the assumption that the α are similar in winning and runner-up locations. Then, I use these parameters to predict the runner-up valuations. The predicted runner-up valuations then enter Equation 6, and I re-estimate the profit parameters.

Tables J.1 and J.2 show the profit parameter estimates under this alternative model, for the manufacturing and trade/services samples, respectively. This model assumes that winning locations have bid up to their valuation, and therefore estimates the valuation parameters ($\hat{\alpha}$) by regressing the characteristics of the winning location that enter the valuation function (x^v) on observed subsidies. This is shown in column (2), and can be compared with the estimates using the baseline model in column (1). The parameter estimates recovered in column (2) can be used to predict the runner-up valuation. The last ingredient of the alternate model is to recover the profit parameters. This is shown in Column (3), where the specification is identical to the baseline model, except that instead of the runner-up location characteristics entering the valuation function, I use the predicted runner-up valuation directly. I repeat this exercise with random coefficients, shown in Tables J.3 and J.4.

[89]Thank you to an anonymous referee for this suggestion.

Table J.1: Alternate Model: Manufacturing

	Baseline (1)	Winner's Valuation (2)	Profits (3)
Profit Function:			
Δ Corporate Tax (%)	-8.86* (3.67)		-14.37*** (2.57)
× Investment Planned ($ B)	-3.73*** (1.11)		-3.33** (1.00)
Δ Income Tax (%)	4.89 (3.59)		3.42 (2.31)
Δ Property Tax (%)	-17.25 (11.26)		-15.95* (6.93)
Δ Industrial Electricity Price (c/KwH) × Investment Planned ($ B)	4.86** (1.71)		5.77** (1.83)
Δ Industrial Land Supply × Investment Planned ($ B)	121.45*** (25.92)		112.46*** (22.40)
Δ Auto Network Density × Traditional Manuf.	72.37*** (20.11)		59.19** (19.79)
Δ Population in Relevant Occupations (1,000)	-3.09* (1.49)		-2.67* (1.34)
× Jobs Promised (1,000)	2.61* (1.17)		2.27 (1.31)
Δ Population with BA+ (%) × High-Tech Manuf.	5.18** (1.94)		6.01*** (1.79)
Δ Population with BA+ (%) × Traditional Manuf.	-3.83* (1.75)		-3.34* (1.69)
Δ Industry Estab. Share (%) × High-Tech Manuf.	266.64*** (73.26)		266.01** (87.02)
Valuation:			
Runner-up Valuation Predicted using Spec (2)			1.02*** (0.05)
Jobs Promised (1,000)	140.92** (46.86)	157.29* (65.37)	
Investment Planned ($ B)	58.73*** (6.42)	53.59*** (10.15)	
Indirect Jobs (Jobs × Multiplier)	1.89*** (0.27)	1.84*** (0.24)	
Income Tax (%)	-7.03 (4.13)	-6.37 (4.02)	
Corporate Tax (%)	7.38 (4.48)	14.40*** (4.02)	
Log(Personal Income per Capita)	-12.84 (18.38)	-45.90* (20.04)	
Relevant Occupation Wage ($1,000)	7.77* (3.84)	0.91 (4.28)	
× Log(Personal Income per Capita)	-2.11* (0.94)	-0.24 (1.11)	
Unemployment Rate (%)	8.92 (7.08)	14.46 (9.25)	
× Jobs Promised (1,000)	-12.11 (7.42)	-12.37 (9.77)	
Term-limited Governor	-31.41 (15.97)	13.86 (17.71)	
Observations	200	200	200
R-squared	0.803	0.736	0.782

Notes: Table J.1 shows the manufacturing parameter estimates for the alternative model discussed in Appendix Section J. This model assumes that winning locations have bid up to their valuation, and therefore estimates the valuation correlates ($\hat{\alpha}$) by regressing the characteristics of the winning location that enter the valuation function (x^v) on observed subsidies. This is shown in column (2), and can be compared with the estimates using the baseline model in column (1). The coefficients recovered in column (2) can be used to predict the runner-up valuation, and a comparison of the predicted runner-up valuations is shown in Appendix Figure J.1. The last ingredient of the alternate model is to recover the profit parameters. This is shown in Column (3), where the specification is identical to the baseline model, except that instead of the runner-up location characteristics entering the valuation function, I use the predicted runner-up valuation directly. I repeat this exercise with random coefficients, shown in Appendix Table J.3.

Table J.2: Alternate Model: Trade/Services

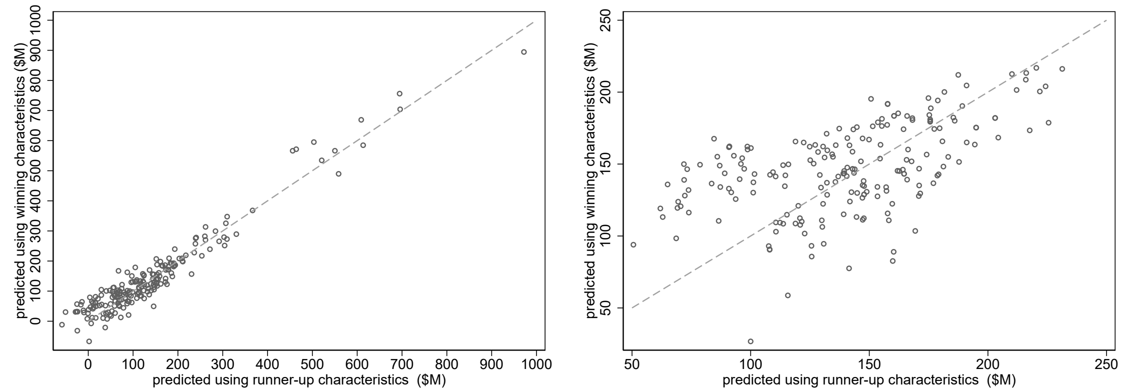
	Baseline (1)	Winner's Valuation (2)	Profits (3)
Profit Function:			
Δ Corporate Tax (%)	-4.96** (1.86)		-4.87*** (1.32)
Δ Income Tax (%)	7.70*** (2.22)		7.40*** (1.54)
× Jobs Promised (1,000)	-3.03** (0.96)		-2.30** (0.71)
Δ Property Tax (%)	-21.50* (9.92)		-18.62* (8.54)
Δ Industry Wage ($1,000) × High-Skill Services	0.07 (0.40)		0.05 (0.36)
Δ Industry Wage ($1,000) × Trade and Other Services	-1.92* (0.91)		-1.77 (0.91)
Δ Commercial Electricity Price (c/KwH)	-3.30 (2.15)		-2.49 (1.94)
Δ Housing Price ($1,000)	0.02 (0.06)		-0.02 (0.06)
× Investment Planned ($ B)	-0.05 (0.03)		-0.01 (0.02)
Δ Right-to-Work State	8.15 (8.45)		9.68 (8.35)
Δ Auto Network Density	21.48* (10.10)		18.07 (9.96)
Δ Large Airport × Trade	49.48** (16.93)		50.76** (15.61)
Δ Research University × Trade	-28.09 (17.67)		-27.01 (16.62)
Δ Research University × Services	5.21 (5.35)		5.90 (5.28)
Valuation:			
Runner-up Valuation Predicted using Spec (2)			1.06*** (0.07)
Jobs Promised (1,000)	10.73* (5.29)	3.53 (4.17)	
Investment Planned ($ B)	48.19*** (8.71)	29.26** (10.52)	
Industry Multiplier	3.08 (2.19)	4.01 (2.21)	
Income Tax (%)	-4.56 (2.61)	-4.43* (2.00)	
Corporate Tax (%)	7.49*** (2.07)	6.33** (2.14)	
Sales Tax (%)	4.72 (2.72)	2.28 (4.65)	
Property Tax (%)	36.03** (10.83)	28.48* (12.16)	
Term-limited Governor	11.17 (8.52)	19.84 (10.90)	
Unemployment Rate (%)	2.03 (2.29)	2.52 (1.60)	
Log(Personal Income per Capita)	-24.69** (8.87)	-15.60 (8.00)	
Relevant Occupation Wage ($1,000)	0.36 (0.22)	0.24 (0.23)	
Observations	177	177	177
R-squared	0.698	0.634	0.684

Notes: Table J.2 shows the Trade/Services parameter estimates for the alternative model discussed in Appendix Section J. This model assumes that winning locations have bid up to their valuation, and therefore estimates the valuation correlates ($\hat{\alpha}$) by regressing the characteristics of the winning location that enter the valuation function (x^v) on observed subsidies. This is shown in column (2), and can be compared with the estimates using the baseline model in column (1). The coefficients recovered in column (2) can be used to predict the runner-up valuation, and a comparison of the predicted runner-up valuations is shown in Appendix Figure J.1. The last ingredient of the alternate model is to recover the profit parameters. This is shown in Column (3), where the specification is identical to the baseline model, except that instead of the runner-up location characteristics entering the valuation function, I use the predicted runner-up valuation directly. I repeat this exercise with random coefficients, shown in Appendix Table J.4.

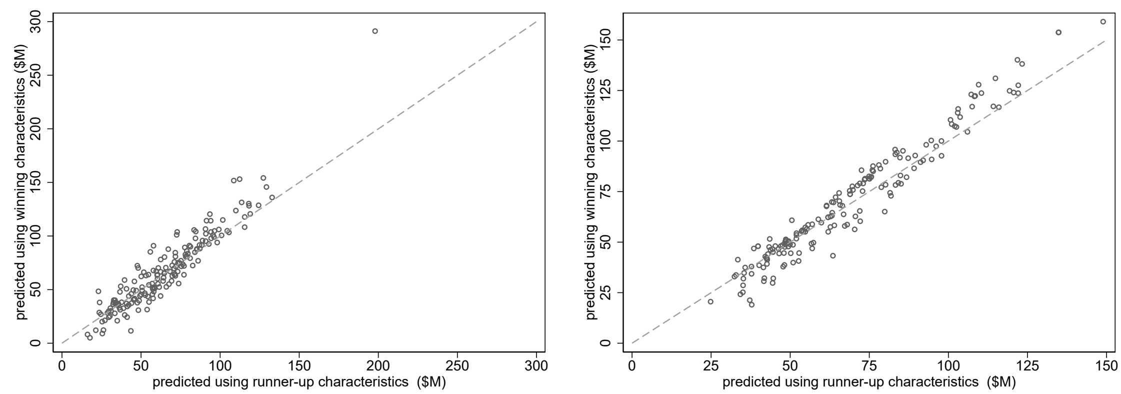
Before moving to the random coefficients specification, it is worthwhile to compare predicted runner-up valuations using the baseline and the alternate model. The alternate model uses the winning subsidies and winning characteristics to recover $\hat{\alpha}$, under the assumption that winning subsidies are close to winners' valuations. The baseline model using the runner-up characteristics in Equation 6, where winning subsidies are equal to the difference in winning and runner-up profits, plus the runner-up valuation. This comparison is shown in Appendix Figure J.1.

The top two figures in Figure J.1 are for manufacturing and the bottom two are for trade/services. The 45-degree line is shown in each figure, and the runner-up valuation predicted using the alternate model is on the y-axis, and the runner-up valuation predicted using the baseline model is on the x-axis. The figures on the left show the unconditional prediction, and the figures on the right shows the prediction conditional on the average project size in the sample. The correlation between the two predicted valuations is high when firm characteristics are included—0.97 for manufacturing and 0.94 for trade/services. When I condition on firm characteristics the correlation drops to 0.55 for manufacturing but increases slightly to 0.97 for trade/services.

Figure J.1: Comparing Runner-up Valuations in Baseline and Alternate Model



(a) Manufacturing



(b) Trade/Services

Notes: This figure shows the correlation between predicted runner-up valuations using $\hat{\alpha}$ recovered from the baseline model (x-axis) and $\hat{\alpha}$ recovered using only the subsidies and winning location characteristics, which I will call the "alternate model" (y-axis). The parameter estimates ($\hat{\alpha}$) used can be found in columns (1), the "baseline", and (2), the "alternate model", of Appendix Tables J.1 and J.1. The figures on the left uses the firm characteristics for the subsidy deal, which factor heavily into the valuation. The figures on the right use the firm characteristics for the average subsidy deal in that sub-sample, therefore reducing the dependence on the jobs and investment of the particular deal. The 45-degree line is the dashed line in each figure. When firm characteristics are included the correlation between the two predicted valuations is 0.97 (manufacturing) and 0.94 (services). When using mean firm characteristics the correlation is 0.55 (manufacturing) and 0.97 (services).

I proceed through the estimation process, following Section 5, but using the alternate model. Tables J.3 and J.4 show the profit parameters under the random-coefficients specification (Step 1 in Section 5). These are very similar to the baseline estimates (Tables 3 and 4), as might be expected due to the similarity in the predicted valuations under the two models. In Step 1, I predict runner-up valuations (using $\hat{\alpha}$ from specification (2) in Tables J.1 and J.2) and runner-up profits (using $\hat{\beta}$ and $\hat{\sigma}$ from Tables J.3 and J.4). Table J.3 shows that, once I allow for random coefficients, the predicted runner-up valuation does not fit the difference between observed subsidies and differences in profits as well as in the OLS, with a coefficient of 0.76 instead of 1.02. The services subsample parameter on predicted valuations, in Table J.4, is consistent with the OLS.

Table J.3: Alternate Model 1, Manufacturing

Variable	Coefficient	Estimate	Std. Error
Profits:			
Δ Corporate Tax (%)	β_{corp}	-10.73	5.24
Δ Corporate Tax × Investment ($B)	$\beta_{corp \times invest}$	-2.84	2.43
Δ Corporate Tax: Random Effect	σ_{corp}	26.41	6.19
Δ Income Tax (%)	β_{inc}	5.15	4.04
Δ Income Tax: Random Effect	σ_{inc}	13.57	5.83
Δ Property Tax (%)	β_{prop}	-4.71	14.82
Δ Industry Wage ($1,000)	β_{wage}	-1.44	0.64
Δ Industry Wage: Random Effect	σ_{wage}	2.74	0.86
Δ Industrial Electricity Price (c/KwH) × Investment ($B)	$\beta_{utility \times invest}$	2.36	6.18
Δ Industrial Land Supply × Investment ($B)	$\beta_{landsupply \times invest}$	114.84	65.7
Δ Auto Network Density × Traditional Manufacturing	$\beta_{auto \times trad}$	100.34	37.6
Δ Pop. in Relevant Occupation (1,000)	β_{occ}	-3.11	1.66
Δ Pop. in Relevant Occupation × Jobs Promised (1,000)	$\beta_{occ \times jobs}$	4.85	1.32
Δ Pop. in Relevant Occupation: Random Effect	σ_{occ}	1.06	1.95
Δ Population with BA+ (%) × High-Tech Manufacturing	$\beta_{college \times high-tech}$	3.6	4.52
Δ Population with BA+ (%) × Traditional Manufacturing	$\beta_{college \times trad}$	-4.74	2.73
Δ Industry Estab. Share (%) × High-Tech Manufacturing	$\beta_{estab \times high-tech}$	255.87	211.33
Valuation:			
Predicted Runner-up Valuation	$\alpha_{\hat{v}_2}$	0.76	0.08

Notes: Table J.3 displays the profit parameter estimates: $\{\hat{\beta}, \hat{\sigma}\}$, for the alternate model. Them manufacturing sample is restricted to deals worth under $1 billion (See Appendix Figure I.1(a)). Descriptive statistics for location characteristics are in Appendix Table F.1, and more details on the selection of these characteristics is in Appendix F. The mean subsidy size for this sub-sample is $144 million, and the median is $83 million.

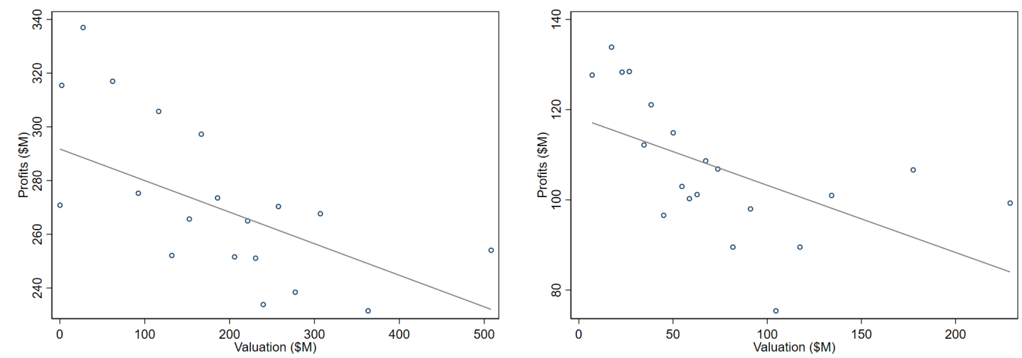
Table J.4: Alternate Model 1, Trade/Services

Variable	Coefficient	Estimate	Std. Error
Profits:			
Δ Corporate Tax (%)	β_{corp}	-5.73	1.60
Δ Corporate Tax: Random Effect	σ_{corp}	9.02	2.00
Δ Income Tax (%)	β_{inc}	7.56	1.52
Δ Income Tax × Jobs Promised (1,000)	$\beta_{inc\times jobs}$	-2.11	0.87
Δ Income Tax: Random Effect	σ_{inc}	-6.37	1.44
Δ Property Tax (%)	β_{prop}	-19.97	7.42
Δ Property Tax: Random Effect	σ_{prop}	2.66	8.34
Δ Right-to-Work State	β_{r2w}	6.61	8.27
Δ Right-to-Work State: Random Effect	σ_{r2w}	35.63	8.38
Δ Housing Price ($1,000)	$\beta_{housing}$	-0.01	0.05
Δ Housing Price ($1,000) × Investment ($B)	$\beta_{housing\times invest}$	-0.01	0.04
Δ Industry Wage ($1,000) × High-Skill Services	$\beta_{wage\times high-skill}$	-0.07	0.45
Δ Industry Wage × Trade/Other Services	$\beta_{wage\times other}$	-1.01	0.84
Δ Commercial Electricity Price (c/KwH)	$\beta_{utility}$	-2.19	1.90
Δ Auto Network Density	β_{auto}	11.68	9.97
Δ Large Airport × Trade	$\beta_{airport\times trade}$	57.88	15.65
Δ Research University × Services	$\beta_{univ\times services}$	6.26	5.73
Δ Research University × Trade	$\beta_{univ\times trade}$	-39.32	16.70
Valuation:			
Predicted Runner-up Valuation	$\alpha_{\hat{v}_2}$	1.01	0.06

Notes: Table J.4 displays the profit parameter estimates: $\{\hat{\beta},\hat{\sigma}\}$, for the alternate model. The trade/services sample is restricted to deals worth under $400 million (See Appendix Figure I.1(b)). Descriptive statistics for location characteristics are in Appendix Table F.1, and more details on the selection of these characteristics is in Appendix F. The mean subsidy size for this sub-sample is $78 million and the median is $45 million.

The correlation between the runner-up profits and valuations is shown in Figure J.2. Specifically, the figure presents the binned scatter plot of predicted profits and valuations in the runner-up location. The correlation coefficient for services is -0.28 and the correlation coefficient for manufacturing is -0.21 (compared to -0.28 and -0.06 in the baseline model). The profits and valuation are conditional on firm characteristics—I use the average jobs promised, investment, and multiplier for the respective subsamples. In Step 2 I calculate the total welfare in the runner-up location. The distribution looks very similar the baseline (Appendix Figure I.2), although the values are slightly higher. Step 3 follows exactly as detailed in Section 5, using the correlation and runner-up welfare calculated under the alternate model.

Figure J.2: Correlation between Runner-up Profits and Valuation under Alternate Model



(a) Manufacturing (b) Trade/Services

Notes: This figure is the binned scatter plot of predicted profits and valuations in the runner-up location ($\hat{\pi}_{2i}$ and $\hat{v}_{2i}$), using the alternate specification to predict profits and valuation. The profits and valuations are predicted using the estimated parameters from Appendix Tables J.3 and J.4. The profits and valuation are conditional on firm characteristics—I use the average jobs promised, investment, and multiplier for each sample.

Lastly, Table J.5 shows the welfare analysis, using the distribution recovered under the alternate model. The total simulated valuation and profits are larger in this setting, due to differences in predicted runner-up profits and valuations using the alternative specification. However, the headline results are very similar to the baseline model, with a welfare gain of 2.6%, compared to 4.3% (Table 5). This result emphasizes the importance of the relative heterogeneity in valuations and profits, compared to the correlation between the two objects. In the range of values that is relevant in this setting, it is the heterogeneity in valuations that is most important for the welfare results.

Table J.5: Welfare Analysis: Alternate Model 1

Policy	Movers	Simulated v ($B)	Simulated π ($B)	Sub ($B)	Payoffs ($B) States	Payoffs ($B) Firms	Total Welfare
Subsidy Ban	-	56.0	101.9	0.0	56.0	101.9	157.9
Competition	46.5%	75.3	86.8	40.9	34.4	127.6	162.0
				Δ welfare from competition:	-38.6%	25.2%	2.6%

Notes: Table J.5 displays the results of the counterfactual welfare analysis for the alternate model where I assume winners are bid up to their willingness to pay. For the "competition" policy, locations are observed, and I calculate profits using $\hat{\beta}$ and $\hat{\sigma}$ (Appendix Tables J.3 and J.4). Then I simulate the valuations of the winning locations from $\hat{H}_V(v|\pi)$. The welfare gain is very similar to the baseline model.

J.2 Alternate Model 2: Discrete Choice

The approach I take in the paper relies on the structure of the English auction to recover firms' profit parameters (Equation 6). This approach assumes that the difference in runner-up and winning location characteristics, Δx, is independent of the unobserved valuation term, ε (Assumption 4). Then, in order to recover the distribution of total welfare across locations, the approach I take in the paper relies on the assumption that the bidders (locations) are independently and identically distributed (Assumption 5).

The reader may have concerns about both of these assumptions. First, if Assumption 4 does not hold then my estimates of β are biased. Selection inherent in the auction process makes this a threat—locations that are less for profitable firms are only likely to become the runner-up by virtue of having a large ε (and the opposite is true for locations that are very profitable for firms). Second, the model explicitly wants to account for differences across locations in terms of profits, but treats bidders as i.i.d. when recovering welfare (Assumption 5).

Instead of relying on the structure of the English auction to recover firms' profit parameters, β, one could use a discrete choice model. I observe firms locating in a certain location, given a set of location characteristics and a choice set of shortlisted locations (though I do not always observe the full shortlist). Further, I observe the identity of the runner-up, i.e. the second choice location. Therefore, instead of taking Assumption 4 on the unobserved location match value in the *runner-up*, I can assume that the unobserved location match over the set of shortlisted locations, ε, is distributed i.i.d. TIEV, with location and scale parameters (0, σ_ε).

To be specific, given the identification argument in the main text through Assumption 2, I make the following assumptions on location valuations and the structure of the error term (which replace Assumptions 3 and 4):

Assumption 8 *The valuation in a location is a function of observed location characteristics, x^v_{cs} and an unobserved location-firm specific match, ε_{ics}.*

$$v_{ics} = x^v_{cs}\alpha + \varepsilon_{ics} \tag{14}$$

where $\varepsilon_{ics} \sim TIEV(0, \sigma_\varepsilon)$.

Assumption 9 *The unobservable portion of the valuation, ε, is independent of location observables, x: $\mathbb{E}(\varepsilon|x) = \mathbb{E}(\varepsilon)$.*

Then, as in the main text, the states compete with subsidies, and the firm will choose the location with the highest total welfare, offering the firm a payoff that is equivalent to the total welfare in the second highest welfare location, where welfare is the sum of valuations and profits:

$$w_{ics} = x^\pi_{cs}\beta_i + x^v_{cs}\alpha + \varepsilon_{ics}.$$

Recall that profits are specified with a random coefficient term, η, such that $\beta_i \sim N(\bar{\beta}, \Sigma)$.

Given this assumption on the structure of the errors, welfare also has an extreme-value distribution with location and scale parameters $(x^\pi\beta_i + x^v\alpha, \sigma_\varepsilon)$. Therefore, I can write the probability of observing the winning and runner-up locations, $\{y_{i1}, y_{i2}\}$, among the set of locations considered, S_i^n, with the likelihood function

$$L(y_{i1}, y_{i2}|S_i^n) = \int \frac{\exp\left(\frac{x_1^\pi \beta_i + x_1^v \alpha}{\sigma_\varepsilon}\right)}{\sum_{k \in S_i^n} \exp\left(\frac{x_k^\pi \beta_i + x_k^v \alpha}{\sigma_\varepsilon}\right)} \frac{\exp\left(\frac{x_2^\pi \beta_i + x_2^v \alpha}{\sigma_\varepsilon}\right)}{\sum_{k \in S_i^n} \exp\left(\frac{x_k^\pi \beta_i + x_k^v \alpha}{\sigma_\varepsilon}\right) - \exp\left(\frac{x_1^\pi \beta_i + x_1^v \alpha}{\sigma_\varepsilon}\right)} dF(\beta_i|\bar{\beta}, \Sigma) \tag{15}$$

Once I account for the set of locations on the short-list, S_i^n, this is a standard logit that I can estimate, and recover β/σ_ε and $\alpha/\sigma_\varepsilon$ with variation in the characteristics of the winning, runner-up, and other shortlisted locations. I simulate η from $N(0,1)$, following the literature. For the choice set, I also simulate potential shortlisted locations, from the potential shortlist sample (Appendix I.5).[90] Therefore, I can proceed by simulated maximum likelihood, simulating η_i and S_i^n.

Now, the assumptions on valuation are not specific to the runner-up location, but across locations in competition for the firm (i.e. locations on the shortlist). Therefore, worries about selection inherent in the auction process—runner-up locations that have low ε are more likely to have high profits, and vice versa—will partly be addressed by using data and variation across *all* locations on the shortlist. However, concerns about the bias generated from correlation between x and ε are still relevant.

This approach does not allow location characteristics that enter both firm profits and locations' valuations; I need $x^\pi \cap x^v = \emptyset$. In order to attempt to separate firm profits from locations' valuations I need to make further assumptions on which location characteristics enter profits, and which enter valuations. I cannot allow, for example, corporate tax to effect both firm profits and the location's valuation for winning a firm, as I have in the baseline model. I assume all of the variables that enter both profits and valuations in the baseline model only enter firm profits.[91]

The remaining element to recover is the variance of ε, σ_ε. I identify σ_ε using data on winning bids. Specifically, I match the distribution of predicted subsidies (model) to observed subsidies (data). The outcome of the English Auction is that the winning location will offer the firm a subsidy that makes it indifferent between locating in the winner or the runner-up (Equation 6). Therefore, given $\hat{\beta}, \hat{\alpha}$, and simulations of η_i and ε_i, I can use Equation 6 to predict subsidies. An important note here is that this method does not require further assumptions on bidder symmetry, which I need in order to recover the distribution of welfare in the main text (Assumption 5).

Estimating Equation 15 gives preference coefficients over location characteristics. Location preferences over deal specific characteristics, z_i (i.e. number of jobs promised, investment planned), cannot be estimated because there is no variation across locations in these characteristics.[92] Therefore I homogenize subsidies using the job promise, investment planned, and industry multiplier before matching data to predicted subsidies (Table J.6). For manufacturing, the correlation on jobs promised is much lower than when it is estimated together with the location characteristics in the baseline model (Table 3).

[90] This is the same methodology that I use to simulate from potential shortlisted locations in the counterfactual.

[91] This is relevant for corporate taxes, income taxes, property taxes, and wages (though for wages I can use two different wage concepts—industry wages in the profit function and "top occupation " wages in the valuation). I experiment with allowing the location characteristics to enter valuations instead, or to be split between profits and valuations. Assigning the variables to firm profits gave the best model fit. Another reason to attribute all of these observables to π is because the model does not allow an additively separable unobservable in firm-location profit.

[92] This is why the specification for v in Assumption 8 only includes x_{cs}^v, unlike the specification in Assumption 3.

Table J.6: Homogenizing Subsidies

	Subsidy ($M)			
	Manufacturing		Trade/Services	
	Estimate	SE	Estimate	SE
Jobs Promised ($1,000)	61.84	13.05	15.56	4.40
Investment Planned ($B)	51.20	5.59	55.26	11.60
Indirect Jobs (Jobs × Multiplier)	2.23	0.39		
Industry Multiplier			6.24	2.86

Notes: Table J.6 displays the correlation between deal specific characteristics that enter v, and the observed subsidy size. The manufacturing sample is 200 deals with an average subsidy size of $144 million. The trade/services sample is 177 deals with an average subsidy size of $78 million. Homogenized subsidies are matched to predicted subsidies (using $\hat{\beta}$ and $\hat{\alpha}$ to calculate π and v) in order to recover σ_ε.

To summarize, the estimation procedure proceeds as follows:

1. Set grid to search over σ_ε, from 0 to G: $\sigma_\varepsilon^g \in [0, .1, ...G]$.
2. For each guess σ_ε^g:
   (a) Simulate $M \times N$ values of the random variables (η_i, S_i^n) where N is the number of auctions, and M is the number of simulations.
   (b) Estimate Equation 15 via simulated maximum likelihood to recover $\hat{\beta}$ and $\hat{\alpha}$, given σ_ε^g.
   (c) For each $M \times N \times n$ simulated location (recall that n denotes the number of locations in the competition), simulate $\tilde{\varepsilon}_{ics}$ from $TIEV(0, \sigma_\varepsilon^g)$.
   (d) Predict subsidies using $\hat{\beta}, \hat{\alpha}$, $\tilde{\varepsilon}_{ics}$ and Equation 6:

$$\text{predicted subsidy}_{ics} = \hat{\pi}_{runner-up} - \hat{\pi}_{winner} + \hat{v}_{runner-up}$$

3. Choose σ_ε^g that minimizes the difference between mean observed and mean predicted subsidies.

I set $G = 100$ and $M = 1000$. Step 3 minimizes the difference between *mean* observed and *mean* predicted subsidies, where observed subsidies are homogenized (Table J.6).

Tables J.7 and J.8 present the β coefficients for manufacturing and trade/services firm profits, respectively, the α coefficients for valuations, and σ_ε. Here, I note that the estimates of both β and α are much different than the baseline results in Tables 3 and 4, and the scale is much smaller, leading to lower predicted profits.

Important differences between the two approaches can partly explain differences in the estimates of β:

1. In the baseline model, observed subsidies are used to estimate β, using the difference in runner-up and winning location characteristics. Here, subsidies are not directly used to estimate β. Instead, I am using homogenized subsidies to pin down σ_ε, which scales the normalized preference coefficients, β. Therefore, I cannot rely on variation in subsidy size to recover

the parameters on the subsidy characteristics that interact with location characteristics (i.e. $\beta_{corp\times invest}, \beta_{utility\times invest}, \beta_{landsupply\times invest}, \beta_{occ\times jobs}$ in manufacturing, and $\beta_{inc\times jobs}, \beta_{housing\times invest}$ in trade/services). The interaction of firm characteristics with location characteristics do not explain much of total welfare in the new approach, nor do the random coefficients. This will lead to less heterogeneity in predicted firm profits.

2. In the baseline model, location observables can enter both profits and valuations. Here, characteristics that potentially affect both π and v are being loaded into π only. This is likely to reduce the magnitude of the parameters, given that the location characteristics that reduce firm profits are the same ones that increase the locations' valuation (i.e. corporate tax).

Table J.9 displays the results of the counterfactual welfare analysis, given the new estimate distributions of profits and valuations. I proceed exactly how I implement the counterfactual in the main text. I simulate shortlists from the potential shortlist, and I simulate η from $N(0,1)$. Then, given η, I calculate profits for each location on the simulated shortlist, using $\hat{\beta}$ and $\hat{\sigma}$ (Tables J.7 and J.8). Then I simulate the valuations of the winning locations from $H_V(v) \sim TIEV(x^v\hat{\alpha}, \hat{\sigma}_\varepsilon)$.

The welfare results are substantially different than the baseline model. This is due to the fact that this model estimates very little heterogeneity in profits across locations, and many negative profit locations. I take the same assumption as I do in the main text—profits must be weakly positive (Assumption 7). Because there is so little heterogeneity in profits across locations, all of the variation loads onto valuations. This causes subsidy competition to change the location choice of more firms (i.e. more movers), and causes the welfare gain from subsidy competition to be larger. However, states would still be better off, in aggregate, with the subsidy ban, just as in the baseline model.

Table J.7: Alternate Model 2, Manufacturing

Variable	Coefficient	Estimate	Std. Error
Profits:			
Corporate Tax (%)	β_{corp}	-0.15	0.13
Corporate Tax $\times$ Investment ($B)	$\beta_{corp\times invest}$	0.10	0.06
Corporate Tax: Random Effect	σ_{corp}	-0.20	0.21
Income Tax (%)	β_{inc}	0.77	0.10
Income Tax: Random Effect	σ_{inc}	0.61	0.21
Property Tax (%)	β_{prop}	-2.01	0.45
Industry Wage ($1,000)	β_{wage}	-0.06	0.04
Industry Wage: Random Effect	σ_{wage}	0.03	0.03
Industrial Electricity Price (c/KwH) $\times$ Investment ($B)	$\beta_{utility\times invest}$	-0.42	0.13
Industrial Land Supply $\times$ Investment ($B)	$\beta_{landsupply\times invest}$	-0.77	1.27
Auto Network Density $\times$ Traditional Manufacturing	$\beta_{auto\times trad}$	2.85	1.09
Pop. in Relevant Occupation (1,000)	β_{occ}	-0.02	0.05
Pop. in Relevant Occupation $\times$ Jobs Promised (1,000)	$\beta_{occ\times jobs}$	-0.03	0.03
Population with BA+ (%) $\times$ High-Tech Manufacturing	$\beta_{college\times high-tech}$	0.64	0.12
Population with BA+ (%) $\times$ Traditional Manufacturing	$\beta_{college\times trad}$	-0.45	0.09
Right to Work	β_{r2w}	2.93	0.69
Industry Estab. Share (%) $\times$ High-Tech Manufacturing	$\beta_{estab\times high-tech}$	-16.07	6.19
Valuation:			
Unemployment (%)	α_{unemp}	0.75	0.27
Unemployment $\times$ Jobs Promised	$\alpha_{unemp\times jobs}$	-0.73	0.58
Term Limit	α_{term}	0.30	0.20
Relevant Occupation Wage ($1,000)	α_{wage}	0.25	0.16
Relevant Occupation Wage $\times$ Log(Income per capita)	$\alpha_{wage\times log(income)}$	-0.03	0.04
	σ_{ε}	11.2	

Notes: Table J.7 displays the results of estimating Equation 15 for the manufacturing sub sample. Equation 15 is estimated using simulated maximum likelihood, where I simulate over shortlists 50 times, and simulate over the firm unobservable, η, 50 times. The potential shortlist is sampled from a set of locations that are relatively similar to the winner and runner-up (Section I.5). The firm unobservable is simulated from the standard normal distribution, $\eta \sim N(0,1)$. The outer loop matches predicted subsidies to realized subsidies, in order to recover σ_{ε}.

Table J.8: Alternate Model 2, Trade/Services

Variable	Coefficient	Estimate	Std. Error
Profits:			
Corporate Tax (%)	β_{corp}	0.42	0.13
Corporate Tax: Random Effect	σ_{corp}	0.79	0.26
Income Tax (%)	β_{inc}	0.78	0.14
Income Tax $\times$ Jobs Promised (1,000)	$\beta_{inc\times jobs}$	-0.24	0.09
Income Tax: Random Effect	σ_{inc}	0.36	0.26
Property Tax (%)	β_{prop}	-0.48	0.73
Property Tax: Random Effect	σ_{prop}	-1.76	1.42
Right-to-Work State	β_{r2w}	3.77	0.80
Housing Price ($1,000)	$\beta_{housing}$	-0.03	0.01
Housing Price ($1,000) $\times$ Investment ($B)	$\beta_{housing\times invest}$	0.02	0.00
Industry Wage ($1,000) $\times$ High-Skill Services	$\beta_{wage\times high-skill}$	0.01	0.05
Industry Wage $\times$ Trade/Other Services	$\beta_{wage\times other}$	-0.05	0.08
Commercial Electricity Price (c/KwH)	$\beta_{utility}$	-1.13	0.22
Auto Network Density	β_{auto}	-6.95	1.03
Large Airport $\times$ Trade	$\beta_{airport\times trade}$	-2.61	1.77
Research University $\times$ Services	$\beta_{univ\times services}$	0.36	0.66
Research University $\times$ Trade	$\beta_{univ\times trade}$	7.36	1.75
Valuation:			
Sales Tax (%)	α_{sales}	0.46	0.22
Term Limit	α_{term}	-1.45	0.70
Unemployment (%)	α_{unemp}	0.91	0.25
Relevant Occupation Wage ($1,000)	α_{wage}	0.08	0.02
	σ_{ε}	10.6	

Notes: Table J.8 displays the results of estimating Equation 15 for the trade/services sub sample. Equation 15 is estimated using simulated maximum likelihood, where I simulate over shortlists 50 times, and simulate over the firm unobservable, η, 50 times. The potential shortlist is sampled from a set of locations that are relatively similar to the winner and runner-up (Section I.5). The firm unobservable is simulated from the standard normal distribution, $\eta \sim N(0,1)$. The outer loop matches predicted subsidies to realized subsidies, in order to recover σ_{ε}.

Table J.9: Welfare Analysis: Alternate Model 2

Policy	Movers	Simulated v ($B)	Simulated π ($B)	Sub ($B)	Payoffs ($B) States	Payoffs ($B) Firms	Total Welfare
Subsidy Ban	-	29.5	48.5	0.0	29.5	48.5	78.0
Competition	55.7%	48.1	48.5	40.9	7.2	89.4	96.6
				Δ welfare from competition:	-75.7%	84.2%	23.8%

Notes: Table J.9 displays the results of the counterfactual welfare analysis for the discrete choice model. I predict profits using the β and σ coefficients from Tables J.7 and J.8. I simulate the valuations of the winning locations from $H_V(v) \sim TIEV(x^v\hat{\alpha}, \hat{\sigma}_{\varepsilon})$.

K Discussion

I chose the private value English auction to model state competition for firms. More specifically, it is a private value English scoring auction, with a scoring rule that is unobserved to the econometrician. I use the English auction because I have evidence from state documents on subsidy-giving that there are multiple rounds of bidding and that states know each others' subsidy offers. In this section I discuss the implications of some of the assumptions of the model.

Budget Constraints

The model does not capture every feature of the incentive competition landscape. One simplification is with respect to the state economic development budgets. In reality the state may be budget constrained. However, discussions with employees at various state economic development agencies made it clear that the "budget" is a very ill-defined concept, and large discretionary subsidy deals are often made under the assumption that the state will "find" or budget the money in the future. This is fairly easy for most states to do because the structure of discretionary subsidies is such that most of the subsidy size is foregone revenue. In other words, the state has a contract with the firm that they will not collect taxes (or collect at a lower rate) for a certain amount of time. Appendix A has a longer discussion of this assumption and the determination of economic development budgets.

One remaining concern about the budget is that smaller states, with already low corporate taxes, will not be able to put together a large enough subsidy to win a firm. I never observe Vermont, New Hampshire, Maine, Wyoming, Montana, North Dakota, or South Dakota winning a subsidy competition in my sample.[93] Does that mean that these states do not have high valuations for firms? These states may be less profitable locations, so they may not even be on the short-list of the firm, or when they are in the competition they simply do not offer the highest payoff, given that they bid up to their valuation.[94] Alternatively, it may be that the budget constraint is sometimes a factor. South Dakota has a corporate tax rate of 0.0% and an average property tax rate of 1.32%. Therefore South Dakota cannot forego revenue in order to attract a firm; it will need to find money in the budget to build the subsidy offer. Understanding the role of the budget in low revenue, low tax rate states, and the trade-off between offering low tax rates and targeting individual firms, is a rich area for future work.

Dynamics

In the absence of a budget constraint, states do not have to consider the effect of winning a firm today on the probability of being able to win a firm tomorrow. Relatedly, I assume the valuations for firms are independently distributed, and thus do not explicitly consider any dynamic interactions in the valuations of firms.[95] For example, the state does not necessarily value a tire manufacturer more or less once they have won a competition for an automobile manufacturer. However, to the extent that winning a firm changes the location characteristics, synergies between firms are in fact encompassed by the model. For example, if winning an automobile manufacturer increases the profitability of the location for the tire manufacturer, the state will be more likely to also win the tire manufacturer.

[93] I restrict the sample to subsidy deals in the 48 contiguous states, so Alaska and Hawaii are mechanically dropped.

[94] However, Vermont, New Hampshire, and North Dakota are all runners-up for deals in the sample, so I know at least some of these states make the short-lists.

[95] See Martin (2000*b*) for a theoretical treatment of this issue, which models the competition for two firms as a sequential auction. Importantly, the theory shows that the first firm will receive a larger subsidy, and the second firm a smaller one.

If winning an automobile manufacturer increases employment in the transportation sector, and the match between existing employment and the industry of a firm is something that affects the states' willingness-to-pay, the state may have a higher valuation for the tire manufacturer. The fact that there are many time varying components that are correlated with valuations—unemployment rates, political cycles—also assuage concerns about correlated draws over time.

Common vs. Private Values

One approach would be to model this as a common value, as opposed to a private values auction. In the pure common value auction, the bidders (states) have different information, but identical values for the good (firm). This means that the firm creates the same amount of value (in tax revenue, indirect job creation, etc.), regardless of the location it chooses. This assumption is not supported by most of the literature (Greenstone, Hornbeck and Moretti, 2010; Bartik, 1991).

In reality this is likely an auction with both a private and common value component. This is a fact of most auction settings. However, most empirical auction work is divided into purely private value and purely common value auctions. One reason for this dichotomy is that it is more difficult to identify the primitives of auctions with both private and common value elements. From the work of Goeree and Offerman (2002, 2003) on competitive bidding in auctions with private and common values, it is clear that much more data would be needed to identify both the common value and private value distributions, namely data on the level that each bidder drops out.

Another way to think about the value structure in my context is that $H_V(v)$ is not the distribution of true values, but the distribution of beliefs about the value the firm will create, which is still location-specific. Throughout the analysis I assume the states can accurately predict the benefit a firm will have in their jurisdiction, and I estimate the state valuations using data on realized subsidy deals. I use a revealed preference approach; the subsidy deals offered by the state reveal the states' underlying valuation for the firm. However, it is possible that states overestimate the effect a firm will have once it locates in the state. If state and local governments overestimate the true benefit, the winning location can suffer from the winner's curse, as discussed in Section 6.4.

Whether states can accurately predict the revenue and job creation effects of a potential entrant is an open question, because the analysis of the economic effects of firms post-subsidy disbursement is limited. Estimated valuations are much larger for firms in industries with high predicted job multipliers, but evidence on the actual spillovers realized is mixed (Slattery and Zidar, 2020; Greenstone, Hornbeck and Moretti, 2010; Patrick, 2016). A recent push for transparency might soon provide the data to study whether (and when) the realized benefit aligns with the ex-ante valuations.[96]

[96] As of 2015, the Government Accounting Standards Board requires that state and local governments disclose all tax abatements to firms (Governmental Accounting Standards Board, 2015). Relatedly, the National Conference of State Legislatures has noted an increase in state-level incentive programs evaluations published post-2014.