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Contents

List of Figures

List of Tables

Abstract

My dissertation chapters study the effects networks play in an auction setting. My first chapter explores how subcontracting creates affiliation between firm's costs in an auction setting. It first offers a theoretical framework associating subcontractor networks in procurement auctions to affiliated costs of potential bidders. Based on the methodology by Li and Zhang (2010), I construct a model that allows for cost affiliation depending on firm-pair observables. The extension is used to test for entry affiliation caused by overlapping subcontractor networks in a sample of Oklahoma Bridge building contracts from 2004 to 2011. The empirical analysis finds a statistically significant presence of affiliation, driven by subcontracting networks, affecting firms' decision to buy for project plans.

Chapter 2 is joint work with my adviser Dr. Georgia Kosmopoulou, Dr. Dakshina DeSilva, and Dr. Rachel Pownall. It aims to identify factors contributing to price fluctuations in artworks after an artist's death. With access to information on seller characteristics from a historical dataset of all art auctions that took place in London between 1741 and 1913, we investigate how trading patterns and network effects affect art sales prices at auctions. Following an artist's death, we capture dynamic effects in sales patterns and find that prices decline by 7%. We attribute this decline on the confluence of non-strategic and strategic effects, firstly on a frequent lack of access to professional consultation and secondly on changes in trading patterns of art dealers posthumously. Our results highlight the long term influence of those factors on high valued art.

The final chapter is again joint work this time, with my adviser Dr. Georgia Kosmopoulou, Dr. Richard Sicotte, and Dr. Hojin Jung. In public procurement, most contracts are renegotiated ex post and involve subcontractors. We examine whether there is a causal link between subcontractor use and the incidence of change orders to amend the original scope of a project. Since subcontracting is likely related to unobserved project complexity, we use a novel IV, the predicted level of subcontracting from a method modeled after Christakis *et al.* (2010), to estimate the likelihood of renegotiation. The results establish that subcontractors are associated with an increased likelihood of change orders as well as a higher dollar amount renegotiated.

Chapter 1

Subcontractor Networks and Affiliated Private Values: Evidence from Oklahoma Bridge Contracts

1.1 Introduction

Networks between economic agents have powerful effects on markets. They provide avenues for information to flow (Montogomery 1991, Trusov *et al.* 2009), trust to form (Karlan *et al.* 2009), and provide insurance in the absence of formalized institutions (Townsend 1994, Fafchamps and Lund 2003). However, at the same time networks raise concerns about assumptions econometricians make when formulating their models. One such concern and the focus of this paper, is potential interdependence of error terms between connected agents.

Consider a class of students who will study for and then take a test. These students can either study alone or in pairs. A researcher might hypothesize that studying with others has a positive effect on average test grades, but that is not the only effect. Students who study together learn the material through the same process and thus answer questions in a similar manner. So, if one student scores high (low) then we would expect their partner to score high (low) as well. Essentially the errors between the pair are related. If this relationship is not considered, then an econometrician will misestimate the average effect of studying with another student.

We study this relationship in the context of highway procurement auctions. Like the above example, bidders in highway procurement auctions share relationships with one another, primarily through mutual subcontracting. In a sample of Oklahoma bridge auctions from 2004 to 2011, the average pair of bidders shared 4.3 subcontractors in the previous year. This paper seeks to answer several questions about how the existence of mutual subcontractors affect bidders' costs in highway procurement auctions both theoretically and empirically. These questions are of interest not just to econometricians, but also policy makers as relationships between bidder's cost change bidding behavior as well, making bidders less aggressive and leading to higher procurement costs for the state.

Researchers in the auction literature are keenly aware of the possibility of interrelated costs or values which they refer to as affiliation, as they are interested in bidders underlying values of items for bid and not just the bids they place strategically. First described in Milgrom and Weber (1982) (hereafter MW), the concept of affiliation is a generalization of the relationships between bidder's values, allowing bids to be positively related throughout the full distribution of values. The introduction of affiliation, as described by MW, changes bidder strategies and makes them bid less aggressively as compared to those with independent private values (IPV).[1] Their theoretical work shows that when affiliation is present, increasing the information access in an auction leads to higher expected revenues. Kagel *et al.* (1987) and Goeree and Offerman (2002) tested MW's work to show that the theoretical predictions on revenue generation hold in an experimental setting. Pinkse and Tan

[1] This accrues because if a bidder wins an auction it means they probabilistic misjudged the value of the item up for auction. This behavior is similar to the winner's curse seen in common value auctions, but to a lesser extent because values are not perfectly related.

(2005) shows theoretically how affiliation in first price auction, can lead to violation of the monotonic properties of the bidding function with respect to the number of bidders, as is the case with IPV, indicating that it may be in the best interest of the seller to limit the number of bidders in order to raise prices.

Relationships between bidders, including subcontracting relationships, have been pointed to as potential causes of affiliation that cannot be controlled for using only auction characteristics. Haile (2001) and Li and Zhang (2010) (hereafter LZ) found that selling timber rights to subcontractors after an auction created affiliation.[2] In a follow up paper, Li and Zhang (2015) studies how this affiliation affects firm mergers using a structural model. The existence of common subcontractors and suppliers in the market motivated the inclusion of affiliation in Nakabayashi (2013) in studying small business set asides, and Rosa (2019) in studying bid preference programs. On the other hand, Krasnokutskaya and Seim (2011) dismiss the inclusion of affiliation in their work on bid preferring, citing the relativity small value that common subcontractors contribute to projects in their sample. While all six papers are concerned about affiliation remaining between bidders in an auction, each treats it as a general phenomenon which affects all firms equally. We allow the effect of mutual subcontractors to vary between bidders by incorporating network information about which subcontractors have work with a bidder in the past.

Affiliation is not the only effect subcontracting has on bidder's costs. Marion (2009) shows that government requirements for the inclusion of minority owned subcontractors increased procurement prices, using California Proposition 209 as an exogenous treatment for a difference-in-difference framework. Using a sample of road construction firms in Texas, De Silva *et al.* (2017) finds that subcontracting helped firms stay in the market longer, especially newly established firms and those without outside options, potential improving

[2] The way affiliation in Haile (2001) effects expected price is different than in MW as affiliation through the possibility of future subcontracting raises, not lowers expected sale price.

long-term competition. Marion (2015) looks at how horizontal subcontracting, whereby a firm is both a bidder in an auction as well as a subcontractor for another bidder, affects behavior in California highway auctions. He finds empirically that the practice has a small negative effect on procurement prices. In his setting there are two competing forces at play: cost reduction and increasing opportunity costs.

The literature on the impact of networks in an auction environment is scarce. De Silva *et al.* (2020a) demonstrates that the network of art dealer in London from 1750-1914 passed information along. Those dealers with advantageous location in the network paid lower prices, earned higher profits, and stayed in the market longer. De Silva *et al.* (2020b) shows dealer's purchase networks of artists helps explain the divergence of art pricing following the artist's death. Jung *et al.* (2020) uses subcontractor networks to causally identify the effect of subcontracting on highway procurement renegotiation in Vermont. Lastly, the most closely related paper to my work is He *et al.* (2020) which evaluates how network opportunities of small and Disadvantaged Business Enterprises (DBE) are affected by opportunities in the subcontracting market, and the resulting impact on bidding outcomes and firms' longevity in the industry. This paper does not explore the role of affiliation in bidding behavior.

This paper contributes to the literature in three ways. First, we layout a simple theoretical framework, by which overlapping subcontractor networks lead to affiliated private values as well as what measures best capture the affiliation. Second, we provide a model by which the theory can be tested expanding the work of LZ. And finally, we use that model to empirically test the theoretical prediction on data from bridge construction projects procured by the Oklahoma Department of Transportation (ODOT), which show there is strong evidence associating subcontracting and affiliation among firms' decision to become planholders and in firm's bid values. This sample includes information about subcontractors used by winning bidders which is used to construct network measures for use in analysis. The most important of which is the measures of subcontractor overlap between pairs of potential bidders.

The rest of the paper is organized as follows. Section 1.2 provides a theoretical framework for how overlapping networks subcontracting would lead to APV, and which measures are most closely related to affiliation. In Section 1.3, an extension of the model of LZ to test for APV, through subcontracting overlap is proposed. Section 1.4 describes the sample of bridge and approach auctions in Oklahoma from 2004 to 2011. In Section 1.5, the results from the smooth simulated maximum likelihood estimation are reported. Section 1.6 offers a number of robustness checks for the results. Finally, Section 1.7 offers discussion of the results and concludes.

1.2 Theory

Two models by which the submission of bids will be affiliated, are proposed in LZ. The first model has potential bidders uncovering their cost prior to the decision to submit their bids. If firms have affiliated costs, their bidding behavior will be affiliated. This is the most likely way to create affiliation between bidder in a procurement auction as potential bidders must buy detailed engineering plans from the state prior to letting. Even before buying plans, ODOT provides details on projects, such as their location, time to competition, and which material and jobs will be need on a project. Thus, firms should have a sense of their private costs for a project, even before buying plans. The second has firms deciding to enter an auction, which comes at some fixed cost, before learning their independent value. Thus, any firm deciding to place a bid, must have expected profits of bidding greater than the fixed entry cost. If the entry costs are affiliated, as might well be expected if a non-trivial part of the bidding process is standardized by the seller, then bidding behavior will be affiliated. This model of affiliation is less likely to exist in the data from ODOT as some firms place bids on projects that have little prospect of winning. About 1% of bids are in excess of 150% of the engineer's estimate.

A subcontracting network would most likely affect bidder behavior through the first model. Using two assumptions and Theorem 3 of MW, we can show that overlapping subcontractor networks create affiliation between bidder's private values. The first assumption made is that the total cost of one contractor hiring a subcontractor to complete a job is affiliated with the total cost of a different contractor hiring the same subcontractor. This assumption seems reasonable and not very strong as it does not require the cost to be the same for both contractors. Marion (2015) makes a similar assumption in his model of horizontal subcontracting, where there are two parts of working with a subcontractor, a direct cost which is the same for all and a coordination cost which differs across contractors.[3] The second assumption made is that all contractors minimize their costs on a project, which is a common assumption in the auction literature (Marion 2009; Miller 2014; Rosa 2019). This assumption is important as minimization is a nondecreasing function in all its arguments. The final piece is Theorem 3 of MW which states that affiliated imputes fed through a nondecreasing or nonincreasing function will lead to an affiliated output.[4] If both assumptions are valid, Theorem 3 of MW holds and thus overlapping subcontractor networks lead to affiliation in bidders' private costs. Furthermore Proposition 1 of LZ,[5] also holds and any discrete-choice decisions by potential bidders will as be affiliated.

Because private values are affiliated through mutual subcontractors, affiliation will not be equal across all pairs of bidders. Bidder pairs sharing more subcontractors will have higher levels of affiliation. Additionally, bidders with more outside options should see lower levels of

[3]The assumption in Marion (2015) is as follows: "[The subcontractor's cost] is comprised of two components, the direct cost of firm j completing the task c_j^B, and an IID contractor subcontractor specific coordination cost ξ_{ij}, so that $c_{ij}^B = c_j^B + \xi_{ij}$."

[4]The full text of Theorem 3 of MW is as follows:"If $Z_1, \dots, Z_k$ are affiliated and $g_1, \dots, g_k$ are all nondecreasing functions, then $g_1(Z_1), \dots, g_k(Z_k)$ are affiliated". The Z_is can be thought of as a vector of input cost for all the items a project requires which are available to bidder i. These input costs can be a firm's cost to provide an item in house, or the cost of hiring various subcontractors to do the same. While $g_i(\cdot)$ is the rule bidder i uses to pick among the set.

[5]Proposition 1 of Li and Zhang (2010): "Let $D = (D_1, \dots, D_N) \in \{0,1\}^N$ denote bidder 1, ... , bidder N's entry decision. If $V_1, \dots V_N$ are affiliated, then $D_1, \dots, D_N$ are also affiliated."

affiliation as the shared subcontractors are less likely to be used. Finally, affiliation will not be transitive. If Contractor A shares subcontractor X with Contractor B, then their private values will be affiliated. Similarly, if Contractor B shares subcontractor Y with Contractor C their values will also be affiliated. However, Contractors A and C's private values will not be affiliated as they do not share a subcontractor.

After establishing the theoretical existence of affiliation, the next step is to propose a measure that best captures the affiliation between two contractors because of overlapping subcontractors. The first possible measure is the count of overlapping subcontractors, but it fails to consider outside subcontracting options. Two other potential measures, from network theory, are good candidates, as they offer a normalization of the number of subcontractors shared between two contractors, by the level of outside options the pair has. They are jaccard similarity and cosine similarity formally defined as:

$$Jaccard_{ab} = \frac{\mathcal{N}_a \cap \mathcal{N}_b}{\mathcal{N}_a \cup \mathcal{N}_b} \quad Cosine_{ab} = \frac{\mathcal{N}_a \cap \mathcal{N}_b}{\sqrt{\mathcal{N}_a \cdot \mathcal{N}_b}} \tag{1.1}$$

where $\mathcal{N}_i$ is the neighbors, in this case the subcontractors, of contractor i. A priori neither measure should be preferred to the other, as both provide a normalization of overlap between two contractors.[6] However, intuitively both offer benefits over the count of overlapping subcontractors, the numerator of both, since the effect of one overlapping subcontractor should not be the same if firms have a different number of private subcontractors.

Here simulation is useful as calculating the exact distribution of the minimum for any distribution, besides uniform, is difficult. First, we begin by randomly assigning 2 contractors, A and B, a number of subcontractors in their network between 1 and 20 inclusive. Then we randomly assign the number of shared subcontractors by both between 0 and the minimum of A and B's subcontractor counts. Finally for each subcontractor 10,000 private values are

[6] please see chapter 2 of Fouss *et al.* (2016) for more details on jaccard and cosine similarity as well as other similarity measures.

drawn, and each contractor's value is taken as the minimum of its subcontractor values, and a correlation coefficient is calculated. then the process is repeated 10,000 times for several distribution (uniform, normal, etc.).

The results of the Monte Carlo simulations can be seen in Figure 1.1. As seen by the R^2 values, both similarity measures do very well in explaining the change in correlation using only a quadratic projection, though the jaccard similarity slightly outperforms the cosine similarity in 4 out of the 5 cases. However, it can be seen quite clearly the count of overlapping subcontractors is a poorer predictor than either normalized method.

The private costs in Figure 1.1 reflect the costs of a single task. When a project includes multiple tasks, the relationship becomes more complicated but both jaccard and cosine similarity performs well. Additionally, the results in Figure 1.1 are that of subcontractor values that are exactly the same for both contractors. If instead the costs a subcontractor offers are more weakly related the relationship will maintain the same functional form but will be compressed along the y-axis so that at similarity (either jaccard or cosine) of 1, the correlation will be less than 1, and the variance will be higher.

1.3 Model

Our test is based on a modification of the method of LZ. They use a smooth simulated maximum likelihood estimation (SSMLE) method to look at affiliated entry behavior in the Oregon timber market. In their model affiliation is constant across all firms in an auction but our modification allows for variation between firm pairs based on a firm-pair observable. SSMLE is a common method of estimating models with correlated error terms, first developed by Geweke (1991); Börsch-Supan and Hajivassiliou (1993); Keane (1994). It shares many of the same properties of maximum likelihood estimation, the most important of which is that as the number of simulations and observations approaches infinity the results will be consistent. The decision to participate in an auction is a discrete choice, and LZ uses a probit specification. The functional form used in LZ serves as the basis for this paper as well is:

$$D_{ait} = I(x_{at} \cdot \beta + z_{ait} \cdot \gamma + \epsilon_{ait} > 0) \tag{1.2}$$

Where D_{ait} is firm i's decision to compete in auction a at time t, $I(\cdot)$ is an indicator function, taking a value of 1 when the firm decides to compete and 0 otherwise, x_{at} is a vector of auction-level observables, z_{ait} is a vector of firm-level observables, and ϵ_{ait} is firm level error. The error is assumed independent of x_{at} and z_{ait}, but allowed to be affiliated with the other error values in the same auction, $\epsilon_{ai'}$, where $\epsilon_{ai'} \neq \epsilon_{ai}$.[7]

Without using subcontractor network information, general affiliation can be tested exactly as in LZ. In their specification the variance-covariance matrix for potential bidder in the same auction is:

$$\begin{bmatrix} 1 & & \rho \\ & \ddots & \\ \rho & & 1 \end{bmatrix}$$

where all off diagonal elements are the same constant, ρ, which is between -1 and 1, as it is a correlation coefficient. Firms submitting bids will have affiliated values only if $\rho \geq 0$.

We go a step beyond and allow ρ to vary for different potential bidder pairs, with respect to a measure of subcontractor overlap between potential bidder pairs, which as shown in the previous section cause firms' private costs to be affiliated. This will allow for the possibility

[7] LZ also include an auction random effect η_{at}, in their model as well, which is excluded as regressions with a random effect found its size to be small (less than 10^{-6}) and were interfering in calculating standard errors, as it made the Hessian information matrix near singular.

of different values in each of the off-diagonal elements:

$$\begin{bmatrix} 1 & & \rho_{ijt} \\ & \ddots & \\ \rho_{jit} & & 1 \end{bmatrix}$$

Where $\rho_{ijt} = \rho_{jit}$ and $-1 \leq \rho_{ijt} \leq 1$. For ρ_{ijt}, we propose the following functional form:

$$\rho_{ijt} = \rho_0 + \rho_1 \cdot P_{ijt} \tag{1.3}$$

Where P_{ijt} is a pair-wise measure of the overlap in the subcontractor networks of potential bidders i and j at time t. A linear specification of the affiliation is chosen because it is more readily interpretable, significance can be shown using standard errors, and it is straight forward to ensure the correlation parameter does not exceed its natural limits.[8] The specification divides affiliation into two parts, the general component, ρ_0, and a network overlap component, ρ_1. Three measure of network overlap are presented in this paper, the jaccard similarity, cosine similarity, and the count of overlapping subcontractors. While all three measures are expected to capture some amount of the affiliation, the count of overlapping subcontractors is expected to be the weakest, due to the measure not being normalized as discussed in Section 1.2.

To conduct SSMLE, first the auction and potential bidder observables are used to predict the first firm's entry decision. Then, the predicted entry probability is compared to the actual entry. Next a simulated error term for the first firm is drawn from a truncated

[8]A previous version of this paper used a functional form of $\rho_{ijt} = 2/(1 + \exp(\tilde{\rho_0} + \tilde{\rho_1} \cdot P_{ijt})) - 1$ which also ensured the affiliation was between -1 and 1, and had the added benefit of having a slight decreasing returns to scale of the overlap measure. However, to determine significance required using the log likelihood ratio test and interpreting the marginal effects was difficult so was replaced. Ultimately because all overlap measure used in this paper skewed toward 0 the change in specification does not change the model goodness of fit.

normal distribution.[9] This simulated value is then used as an additional control variable with is coefficient determined by the error variance-covariance matrix. This continues until reaching the last potential bidder in an auction, which will use all errors up to that point to predict its entry decision. The process is repeated in each auction many times to get an unbiased estimate of the errors. Repeating for each auction and taking the natural logarithm of the probabilities, allows for a straightforward method to minimize the error term as in standard maximum likelihood estimation.[10]

We choose a probit specification over a logit specification because we are interested in the correlation between observations. A logit model cannot readily incorporate correlation into the error term as the conditional logistic distribution is not a logistic distribution. On the other hand, a probit model, with normally distributed errors, can incorporate correlation with nonzero off-diagonal elements of the error variance-covariance matrix.

Using the method outlined above, it is possible to establish if contractors have affiliated private costs, with only a firm's binary decision, and not their bid value. This property is valuable as determining private costs through bid values requires assumptions about how bidders markup their bids from their private costs, and thus is more susceptible to misspecification.[11] However, not using bid values is throwing out information and can be problematic if bidding decisions are not closely tied to costs as might be the case if the marginal cost to preparing a bid is low.[12]

While the method we propose does have the potential to assign affiliation to the intersec-

[9]The distribution is truncated because the error term cannot be known exactly, only that if it is above $\frac{-x_{at} \cdot \beta - z_{ait} \cdot \gamma}{h_{ait,ait}}$, when the firm bids or less than $\frac{-x_{at} \cdot \beta - z_{ait} \cdot \gamma}{h_{ait,ait}}$ when the firm does not.

[10]Please see Li and Zhang (2010) for a complete understanding of the methods.

[11]Misspecification concerns often arise from assumptions about the firms attitudes towards risk (i.e. are firms risk neutral or risk averse, if they are risk averse what functional form will the risk aversion take, and are they all equally risk averse).

[12]As a robustness check we test for affiliation between bid values in Subsection 1.6.1. These results also point towards affiliation created by subcontracting overlap but requires additional assumptions on bid discounting.

tion of subcontracting networks, one must be cautious declaring the observed relationship causal. There are other ways that bids could be affiliated, such as overlapping suppliers, which might be expected to be related to overlapping subcontractors, as suggested by Nakabayashi (2013). Supplier overlap would create affiliation in a similar way to overlapping subcontractors. Unfortunately, the data is not available to us to explore this hypothesis. Another potential way for bidders to have affiliated values is through joint ventures between bidders. Firms which participate in joint ventures may learn about the methods of the other by working together, which could lead to affiliation in the future if they compete against one another, while also sharing subcontractors, because of the relationship. While we do know which firms have worked together as joint ventures incorporating an additional pairwise variable greatly increases the difficulty of ensuring ρ_{ijt} does not exceed its bounds. Even with these shortcomings, this paper still contributes to the literature, as no work has been done on factors which empirically predict affiliation.

1.4 Data

The data for this paper consists of all projects the ODOT auctioned off between 2004 and 2011. While the dataset includes all auctions, only bridge and approach contracts, which are contracts to build new bridges, are focues on for analysis because they offer a more homogeneous set. This decision is in line with previous research in the auction literature. Ji and Li (2008) used only auctions involving bridge repair in their study of secret reserve pricing, and LZ considered only auctions of a single species of timber. In addition, bridge and approach projects rely heavily on subcontracting, making them ideal for testing the importance of subcontracting on affiliation. Of the 516 contracts in the sample, 474, or 92% of winning firms used at least 1 subcontractor, and on average used 4.9 subcontractors. Subcontracting also contributes significantly in terms of dollars spent. The average firm awarded a contract during the period paid subcontractors \$358,088, or an average of 24% of the winning bid.

Next, it is important to know which firms are potential bidders. LZ assume firms are potential bidder, based on the firms that bid on project in a similar time frame. We use two different definitions in this paper. The first is the set of firms which become planholders for a project. ODOT requires all bidder to buy the project's plans before bidding. Becoming a planholder is nearly costless with the average cost of plans being 0.0024% of the estimated value of the associated project. While low plan costs should not discourage firms with positive expected profits for a project from participating, they will prevent extremely disadvantaged firms from competing. For example, firms which already have large commitments on other projects or firms located far from the project sight may be discouraged from buying plans. As such, a second broader definition of potential bidder is also used, which we call a potential planholder. A potential planholder is defined as any firm which was a planholder for any bridge and approach auction in the month of observation. Using potential planholders also allows for running regressions on a second discrete choice firms make, the decision to become planholders.[13]

In the ODOT dataset there are 128 unique planholders for bridge and approach contracts, 89 of which went on to bid at least once, and 50 of whom went on to win at least one project. The dataset includes 516 auctions with 3,061 planholders, and 9,524 potential planholders.[14] About 60% of planholder end up submitting bids in any individual auction. A much smaller number of potential planholder participate, with only 30% becoming planholders and 18% becoming bidders.

The subcontractors in the sample are even more diverse than the planholders, and involved 268 unique firms, which completed 2,513 different jobs over the course of the sample

[13] In Appendix A1.1, we repeat all analysis on potential planholder's decision to bid.

[14] One outlier auction is dropped, because the engineer's estimate is 6 times that of the next largest project.

period. The mean amount a subcontractor is hired for was $73,700, though the median was only $15,750. The itemized lists of the jobs completed by subcontractors suggests that they mainly perform peripheral jobs, which lines up with previous research (Miller 2014). Of the 8,057 items that could be linked to subcontractors, the most common type of items fulfilled by subcontractors where signage (699), guardrails (585), asphalt and surfacing (416), mulching (390), painting (325), and excavation (292).[15]

The auction variables available include the number of planholders in the auction,[16] the engineer's estimated value of the contract,[17] the number of contract days, the number of items in a contract, the percentage of contract that is supposed to be set aside for disadvantaged business enterprises (DBE), and the unemployment rate in Oklahoma[18]. Most variable are standard to include in the procurement literature models, except the DBE goal and the unemployment rate. Prior work offers conflicting effects of DBE goals, with Marion (2009) finding that they lead to an increasing procurement costs while De Silva *et al.* (2017) finds no such effect. Finally, the unemployment rate is included as a proxy for the effect of the Great Recession on the demand for new construction in the private sector, which may affect firm's outside options. Summary statistics for auction variable can be seen in Table 1.1. Several of the variables have a significant right-skew as indicated by their means being greater than their medians. This is a common occurrence in highway procurement auctions as there are a small number of projects that are significantly larger than majority. To counteract the skew, the natural logarithm of the following variables is taken: engineer's estimate, contract days, and project items.

The potential bidder specific variables include the distance from the job site,[19] and the

[15] It is not until the 13^{th} most common task that a non-periphery job appears, drilling shafts (151).

[16] For any models involving potential planholders, total potential planholders are used instead.

[17] For any models involving potential planholders, plan cost is used instead as firms would not have detailed information about the project until reviving plans. Plan costs closely relate to engineer's cost as the price of plans is a function of how many printed pages the plans take up.

[18] Gathered from the Bureau of Labor Statistics

[19] Distance from the job site is calculated by taking the distance in miles from a planholder's mail address,

backlog of the firm.[20] Both variables have been shown to be important in assessing an individual firm's private values in prior works: distance from the job sight in LZ, and backlog in Jofre-Bonet and Pesendorfer (2000).

Lastly, there is the contractor's network of subcontractors. Ideally, to construct each firm's subcontracting network all subcontractors a potential bidder considered using for a project should be included. Obviously, that is impossible to measure, so past subcontractor use is constructed as a proxy. Previous research shows repeated relationships between firms are a mechanism by which to lower transaction costs and manage risk in the face of incomplete information (Kvaløy and Olsen 2009). To construct the subcontractor network, all subcontractors a potential bidder used in Oklahoma in the prior 12 months are linked to the firm.[21] The 12-month window is chosen as that is the 75$^{\text{th}}$ percentile length between repeated subcontractor uses by a contractor in the sample. 54% of links are repeated in this time frame. Framed another way, if all subcontractors active in the market have the potential to be chosen to work with the winning bidder, previously unconnected subcontractors are hired 1% of the time, while connected subcontractors are hired 16.6% of the time. To initialize the network all observations from 2004 are dropped from analysis. The auctions from 2004 also help to set up the firm backlog.

The network formed by subcontracting is a directed one, because subcontracting is not a reciprocated action. This can be seen in Figure 1.2 where the potential planholders (the red nodes) are connected to the subcontractors (the blue nodes) by arrows. Figure 1.2 looks at four slices of the network, in January 2005, April 2007, September 2009, and December 2011. Over time the network becomes denser with more potential bidders and subcontractors

gathered from ODOT's preapproved contractor list, and the center of the county that a project is located in.

[20] Backlog is calculated as the value of all current contracts a firm is currently working on with ODOT, whether as a contractor or a subcontractor, divided equally for the length of the contract in months, beginning with the month following the award date.

[21] This includes subcontractors used on projects outside of the bridge and approach contracts focused on in the estimation stage.

entering the market. While most of the links are between the potential bidders and subcontractors, there are also links between potential bidders. Thus, horizontal subcontracting exists in the sample which should be accounted for. Those firms which are horizontal subcontractors may be less likely to bid as their opportunity costs of winning a contract are higher (Marion, 2015). Lastly on the periphery of the network can be seen a number of potential bidders who did not use any subcontractors in the sample.[22] These firms create a problem for properly analyzing affiliation generated by overlapping subcontractor networks since these firms likely have relationships with subcontractors, which are unobserved. This will lead to a downward bias in any network variables. This is particularly concerning regarding the similarity measures which will be used to predict affiliation. Thus, all firms with no observed subcontracting relationships are dropped from analysis.[23]

The contractor-subcontractor network can create several useful measures that can be used as explanatory variables to capture a potential bidder's place in the network. The measures used in the paper are seen on the bottom of Table 1.2 and are referred to as centrality measures. The simplest of these is outdegree centrality, which measure how many subcontractors a potential bidder is linked to. Next, potential bidder's hub centrality is calculated, which measures a firm's relative importance in the network by looking at the subcontractors it is connected to.[24] Potential bidders with high hub centralities work with subcontractors involved with many others in the network. Finally, network information is also used to determine whether firms are horizontal subcontractors to other contractors in the network which about half of potential bidder are.

The final variables of importance are the potential bidder pair data, which are theoretically predicted to cause affiliation. Descriptive statistics of these variables can be seen in

[22] Though difficult to see because of the many overlapping lines in the center, there are also several other potential bidders who have no observed subcontractors, but who are connected as horizontal subcontractors.

[23] We incorporate the firms with no network in Subsection 1.6.3 by including additional pairwise variables.

[24] In mathematical terms, hub centrality is the eigenvector corresponding to the largest eigenvalue of $A \times A^T$, where A is the Adjacency matrix of the network incorporating all link information about the network.

Table 1.3 and histograms of the distribution can be seen in Figure 1.3.[25] Overlap is calculated as the count of subcontractors shared between potential bidders. For planholders, the average pair shares 4.6 subcontractors though the distribution is right skewed since 7.5% of pairs have no overlapping subcontractors. For potential planholders the average pair shares fewer overlapping neighbors at 3.3 subcontractors and 12% of pairs have no overlapping networks.

To create the jaccard similarity, the number of overlapping subcontractors is divided by the total number of subcontractors used by the pair. For cosine similarity, the number of overlapping subcontractors is divided by the square root of the product of the two firms' total subcontractors used. Both similarity measures are laid out in Equation 1.1. Because of the presence of horizontal subcontracting, firms are linked to themselves so that they appear in their set of subcontractors. For the average planholder pair the jaccard similarity is 0.13 while for potential planholders it is only 0.10. Again, these number are skewed because there are many firms which share no subcontractors. The average and standard deviation of the cosine similarity is larger as the denominator is smaller. For planholders the average is 0.25 while for potential planholders it is 0.20. The distribution of both similarities can be seen in Figure 1.3. Most of the data has low levels of overlap, but the long right tail indicates that some firm pairs have high levels of overlap.

1.5 Results

With the ODOT data detailed in Section 1.4 and the discrete-choice method outlined in Section 1.3, it is possible to test for the existence of affiliation brought about by overlapping subcontracting, which is theoretically predicted in Section 1.2. General affiliation is also checked for as well, with the method outlined in LZ. We also explore the role of subcontracting

[25] Again, we take every subcontractor used in the prior 12 months by a potential bidder as in a bidder's network.

relationships on potential bidder's costs using the network centrality measure controls. When using SSMLE, the number of simulations done is a tradeoff between computational efficiency and statistical efficiency. LZ ran 100 simulations, but the nature of the method requires an increased number of simulations as the number of observations increase. For regressions on planholders, 400 simulations are used, and those on potential planholders, 700, to counteract the increased number of observations in the ODOT data, compared with Oregon timber data.[26]

The results for planholder's decision to bid, can be seen in Table 1.4. Column 1 is a standard probit model to compare the other models with. Column 2 contains a regression with only a general affiliation parameter. There is no evidence of affiliation between planholders decision to bid, and in fact the point estimate for ρ_0 is less than 0, but insignificant. Moving to the models with variable affiliation in Columns 3, 4, and 5, there is no indication of subcontractor created affiliation from the jaccard similarity, cosine similarity, or count overlap. The results do not show evidence of the theory, but there are concerns with the model. First, it does not have a great deal of explanatory power with a Pseudo R^2 of 0.044 in all five specifications. Second, the average probability of entry is 60%. Taken together these two facts mean the predicted errors feature little variation to find an effect, as conditional errors do not feature much variation.

As for the other coefficients, most traditional independent variables have the expected sign, or are insignificant. Turning to the network parameters, only the hub centrality has a significant effect on bidding behavior. Firms with higher hub centrality are shown to be more likely to bid. The high value for hub centrality suggests that it is not the number of subcontractors which affects a firm's cost on a project, but a firm's connections to highly used, and therefore experienced subcontractors.

[26] LZ dataset contains 282 timber auctions with 2,055 potential bidders. For a better understanding of the asymptotic properties of simulation-based methods, see Train (2009).

Turning to potential planholders' decision to become actual planholders, in Table 1.5 Column 2, there is evidence for generally affiliated costs. The point estimate for ρ_0 is 0.031, and is statistically significant. Bringing in variable affiliation leads to a substantial improvement in the model and ρ_1 being positive and significant at the 1% level in all three cases but is strongest with the cosine similarity. Once variable affiliation is allowed ρ_0 is no longer positive and significant. In fact, in the case of cosine similarity, ρ_0 is negative and significant. This result may be a product of plan buying being a sequential process, where a firm deciding to buy plans later can observe the firms which have already bought plans and avoid projects with high levels of competition and thus lower expected profits. Overall the potential bidder's plan buying decision is better predicted then the bidding decision with a Pseudo R^2 of 0.130 in the general affiliation case. This means the simulated errors contain more information about that can be used to forecast the other firms' decisions.

A few of the significance levels changed between Tables 1.4 and 1.5 particularly among the auction variables. Log working days and firm, went from being insignificant in planholder's bid decision to significant. This is again likely a product of firms choosing to avoid becoming planholders on less profitable projects.

The network variables continue to show similar effects as in Table 1.4, but the outdegree centrality and horizontal subcontractor dummy both become negative and significant. The horizontal subcontractor finding supports the theory of Marion (2015), that horizontal subcontractors face higher opportunity costs in bidding decisions. The finding about outdegree centrality combined with the continued positive sign on hub centrality reinforces the hypothesis that connections to subcontractors on the periphery of the network are less important compared to those in the center.

Throughout both decisions, cosine similarity served as the best predictor of affiliation between pair of potential bidders, while overlap served as the worst predictor. While the later results are not surprising since based on the theoretical discussion from Section 1.2, the former is. In the simulation results jaccard similarity and cosine similarity were about equal, but the empirical results show a clear preference for cosine similarity. We speculate that the increased variation within the cosine similarity distribution, due to the smaller denominator, is the reason for the improvement.

1.6 Robustness Checks

In this section several robustness checks are provided to show the results are not brought about by the assumptions made in the model. First in Subsection 1.6.1, we show that bid values are also affiliated with one another. Next in Subsection 1.6.2, we change the window size for the network from 12 months, up to 18 months and down to 6 months. Subsection 1.6.3 works to included potential bidders without networks into the model, with the inclusion of more potential bidder pair measures. Lastly in Subsection 1.6.4, we change the network so that subcontractor links are weighted by the dollar value of service instead of just a dummy for previous work.[27]

1.6.1 Affiliation in Bid Values

In Section 1.5, affiliation is found only between potential planholder and is strongest in the decision to buy plans. Potentially, affiliation could only be applicable to the early phases of the bidding process, after which affiliation no longer exists when firms submit their bids, due to information gained throughout the process. Alternatively, the inability to find affiliation between planholders could be due to the low level of predictive power of the model. To differentiate between the two possibilities, we test for affiliation between firms bid values. However, unlike the discrete decisions previously examined, affiliation between bid values is not proof of affiliated private costs, as firms may strategically change their bids to maximize

[27] While we present the robustness checks one at a time in the paper, there is nothing to prevent multiple from being tested at the same time. Any additional checks are available upon request.

profits. If firms are assumed to markup their bids linearly, as is done by others such as Kagel *et al.* (1987), then affiliation between bids is evidence that subcontracting causes affiliation in private costs. This assumption is stronger than those made above, and is unlikely to hold in practice, but the results still shed light on affiliation of bidder's costs.

The method used to test for affiliation between bid values is Bayesian, and is modeled as follows:

$$\log(bid_{ait}) = x_{at} \cdot \beta + z_{ait} \cdot \gamma + \epsilon_{ait} \tag{1.4}$$

just as in the discrete choice models x_{at} is a vector of project characteristics, z_{ait} is a vector of bidder characteristics and ϵ_{ait} is a normal distributed error term which is potential related across bidders in the same auction. The switch from a maximum likelihood framework in Section 1.5 to a Bayesian one is because the model now includes a contentious value errors, which can be found through analytically techniques instead of simulation. Still, the model has complex derivatives, but these can be sidestepped with the Bayesian model.

For the model's prior distributions, we assume an uninformed prior, with the affiliation parameters this is a uniform distribution between -1 and 1, while for the rest it is a normal distribution with mean of 0 and standard deviation of 10 times the variable standard deviation. The model uses a Gibb's sampler to sample from the posterior distribution. A sample from the posterior distribution is found using 4 chains of 10,000 samples thinned by 20 steps. Again, general affiliation as well as affiliation cause by subcontractor overlap are tested.

When looking to bidding behavior the sample size is greatly reduced with 1,921 bidders, 3,530 pairs, across 514 auctions. However, more information about the errors is revealed through the estimation process so correlation is easier to detect if present. Table 1.6 shows the results of the Bayesian regressions. Column 1 show a regression without affiliation. Due to the strong relationship between the engineer's estimate and bid costs the predictive power of the model is much stronger than the previous regressions. Column 2 shows a regression with only constant correlation parameter between bidders in an auction. The results indicate that there is a general correlation between bids which is significant at 1%. While this may indicate a general level of affiliation, it could also indicate there is an unobserved project characteristic which are causing bids to be correlated as well. Columns 3, 4, and 5 allow for affiliation related to jaccard similarity, cosine similarity and number of overlapping subcontractors just as above. In all 3 cases ρ_1 is positive and significant at the 1% level. The point estimates for all 3 are comparable to those found in Table 1.5. Finding variable affiliation among bid values supports the hypothesis that affiliation is present throughout the bidding process but is difficult to find between bid decisions since information on the error is scarce.

As for the other parameters all except the bidder's backlog have the expected sign or are insignificant. This may be due to backlog being correlated with a firm's size, which may indicate that there are returns to scale in the marketplace. Of the three network variables only the hub centrality has a significant effect, with firms with more extensive networks placing lower bids.

The results of Table 1.6 also highlight the importance of including pairwise affiliation to avoid bias in a model. Several control variables saw their point estimates shift due to the inclusion of affiliation. The most dramatic shift is seen for hub centrality, which fell by 21% from Column 1 to Column 4. If affiliation is not included the direct benefits of subcontracting are overestimated.

1.6.2 Changing Network Window

As mentioned in Section 1.4, a 12-month window for the network was chosen because in lined up with the 75$^{\text{th}}$ percentile of time between links that where repeated. But it is possible the window is too long or too short. As such in this section, the same regressions from Section 1.5 are presented with a 6-month and an 18-month network window. Both come to the same conclusions as the main results, though the 6-month window's finding are weaker.

Due to the requirement of setting up the network and dropping and firms without networks, the sample sizes change due to the changing network window. The models with only a 6-month window have more auctions, but fewer potential bidders and fewer pairs, giving less power to find affiliation, while models with an 18-month window have less auctions, about the same number of potential bidders, and more pairs, giving more power to find affiliation. For the sake of brevity only the estimates for ρ_0 and ρ_1 are presented in Tables 1.7 and 1.8. Both show the same effects or are insignificant, for jaccard and cosine similarity, though there are differences with regressions using the number of overlapping subcontractors with a 6-month window in the bid decisions. There potential bidders with higher overlaps see negatively affiliated values. This may occur because given the short window subcontractors who have worked on multiple projects may be near capacity and unable to perform work for either firm, forcing them to seek different firms to work with instead.

1.6.3 Incorporating Potential Bidders without Networks

In the main results, due to constraints viewing the past network all firms which had no observed subcontracting links in the previous 12 months were dropped. Without further additional variables, their inclusion would lead to a misestimation of the results since these firms would likely use some subcontractors from the available pool, and lead to potential affiliation. To include these previously dropped observations, three additional pairwise variables are added to equation (3). Thus, the affiliation between 2 potential bidders' errors is now:

$$\rho_{ijt} = \rho_0 + \rho_1 \cdot P_{ijt} + \rho_2 \cdot m_{ijt} + \rho_3 \cdot m_{ijt} \cdot c_{ijt} + \rho_4 \cdot mm_{ijt} \tag{1.5}$$

The new pairwise variables are m_{ijt} which measures if one, but not both potential bidders have no observed network in the past 12 months, c_{ijt} which measures the number of subcontractors the other firm has used in the previous 12 months, and finally mm_{ijt} which measures if both firms have no observed network in the past 12 months. In effect these cover the 3 possible cases the network coverage between 2 bidders. If both have an observed network only the P_{ijt} will be nonzero, if one has a network then m_{ijt} and c_{ijt} will be nonzero, and if both have no network then only mm_{ijt} will be nonzero. As such this specification does not make it more difficult to ensure the model is not violate the bounds of ρ_{ijt}, despite the increase in parameters.

Under the hypothesis of subcontractor network driven affiliation both, there should be variations in affiliation between these 3 cases. When only one firm has a network, theory suggests that affiliation rises as the firm with an observed network has more links, since there are more chances the subcontractors the firm without a network connects to one of the firms the other used. Similarly, if both firms have no observed network, they should be more closely related than 2 unlinked firms with networks, since they have a higher likelihood of subcontracting out to similar firms.

The results of incorporating the firms with missing networks are presented in Tables 1.9 and 1.10. For the sake of brevity only the pairwise variable results are presented. An additional dummy variable indicating if a firm has no observed network is also included when running the regression. Lastly, an increased number of simulations are run due to the increased sample size of including more firms. For Table 1.9, 450 simulation are used, while Table 1.10 uses 800.

The effect of network overlap, ρ_1, remains similar in all cases, to the main results where the unlinked firms were dropped. In further support of the theory the interaction between 1 firm having a missing network and the others count of subcontractors, ρ_3, is positive in all specifications though not always statistically significant. Similarly, pairs where both firms have no network, ρ_4, is also positive and statistically significant in all specifications.

1.6.4 Incorporating Dollar Weighted Networks

So far, we have assumed that all links between subcontractors are the same, both for the centrality measures and for the level of overlap for affiliation. However, subcontractors are used at different intensities so a weighted measure may be more appropriate. As such in this subsection, a weight is given to links based on the dollar value of projects subcontracted out in the previous 12 months.

To adapt the jaccard and cosine similaries to include weighted edges the following definition is used:

$$Jaccard_{abt} = \frac{\sum_{i=1}^{N} \min(link_{ait}, link_{bit})}{\sum_{i=1}^{N} \max(link_{ait}, link_{bit})} \quad Cosine_{abt} = \frac{\sum_{i=1}^{N} \min(link_{ait}, link_{bit})}{\sqrt{\sum_{i=1}^{N} link_{ait} \cdot \sum_{i=1}^{N} link_{bit}}}$$

where $link_a it$ is the dollar weighted link between contractor a and subcontractor i at time t. The set of subcontractors also includes the set of prime contractors, which leads the values of weighted jaccard and cosine similarity to be much smaller than that the unweighted versions because firms fulfill about 80% of a contract's costs themselves. Changing the network to a weighted network also changes the values of outdegree and hub centrality for the firms as well.

The results for this robustness check are shown in Tables 1.11 and 1.12. For brevity only the affiliation parameters and network parameters are included in the tables. The results for the jaccard and cosine similarities continue to be consistent with earlier results, though the overlap amount is insignificant. However, the centrality measures are less significant predictors as compared to the unweighted network. These contribute to a lower Pseudo R^2 values for all three decision. While initially surprising, the result may be due to another effect such as subcontractor backlogs, leading to the unintuitive result. It could be useful in future research to include both weighted and unweighted network measures simultaneously to separate the effects.

1.7 Conclusion

On the theoretical side, we find that the presence of overlapping subcontractor networks creates affiliation among the private values of firms. This theoretical prediction is then tested and found in the decisions of potential planholders, but not planholders on a sample of bridge auctions from Oklahoma. The difference in results is likely caused by several factors. First, statistical power is greatly increased when the definition of potential bidder is expanded to include 9,524 observations instead of 3,093.[28] Second the independent variables available at our disposal are better able to predict the potential planholder outcomes than the planholders based on the pseudo R^2, which reduces the overall noise in the model. Though the affiliation is found only using the broader definition of potential bidders, the finding is robust to changing the assumptions made in the paper about the network. Lastly, bid values are also affiliated in the sample because of subcontractor overlap, which under more restrictive assumptions also implies that private values are affiliated.

The results shown in this paper are likely of interest to both policy makers and econometricians. For the policy maker, the findings raise questions about how subcontracting affects government procurement costs. Previous work, including Milgrom and Weber (1982) suggest that the presence of affiliation will lead to decreased bidder aggressiveness and thus lead to higher cost for the state. However, our work also shows that subcontracting networks have a direct negative effect on costs. This leaves the overall effect of subcontracting on government costs ambiguous. Further work on the topic will still need to be done to determine which effect dominates. It is also possible that subcontractor related affiliation does not affect costs exactly as the standard models suggests. Affiliation has been shown to affect competition in different ways in different settings (see Haile 2001). Still, we recommend caution when evaluating policies that encourage intensive use of a narrow set of subcontractors, such as

[28]the increase in pairwise observations increases even more from 9,471 to 91,497 due to their being $N \cdot (N-1)/2$ pairs per auction.

DBE goals.

For the econometrician looking into firm behavior in auctions, the results reveal a new feature which must be considered. If overlapping subcontracting exists and she assumes an IPV framework in her model, results will be biased and inconsistent. This effect will likely be most severe when looking at variables related to subcontracting, as seen in Table 1.6. The methodology laid in this paper, also has potential applications beyond auctions to any setting where economic agents are making decisions and a network is likely to lead to correlated behaviors, such as students test taking in the example from the Introduction.

More work is still needed in this area beyond what has been done here. While work in this paper demonstrates that subcontracting overlap leads to affiliation, there are questions about how affiliation changes bidder aggressiveness as well. There are also other relationships such as common suppliers or joint ventures which could create affiliation in a manner like that of common subcontractors that exists in the market and are worth exploring in the future. Finally, work to incorporate variable affiliation into a structural model is another avenue for future research.

Chapter 2

Posthumous Trading Patterns affecting Artwork Prices

2.1 Introduction

Prior to their deaths, two 19^{th} century British landscape artists, J. M. W. Turner and Horatio McCulloch, experienced similar patterns of success selling paintings at auctions. Both were quite popular in terms of the breadth and depth of trading connections their art had established through the years. After their deaths, their popularity diverged. Turner became the eminent landscape painter of this era, with art dealers purchasing a larger share of his paintings. Dealers bought 77% of Turner's paintings compared to 42% of McCulloch's work. The most prominent art dealer of this period, Agnew, bought 28% of all Turner's paintings sold after his death. Changes in popularity were further mirrored in art prices. Turner's paintings appreciated by 122%, while McCulloch's sales prices fell by 32%. This divergence in prices can be seen up to the present day. The last 24 Turner paintings that went up for sale at Christie's and Sotheby's had an average hammer price of $926,000, while

McCulloch's last 16 paintings sold for only $25,800 on average.[1] Why did their popularity diverge so drastically? The prices at which their artwork sold following their deaths seem to have been influenced by the network of dealers and auction houses connected to them at the time of death.

Posthumous effects on art prices have been observed in the literature before, but previous work about its size and attribution have largely been inconclusive. Does the art market value the fact that an artist is alive, and can potentially produce more work? Or being alive is an impediment to posthumous market success once the artist has reached his or her peak? These questions remain unanswered. It is perhaps rather elusive to try and find a one-size fits all answer to the question of why it occurs and how it manifests itself. Nevertheless, we have now an opportunity to use comprehensive records from more than 37,000 transactions sold in London auction houses over a period of a century and a half containing information on artists who lived and died in that period. We combine these records with a set of tools to distill the effect of trading networks and provide a more in-depth analysis of the competitive landscape in this market around the time of an artist's death and beyond, tracing subsequent posthumous pricing patterns.

The influence an artist's death has on the price of their art depends on factors that affect demand and supply. Since art serves as an investment tool, the change in the pricing of artworks triggered by an artist's death has drawn attention from scholars in economics and finance. Agnello and Pierce (1996) were first to estimate an increase in prices after an artist's passing using regression analysis. Posthumous effects were documented anecdotally, however, well before Agnello and Pierce with comments by art dealers and even a play on the subject written by Mark Twain titled "Is He Dead".[2] Two plausible explanations have been offered for this trend. First, a temporary demand spike after death could be caused by an

[1] https://www.christies.com/ and https://www.sothebys.com/en/ Accessed January 4, 2020

[2] The play is about a famous French painter Jean-Francois Millet. An American artist helps Millet fake his death with the idea that the price of his paintings will skyrocket, and they will escape poverty.

increase in media attention (Ekelund, Ressler, and Watson 2000 and Matheson and Baade 2004). Alternatively, elimination of supply uncertainty could lead to a permanent increase in prices. Maddison and Jul Pedersen (2008) use data on Danish artists, and Danish life expectancy, and their findings suggest that conditional life expectancy of the artist at the time of sale (which is a proxy for anticipated supply conditions) has a statistically significant negative effect on art prices. Once conditional life expectancy is included, the posthumous effects are no longer statistically significant. Ursprung and Wiermann (2011), show that the death effect is negative for young artists, becomes positive with age and eventually disappears.

The demand for artworks depends crucially on an artist's reputation. Reputation effects are hard to measure and have largely been absent from the literature. Reputation is managed in the primary market for art by gallerists and art dealers. Schrager (2013) notes that "the industry has developed an intricate signalling process where a handful of galleries, collectors and museums, determines what is good and valuable." Grant (2010) points out that "the factors determining whether prices will go up or down are much the same when an artist is dead or alive. These factors include the degree to which the market of an artist's work is controlled, changes in critical and popular appreciation, the manner in which dealers heirs or estate executors handle work in their possession and how collectors behave." The dealer's ability to strategically drive demand through developing an artist's reputation depends on a dealer's network and the strategic planning of sales following an artist's death. Greater access to art professionals prior to an artist's death is likely to affect the trajectory of prices of his work providing vital information in addressing this puzzle.

In this paper, we construct measures of network access and use a quantile regression technique with selection, developed by Arellano, Blundell, and Bonhomme (2017), to evaluate the drivers of art prices, with focus on the ''death effect" and posthumous trading patterns extending to 20 years after an artist's death. Even though there is a vast literature on networks in economics and broadly the social sciences[3], there is very little empirical work examining the effect of trading networks on prices. Oestreicher-Singer and Sundararajan (2012) find that co-purchase networks have an effect on the demand for books sold on Amazon. Aral and Walker (2012, 2014) find that influential users of Facebook cluster together and have differential effects on other users based on observable characteristics, such as age and sex. In the art world, Mitali and Ingram (2018) find that artists with many personal connections but who are not clustered together are more successful in raising their artistic profile. De Silva *et al.* (2020a) find that networks between art dealers and sellers create informational advantages that are reflected in beneficial trade conditions. Our results indicate that the strategic planning of sales following an artist's death can have a significant impact on art prices in the short and long run.[4] Access to art professionals prior to an artist's death significantly affects the trajectory of prices for the most highly priced works of art.

In a similar approach to Etro and Stepanova (2015), we use an historical set of data which uniquely allows us to look at all art auctions that took place in London from 1741 to 1913 to study the death effect. We find, contrary to most of the literature, a decline in unconditional prices by 7% on average in the 20 years following the death of an artist. At that time, the art seller is much more likely to be listed as a member of the artist's family (0.7% of art was sold before death under an artist's last name versus 13% that was sold after death). These works are sold for much less than other artworks by the same artist bringing forth considerations of poor quality and strategic planning. Artists themselves may strategically withhold some artwork from the market, while families acting without consultation with professionals may engage in nonstrategic liquidation of assets. While these considerations

[3] Examples include friendship formation in Christakis *et al.* (2010), job searching in Granovetter (1977), and microfinance adoption in Banerjee *et al.* (2013), and Schilling and Phelps (2007) and Gaonkar and Mele (2018) dealing with interfirm patent collaboration, among many others.

[4] The impact of various strategic and non-strategic effects on price trends in sequential sales has been studied among others by Black and De Meza (1992), Ginsburgh (1998), Deltas and Kosmopoulou (2004) and Ginsburgh and Van Ours (2007). Deltas and Kosmopoulou also provide an overview of conditions under which various price patterns can arise in equilibrium.

might hold in a short period after the death of an artist, the negative effect in the long term is mostly predicted by changes in the composition of the pool of buyers. Artists who see a rise in price posthumous are bought more often by emerging art dealers. Since only a few artists experience an increase in dealer interest, most artists' works see a decline in price after the artist's death. The lack of a significant trading network developed through auctions prior to death diminishes the chances of an artist's work gaining popularity postmortem. These changes in the buyer pool is likely not the direct cause of the price change, rather underlying evolution of collector's taste is at play. However, without a good measure for taste we argue eigenvector centrality is a useful proxy.

The rest of the paper is organized as follows: Section 2.2 describes the data and how we construct the trading network measures for the artists and sellers; Section 2.3 describes the model and the results. Finally, Section 2.4 offers concluding remarks.

2.2 Data

The source of our unique historical data set is the auction transactions recorded by (Graves, 1918). In three volumes, Graves documents art auctions that took place in London-based auction houses from 1741 to 1913, including the name of the auction house. We retrieved these three volumes from the Victoria and Albert Museum Library in London. Graves recorded the name of the artist and his/her living status, the name of the artwork and year of origin, and the medium (painting, figurine, etc.). Using the name of the artist, the painting, the title of the painting, and the year of origin, we can categorize each artifact into a school, movement or a period. The unique feature of the data is the availability of the original sellers' and buyers' identities in the transactions. However, besides the first and last names of the buyers, the original data does not provide any other biographical information. Therefore, we used museum archives to identify art dealers among our buyers. With this search, we were able to classify 138 distinct buyers as dealers who, in total, account for 43% of all transactions.

Note that all lots were sold using an English auction format and only the final hammer price is recorded. The size of the dataset, and the length of the time period that it covers, provide a unique opportunity to trace price fluctuations and trading network connections throughout an artist's lifetime and beyond his death.

The data allows for the construction of two time-evolving networks used to capture market influence. The first is a bipartite network that links buyers and artists through auction trades.[5] The second is a directed network that links buyers and sellers.[6] Both networks are updated monthly and use a 10-year moving window to capture the relevance of recent information and limitations in institutional memory for dealerships.

Based on the artist-buyer network, we calculate the artist's eigenvector centrality, weighted by the number of artworks sold. This measure captures the relative importance of individuals in the trading network by considering their full set of trading links across the market that occurred before the transaction. It is a proxy of the influence that an artist's buyers have in the market and reflects the confluence of reputation and popularity of the artist.[7] Reputation is keenly important in the art world but is often difficult to measure. Ursprung and Zigova (2020) use the length of an artist's obituary as a indicator of reputation. Similarly, in another effort to isolate general reputational effects, Campos and Barbosa (2009) find that paintings exhibited prominently or listed in a *catalogue raisonné*, a compendium of an artist's work, sell for a premium.

Eigenvector centrality is a measure attempting to find the most important nodes (indi-

[5] A bipartite network is one in which there are two distinct types of nodes that always connect to a node of a different type. The network is considered bipartite because the set of buyers and artists do not overlap.

[6] A directed network is an appropriate framework to represent links between buyers and sellers, since they have distinct roles with potential overlap. The same individual could be a buyer in one occasion and a seller in another, which occurs for about 10% of the buyers and sellers.

[7] Even though the reputation of an artist's work is often difficult to assess, Fraiberger *et al.* (2018) use eigenvector centrality to assess museum and gallery prestige.

viduals) in a trading network by incorporating information about the buyers who purchase the work of an artist.[8] An additional link to any buyer will increase an artist's eigenvector centrality, but the size of the increase will vary based on the number of connections the buyer has. A buyer with no other purchases will cause only a minimal increase, while a purchase by Agnew, the biggest art dealer, will increase it much more. Thus, artists with many connections to important buyers will have high eigenvector centrality.[9] In our sample, those important buyers tend to be art dealers, who buy about 50% of art. The eigenvector centrality is weighted according to the number of art pieces sold, to assign weight and importance to artists who are repeatedly bought at auction by the same buyer. The buyer-seller network allows us to capture which sellers have been present in the auction market before, and how often they sell. Because of the heavily right-skewed nature of the network variables, we include them in their logarithmic form in all regressions.[10]

Reputational effects of other parties involved in the auction might also affect the prices at which artworks are sold. Sellers with frequent dealings in the market may see their lots sell for more as the risk of forgery is lower. Similarly, works with anonymous sellers may suffer a penalty for not revealing their identities. Lastly, the reputation of the auction house must also be considered. During the time frame, Christie's was the preeminent auction house responsible for 95% of all auction sales.

We restrict the sample to include only those artworks sold within 20 years of an artist's death and only artists whose paintings were sold before and after their death. In Table 2.1,

[8] The eigenvector centrality of all the nodes in a network is the principal eigenvector of the adjacency matrix, which is an $\mathbf{N} \times \mathbf{N}$ matrix containing all the information about links between nodes. Bloch, Jackson, and Tebaldi (2019) includes a full explanation of eigenvector centrality and as well as other centrality measures.

[9] Calling the importance of each node in the network as its centrality score, in measuring eigenvector centrality we want the centrality score to be proportional to the sum of scores of all nodes which are connected to it. This way if a node is connected to another important node, it will also be important and vice versa. A more detailed definition of eigenvector centrality and the other variable included in the paper are included in Appendix Table A2.1.1

[10] Many networks, including our networks, follow a power-law distribution characterized by a long right tail.

we provide summary statistics broken down by sales before and after death. We observe 3,127 artworks sold before death and 4,633 sold after death by 160 different artists. This is a substantial increase in sample size relative to most of previous research. Ekelund, Ressler, and Watson (2000) included only 21 artists in their sample, Matheson and Baade (2004) had 13 baseball players, and Maddison and Jul Pedersen (2008) included 93 artists. An exception is in the work of Ursprung and Wiermann (2011) who, despite their considerable sample size, focused on the most prolific artist who sold more than 250 pieces over 26 years. Most of our observables about the artworks remain largely unchanged, with a few notable exceptions. First, the average price falls significantly after death from £382 to £355, while the standard deviation rises from £508 to £566. These two changes suggest that there are differential effects throughout the price distribution. Second, art sold with a seller's name that matches the artist's name increases from 0.7% before death to 13% after death.[11] Since an artist cannot sell work after death, this increase is mostly because the families of artists were typically selling off art from their workshops by way of an estate sale. Thus, we refer to this sales as those sold by family. Artworks sold by the family sell for much less on average than those sold by others (£184 compared to £382) and have a strong effect on price within the first two years of an artist's death. Panel A of Figure 2.1 shows the density in log prices, identifying whether a seller's name matches the artist's name, in the 20 years after an artist's death. The artworks sold by the family of the artist are sold at far lower prices compared to the full sample and are commonly found on the left tail of the combined price distribution. Panel B of Figure 2.1 shows the timing of pieces sold. For works not sold by family, sales are consistent throughout the 40 year time period, but 47% of all works sold by family happen in the year immediately following an artists death, and an additional 8% are sold the following year.[12] The lack of strategic consideration on behalf of the artists' families is a considerable

[11] Names were matched according to the last name and first initial.

[12] The other large spike at nine years after death is from sales of a single artists work, Benjamin West.

factor contributing to the short-term fluctuations of prices posthumously. While art sold by the family may be an important determinant of price changes after death, this observation offers an incomplete explanation of the price trend as 79 out of the 160 artists did not have family sell their works after death.[13]

Finally, there is an increase in both measures of artists' trading networks. An artist's market influence measured by his eigenvector centrality increases from 0.0055 to 0.0113 and the number of pieces sold increases from 30.6 to 43. This raw change misrepresents how artists' networks are changing, as it oversamples artists with many paintings sold. By comparing an artist's eigenvector centrality at death to later times, we avoid this problem. Only 33.8% of artists have higher eigenvector centrality ten years after death than at the time of death, while 37.5% did not have any artworks sold during the same period. The decline is even more dramatic 20 years after death, with only 25.6% of artists having higher eigenvector centrality than at death, while 45.5% of artist had no artworks sold for ten years.

Those artists with high eigenvector centralities at death continued to have higher eigenvector centralities after death as well. Due to the skewed nature of eigenvector centrality the natural logarithm is taken. At 10 years out, current log eigenvector centrality and log eigenvector centrality at death still strongly correlated, with a correlation coefficient of 0.532.[14] At 20 years out, the correlation remained strong at 0.432. In a similar vein, artists with high eigenvector centralities were more likely to continue to be sold after death. Those artists with sales 10 years after death had an average log eigenvector centrality at death of -8.34, significantly higher than that of artists with no sales, at -9.58. The difference is even more stark at 20 years out, where those with sales had a log eigenvector centrality at death of -7.74 compared to a log eigenvector centrality of -9.41 of those with no sales.

[13] This includes J. M. W. Turner and Horatio McCulloch, the two artists mentioned in the introduction.

[14] This is despite the fact that no artworks have been included in both groups as the window for link formation is 10 years.

2.3 Empirical Analysis

In this section, we model how changes in network structure can explain the downturn in artwork prices following an artist's death in the 19^{th} and early 20^{th} centuries. The first model we estimate is a hedonic regression model of logarithmic prices with artist fixed effects, followed by a quantile regression analysis to study behavior across the distribution. Ashenfelter and Graddy (2006) provide an excellent overview of the merits of the hedonic pricing model relative to the repeat sales methodology for art price indices, where the price of the ith artwork sold in time period, t, is determined by a small number of by now, conventional hedonic characteristics, x, controlled for in the regression. We control for all the usual characteristics that are used in these hedonic pricing models, such as artist, size, medium, and genre. The unique contribution of this dataset is that in addition to the usual hedonic characteristics, we have the identity of the buyers and the sellers, and can identify their status, for example, as a dealer, collector, aristocrat, or artist.

Since all prices are determined through an auction process, selection on buyer observables is a consideration. Different classes of bidders, such as art dealers, may have different willingnesses to pay for attributes creating differences in price. Because our main variable of interest relates to who buys a work, selection bias would be problematic. Thus, we use the two-step Heckman process (1979) to estimate the mean, and the method of Arellano, Blundell, and Bonhomme (2017) to estimate the quantiles of the response variable. Their method corrects for selection by adjusting the percentile level of each observation based on the probability of selection. In practice this requires a three-step process. The first step uses a probit model to predict selection, which in our case is the probability that a bidder wins the auction. The second step estimates the correlation between the probability of winning and the price. This correlation, along with the probability of winning and the Gaussian copula[15], determine the level to which each observation's 'check' function, from a standard

[15] The Gaussian Copula describes the joint probability distribution of correlated normal random variables

quantile regression, needs to be rotated. To find the correlation parameter that best fits the data requires a grid search, testing values from the full range and selecting the one with the best fit in selected quantiles.[16] The final step then estimates all the quantiles of interest utilizing the estimated correlation.

Since all works are sold in an English auction, the hammer price will be determined by the second-highest bidder's willingness to pay. Thus, we allow bidders of different types-in particular, art dealers-to have differing values of an artwork based on its observable characteristics. As such, we interact a dealer dummy variable with all observable characteristics. Introducing a selection model allows inclusion of additional buyer specific variables which are determined endogenously through the auction process. Thus, our first stage model is:

$$Pr[win_{abt}|X_{abt}, dealer_{bt}] = \Phi(\beta \cdot X_{abt} + \gamma \cdot X_{abt} \cdot dealer_{bt}) \tag{2.1}$$

where X_{abt} captures seller, artist, bidder, and artwork characteristics, and includes a variety of controls such as dummy variables for seller's type (artist, collector, unknown, etc.), the logarithm of the seller's volume of past sales, an artist's log eigenvector centrality and log of the number of artworks sold. X_{abt} also includes the buyer's log eigenvector centrality and log capacity, time trends, and the logarithm of the number of buyers. The estimation incorporates a dummy variable for whether a work of art was sold at Christie's, whether it was part of a collection, the artist's age, artistic school, artwork medium, and artwork genre.[17] Lastly we also include variable incorporating information about the rival bidder likelihood of winning including the maximum rival log eigenvector centrality, maximum rival capacity, and the percentage of bidders who have purchased the artists work previously. Since a full record of all bidders of an artwork are not known, we consider all winning bidders at

and is used to connect the error of the selection stage to the pricing stage.

[16] We use the 0.20, 0.40, 0.60 and 0.80 quantiles just as Arellano, Blundell, and Bonhomme (2017) did.

[17] We could not adequately control for art size, as only a third of artworks have size measurements in the data.

the auction house on the day of sale as potential bidders. The bidders who won items in an auction sale were typically present throughout the day's auction on the floor assessing competition and planning their bids. The average auction had 112.8 pieces for sale, bought by 41.3 buyers. Bidders had an opportunity to submit 316,512 potential bids on artworks sold within 20 years of an artist's death, of which about one-third could have been generated by dealers.

The results of this first-stage regression can be seen in Table 2.2. Non-dealers are less likely to purchase art created by artists with higher eigenvector centrality and more likely to purchase art from artists with many artworks sold in the past or from unknown sellers. Art dealers are more likely to purchase art by contemporary British artists. A buyer's eigenvector centrality is of importance to only the dealers' likelihood of purchase. Interestingly, the rival eigenvector centrality and capacity only affect a dealer's likelihood of winning but not a non-dealer's, hinting at strategic consideration more prominent in dealer's actions.

In the second stage for the mean regression, the log price is estimated using a Heckman two-step process:

$$lnprice_{abt} = \beta \cdot ph_{abt} + \delta \cdot X_{abt} + \sigma_{12} \cdot \lambda_{abt} + \alpha_a + \epsilon_{iat} \tag{2.2}$$

where λ_{abt} is the inverse mills ratio of bidder b on piece i by artist a, generated from the estimation of the probit model. The model also includes artist fixed effects. Lastly, ph_{abt} is a dummy variable identifying whether an artwork is sold after an artist's death.

Due to the price variance increasing after death, we then estimate a fixed effect version of Arellano, Blundell, and Bonhomme (2017) to assess how the death and network effects change the distribution of prices. The same first stage from the Heckman model is used to find the selection error, but the method for calculating the correlation between the first and second stage errors is different. The correlation coefficient, $\hat{\rho}$, is estimated through a grid search. Using $\hat{\rho}$ from the second stage grid search and the inverse Gaussian copula the final stage becomes:

$$Q_{lnprice_{iat}}(\tau|ph_{iat}, X_{iat}, \hat{\rho}) = \beta_{G^{-1}(\tau,\hat{p}(z);\hat{\rho})} \cdot ph_{iat} + \delta_{G^{-1}(\tau,\hat{p}(z);\hat{\rho})} \cdot X_{iat} + \alpha_{aG^{-1}(\tau,\hat{p}(z);\hat{\rho})} \quad (2.3)$$

where $G^{-1}(\tau, \hat{p}z; \hat{\rho})$ is the inverse Gausian copula, between the first and third stages. Due to the nature of the model, standard errors are estimated using bootstrapping.

The results of the panel quantile regression can be found in Table 2.3. In Panel A, we included only an artist fixed effect and a dummy variable for the living status of the artist, but no correction for sample selection. A significant negative effect is observed in all but the 0.10 conditional quantile. In contrast, when controls are added in Panel B, there is no significant posthumous effect at any quantile, suggesting the observable changes in an artist's network and estate sale strategy can explain the large decline in prices. The same results are shown graphically for all quantiles in Figure 2.2. While sample selection was possible, we did not find a statistically significant relationship between the first- and second-stage errors as seen in $\hat{\rho}$ being insignificantly different from 0 at both the mean and across the entire distribution.[18] This low correlation is most likely due to the winner being the bidder with the highest private value for the artwork but the price being determined by the second-highest private value. Of the controls introduced in Panel B, the sale of artwork by family members has the most profound negative effect on prices. The effects can also be seen graphically in Panel B of Figure 2.3. Consistently, across the distribution, we observe a steep decline in sales prices for those families who did not use professional consultation and chose to sell directly at auction.[19] The art market, in general, seems to place a heavy premium

[18] Results of the regressions without sample selection are quantitatively the same and are available from the authors upon request.

[19] Interestingly, the mean estimate is below all the quantile point estimates between the 10^{th} and 90^{th} quantiles. This is most likely caused by a severe penalty in the quantiles below the tenth. Due to the artist fixed effects, a consistent estimate below the tenth conditional quantile is impossible.

on reputation, with art sold at Christie's, the leading auction house, selling for a premium. Paintings sold by anonymous sellers sell for significantly less. The insignificant effect of the seller's volume of transactions is most likely due to low variation of sales numbers per seller.

Networks developed through the auction trades have a beneficial effect on prices. An artist log eigenvector centrality has a strong positive influence on prices, with the strongest effect observed near the median of the distribution. The effect at all quantiles can be seen in Panel A of Figure 2.3. Note that, the volume of artwork is controlled and has a negative effect throughout the distribution.[20] The buyers log eigenvector centrality has a negative effect on prices, suggesting that those buyers with large networks are able to discover underpriced works. The result is in line with findings in De Silva *et al.* (2020a) suggesting that a network is a source of information creating advantages that are reflected in beneficial trade conditions. This effect is strongest at the upper end of the distribution. Similarly, dealers pay lower prices when they buy, compared to non-dealers.

Prices continue to evolve overtime estimated through the use of a cubic time trend included in all regressions.[21] However this trend does not intuitively describe price changes overtime. As such, we ran a second regression replacing the time trend with three dummy variables identifying non-overlapping time intervals after an artist's death. The first covers the first two years after death, the second from two to ten years after death and the final from ten to twenty years after death. Since all other coefficients are nearly identical to the first model, only the estimates of the dummies are shown in Figure 2.4. None of those point estimates are statistically significant at the 5 level, though the point estimates are lowest

[20] Results of a robustness check replacing the artist's log eigenvector centrality with the log count of dealer purchases is available upon request. This measure is more intuitive but lacks the ability to differentiate within groups. It does not capture the relative importance of a dealer in comparison to others. As such, it suggests that dealers with a high count of previous purchases buy a lot more inexpensive art, while the results on eigenvector centrality suggest that important dealers (in relative terms) not only buy inexpensive artwork but highly-priced pieces as well.

[21] The cubic time trend was chosen as it offered flexibility about the evolution of prices around an artist's death.

between the 0.5 and 0.75 quantiles and in the second window.

While artists' trading connections have a significant effect on prices, it is less clear whether a network that has been developed around the time of death is a good indicator of prices in the years after an artist's death. To explore this question, we focus on the log eigenvector centrality in the 10-year window ending with the month an artist died, as a measure of the artist's importance in the network. In particular, we estimate the following model:

$$lnprice_{it} = \beta \cdot lneigenvector_{it} + \delta \cdot X_{it} + \epsilon_{it} \tag{2.4}$$

The regression includes all the same controls introduced earlier except for the artist fixed effects and sample selection, since eigenvector centrality at death is constant per artist, and there was no evidence of statistically significant sample selection in the previous regressions. We run this regression on both the mean using OLS, and on the distribution using quantile regression, similar to the previous estimation efforts. The regression is repeated for three time windows after death. The first includes information for two years following death, the second from two to ten years, and the final from ten to twenty years.

The results for the effect of log eigenvector centrality at death on log price can be seen in Table 2.4 and Figure 2.5. At the mean, the log eigenvector centrality is significant only in the first window. The point estimate also falls as the window span increases. If we instead consider the conditional quantiles, an interesting pattern emerges. For the 0.25 conditional quantiles the effect of the eigenvector centrality at death is indistinguishable from zero in all three windows. It is only at the upper tail that a significant effect can be seen. At the 0.90 conditional quantile, the effect is highly significant with a magnitude that diminishes gradually after death. In fact when looking at the upper tail, the eigenvector centrality at death is a stronger predictor of price in the ten to twenty year window, compared to the two to ten year window. Even twenty years after death the network at death remains significant at the 1% level for high priced art. For all the other quantiles there is a steep decline in the effect of this measure on price with distance from death.

The dataset provide us with a unique opportunity to investigate the role of the family on the price distribution following an artist's death. In Table 2.4, we see that sellers with the same family name as the artists sell the most expensive artworks first, with the highest coefficient on the 90% quantile. The coefficient is negative and statistically significant, providing empirical evidence that the artworks are sold at a discount and indicating that families sell the most valuable paintings first. Since we only capture a fraction of the owners of the estate, it is likely that we underestimate the effect of family sales. It is interesting to note that, in the time horizon between ten and twenty years after the death of an artist, the results become positive and statistically significant in the center of the distribution, reinforcing the belief that nonstrategic sales dominated family actions in the period immediately after an artist's death.

The quantile regression results in Table 2.4 for the 0.9 quantile, which represents the high end of the price distribution, is reflective of the masterpieces of the time. Our findings suggest that, network effects increase sales prices more at the higher end of the sales distribution and could help bridge studies of repeat sales data to network effects in primary sales, to shed light on price patterns for masterpieces of this era, especially the subsequent under-performance of Masterpieces noted in the seminal works by Pesando (1993) and Mei and Moses (2002), but notably not by Goetzmann (1993). Our findings suggest that, any subsequent sale would need to incorporate the price premium for network effects at the higher end of the sales distribution affecting the performance of this art in the secondary market.

2.4 Conclusion

The results of this study identify two factors contributing to price fluctuations in artwork after an artist's death. Nonstrategic estate sales by family members of an artist and a dealer's buying interest both have a significant impact on the change in art prices over time with differing short and long term effects. Analysis of network measures allows us to capture factors that were not accounted for in the literature before, to explore the death effect in art prices. Once several network measures are introduced (to capture the reputation of artists and influence of buyers) and we consider the dynamic evolution of prices in the 19$^{\text{th}}$- and early 20$^{\text{th}}$-century English art market, the negative death effect captured by a unique identifier gets to be attributed to other distinct factors.

The development of network measures also allows us to observe a mechanism by which art prices change over time. J. M. W. Turner's paintings saw an appreciation in value after his death because his works were overwhelmingly bought by art dealers with high connectivity captured by their eigenvector centralities. These purchases by dealers helped elevate his reputation and sale prices significantly over time. Horatio McCulloch's works conversely saw a decline in value due to his art being bought more frequently by individuals with no professional market engagement, who were less likely to make repeat sales (see Figure 2.6). While McCulloch did not see a decline in the number of dealers who purchased his art, the dealers who did buy his work were less connected through trades than those who bought from Turner, as seen by the smaller size dots representing them in the scatter plot.

While our results are able to explain away the death effect, the question still remains as to why a negative unconditional death effect exists in the 19$^{\text{th}}$- and early 20$^{\text{th}}$-century art market, while the opposite is observed in other more modern samples. We would point to the increased sample size of our dataset, especially the number of artists. Smaller datasets tend to focus disproportionately on artists with more prominence, creating a bias toward positive effects in prices. Even Ursprung and Wiermann (2011) who use a large dataset spanning 26 years, are still basing their conclusions on a sample of top achievers who have been sold at least 250 time throughout the period. In that sense, our dataset provides the opportunity of tracing a large number of artists for a long period of time, providing a more complete sampling from the distribution of sales.

Chapter 3

Subcontracting and the Incidence of Change Orders in Procurement Contracts

3.1 Introduction

A pervasive feature of procurement contracts is their susceptibility to ex post renegotiations. Typically, these renegotiations are executed through "change orders." Government agencies, while recognizing their ubiquity, are keenly aware that change orders are costly. On the one hand, there are costs associated with adapting the project due to delays, the re-scheduling of tasks, haggling and legal expenses. Bajari *et al.* (2014) estimate that adaptation costs add between 8% and 14% to the average California highway construction contract. On the other hand, in itemized-bid contracts, firms that anticipate change orders in some items, can skew their itemized bids strategically, thereby inflating ex post project costs (Jung *et al.* 2019; Miller 2014). If letting agencies are better able to forecast the incidence of change orders, they could reduce total project costs and accordingly benefit taxpayers.

Previous studies of change orders tend to emphasize the complexity and uncertainty surrounding contracting as key influences on the likelihood of renegotiation (see Anastasopoulos *et al.* 2010; Bordat *et al.* 2004; Hsieh *et al.* 2004; Iossa *et al.* 2007; Oudot 2006). Our focus is on the role of subcontractor use on contract renegotiation. Like change orders, subcontracting is widespread in many procurement contexts. In our dataset of Vermont highway projects, the average project employed 5.09 subcontractors, while 90.7% of projects used at least one subcontractor. Government interventions in highway procurement encourage the use of subcontractors through disadvantaged business enterprise (DBE) programs. Previous work on the effectiveness of DBE programs stops short of considering their entire impact by analyzing only the bidding stage of the process. These studies find mixed results ranging from no increase to small and in some cases insignificant increase in procurement costs (De Silva *et al.* 2012; Marion 2009). If subcontracting leads to disproportionate increases in procurement costs at the implementation stage of the project, then the evaluation of different DBE programs is incomplete.

Our dataset consists of all Vermont Agency of Transportation construction (VTrans) contracts procured between May 2004 and December 2009. In OLS regressions using these data, the number of subcontractors significantly raises the number of change orders and the dollar amount of the contract that is renegotiated. There are two possible interpretations of this association. First, more complex projects that use more subcontractors are more likely to require renegotiation. In this interpretation, the positive conditional correlation is caused by an omitted variable capturing unobserved complexity. The second possibility is that the number of subcontractors on a project directly increases the probability of renegotiation. Subcontractors might have a direct impact on the probability of renegotiation because of poor coordination and miscommunication between subcontractors and prime contractors. This possibility is substantiated in the literature (Masten *et al.* 1991; Miller 2014). An additional reason that subcontracting might contribute to change orders is because of incentives resulting from procurement regulations. For instance, in Vermont, the Agency of Transportation applies a ten percent premium payment to primes above subcontractors' costs when new items are added to the contract.[1] It is conceivable that this regulation could lead prime contractors to engage in behavior that increases the likelihood of new items being added, and then to employ subcontractors for the task in order to obtain the ten percent profit.

To determine which interpretation is correct, we use an instrumental variable, the predicted number of subcontractors estimated from a sequential Bayesian framework modeled based on Christakis *et al.* (2010) and adjusted to a dynamic setting. This IV helps us disentangle the subcontracting activity from unobserved project complexity as a cause for renegotiation. The model allows for interdependencies in subcontracting decisions and includes information on the experience of subcontractors and the networks developed by both contractors and subcontractors. Our analysis includes control variables representing project characteristics, such as the size and complexity of the project, and its geographic location, that make the work of the state engineer who is tasked with project planning more difficult. These increase the likelihood that the plans will need to be revised after the contract is awarded. We also control for the characteristics of the prime contractor. It is possible that large firms exert more influence on project design ex post and are more likely to be able to convince the state authorities that change orders are required. The IV provides additional information about a firm's subcontracting needs and habits that are independent of any unobserved complexity of the project. We find that subcontracting leads to significantly higher ex-post change orders and a higher dollar renegotiation amount, supporting the view that there is a causal link between the use of subcontractors and contract renegotiation. In doing so we contribute to a growing literature on the indirect effects of subcontracting on procurement auctions (Branzoli and Decarolis 2015; Marion 2015; De Silva *et al.* 2017).

[1] See page 1-137 of the VTrans Standard Specifications for Construction 2011.

The paper proceeds as follows. Section 3.2 provides a description of the data. Section 3.3 describes our model. Section 3.4 presents empirical results and section 3.5 offers concluding remarks.

3.2 Data and Descriptive Analysis

The data used in this paper contains information on all 312 construction projects auctioned by the Vermont Agency of Transportation between May 2004 and December 2009. Our dataset provides information on project scope, date, duration, and cost estimates made by state engineers prior to the auction. The engineers stipulate all items required for the contract, and the quantities of each item. Firms provide itemized bids, from which a project-level total bid is calculated. The state awards the contract to the lowest-bidding qualified firm. Change orders are either adjustments in the quantity of a pre-specified material or task, such as asphalt or roadside flaggers, or the addition of a new item not originally contemplated in the plans.[2] For each change order on each project, we know the changed quantity and unit-price for every renegotiated item within a contract. Regulation requires that change orders be filed if the changes of plans or specifications impose at least a 5% increase in costs. Nevertheless, it is the practice of Agency engineers to submit change orders whenever the quantity of any item in a project increases by more than ten percent, even if total project costs increase by less than the five percent threshold.[3]

As shown in Table 3.1, 254 of the 312 contracts in our sample had at least one change order. The mean number of change orders in those projects was 4.27, resulting in an average

[2] A special case of quantity adjustments are when the item is dropped entirely from the project. Besides those quantity adjustments, there are some limited price adjustments applied to asphalt or fuel items when unforeseen circumstances lead to large fluctuations in the price of oil. These price adjustments are made according to formula linked to the price indexes of those items and are beyond the discretion of the firm or the agency. We restrict attention to change orders filed for quantity adjustments.

[3] The engineers do this in order to avoid onerous reporting requirements if those increases are only reported after the project is completed, rather than while it is in progress. We thank Deputy Chief Engineer Ann Gammell for this information.

cost increase of 7.2% over the winning bids. Over the period of analysis, VTrans spent an average of $105,020 on renegotiations per contract. Most change orders include some renegotiation about unanticipated tasks in the field. The histograms presented in Figure 3.1 clearly show skewed distributions for both the number of change orders, and for the dollar amount of the change order.

The Vermont Agency of Transportation awarded the 312 contracts to a total of 62 firms. These firms used an average number of 5.09 subcontractors on each project. The distribution of subcontracting use is depicted in Figure 3.2. The histogram shows the distribution of subcontractors. The most frequent number of subcontractors is 5 or 6. Projects are relativity likely to feature 0 or 1 subcontractors, but relatively unlikely to use 2 or 3 subcontractors. The average project consisted of 60.2 items, 31.9 of which on average were subcontracted out, representing 19.8% of the winning bid. Figure 3.3 presents the distribution of items and the percentage of those completed contracts by subcontractor on projects that used at least one subcontractor. The percentage of contracts completed by subcontractors, follows a similar distribution to that of the number of subcontractors. The distribution of items shows that while in most projects few items are completed by subcontractors, there is a long tail. Both panels in this figure show that while subcontracting is an important part of highway construction it makes up only a relatively small portion of the monetary cost of a project.

From the data on subcontracting, we create a time evolving directed network which connects contractors to the subcontractors they used over the previous 12 months in Vermont. An image of the network can be seen in Figure 3.4. Each node represents a firm in the market over the full length of the dataset. Nodes are colored according to their position in the network. Firms which worked only as contractors are represented by white nodes, while firms which worked only as subcontractors by red. The pink nodes represent firms working as both. Only 30 of 277 firms worked in both capacities. Nodes are adjusted in size to reflect the relative number of connections in the market while the thickness of links between nodes represent the number of times firms worked together. At the center of the network are a few contractors and subcontractors who are very active in the market. In the periphery are located firms with lower level of activity. Finally, there is a group of subcontractors that have only been involved in one contract and are placed at the network's outermost edges. These firms represent a large fraction of the network, with 118 out of 277 firms being used as subcontractors only once.

From this network, we can create several variables which provide information about firm engagement, seen at the bottom of Table 3.1. First, we represent the presence of links between a contractor and subcontractor. Prime contractors have a strong affinity to working with subcontractors that they have already contracted with in the past. In our sample, on each project a subcontractor has a 24.2% chance of being hired as long as the prime contractor on that project has previously used them, whereas if they had not previously been used that probability drops to 2.8%. The table also presents centrality measures which attempt to ascertain a firm's importance in the directed network. For contractors, we use the firm's outdegree centrality and hub centrality, while for subcontractors we use the firm's indegree centrality and authority centrality. The outdegree (indegree) centrality is simply the count of unique subcontractors (contractors) the contractor (subcontractor) has worked with. The hub and authority centralities are more complex measures. Both use eigenvector theory and the adjacency matrix to calculate a firm's importance in the network. Conceptually, a contractor (subcontractor) will have a high hub (authority) centrality when it is connected to subcontractors (contractors) with high authority (hub) centrality.[4] Lastly, we use the network to identify those firms which work both as contractors and subcontractors in the market. These firms may behave differently than other firms due to differences in opportunity costs (see Marion 2015).

[4]For more complete explanation of hub and authority centrality, and how they differ from out- and indegree centrality, please see Appendix A3.2.

Our dataset also includes information about the tasks required to complete each project and the firms that performed these tasks as either contractors or subcontractors. These projects consist of nearly 1000 unique jobs. We aggregate those tasks within a category, as defined by VTrans, since tasks in the same category are typically similar and a firm proficient in one such task is likely to be competitive in the execution of other similar tasks as well.[5] After aggregation, the average project has 24.6 different categories. With these data, we determine the percentage of categories, the prime contractor and subcontractors have experience with, from the beginning of the sample to the auction date. We also determine if a subcontractor has proficiency in a category in which the winning bidder does not.

Beyond subcontracting, we include other variables relevant to renegotiation. Given Vermont's varied terrain, geography is chief among these. The maps in Figure 3.5 show the spatial distribution of contracts and their likelihood of renegotiation. There are blue and red marks displayed on the figure that vary in size by the number of contracts procured and renegotiated. Red marks are superimposed on the blue marks. A blue ring surrounding a red mark shows that some contracts procured in this region have not been renegotiated. Red marks dominate the picture as renegotiations seem to be widespread. The right panel shows the percentage of contract value renegotiated. It is evident in this figure that the contracts renegotiated in higher proportion are those in remote, less populated areas or in mountainous terrain. There is a lower percentage of renegotiations on the more frequently repaired interstate highways. This figure suggests that the frequency of renegotiation is directly related to the degree of uncertainty, because engineers face greater uncertainty with projects in more difficult topography, and lower uncertainty on interstate projects that have been repeated many times over the same stretch of road. Accordingly, we include variables

[5] Tasks are encoded as a number with the numbers before a decimal indicating the category and the numbers after. For example, all item beginning with 201 correspond to clearing trees. Item number 201.15 corresponds to removing medium trees, 16 to large trees, etc. Vermont Agency of Transportation 2015 English/Metric Construction Manual.

indicating a project's elevation. We also incorporate the following project-level controls: the engineer's cost estimate, the expected duration, the number of items, and the type of project (highway, bridge and other).

In addition, it is necessary to control for characteristics of the prime contractor, as there are significant differences in their tendency to employ subcontractors. The top firms in the market use an average of 6.36 subcontractors per project while the remaining firms use only 3.66. Top firms also subcontracted out 25.8% of the value of their projects compared to only 17.7% by smaller firms. Unsurprisingly the top firms are also central to the network presented in Figure 3.4. The labels on the nodes correspond to those in Table 3.2. In addition to information on prime contractors' use of subcontractors, we know all firms' years of experience, their assets and liabilities. Table 3.1 provides summary statistics on some of these variables, and Table 3.2 displays information on contract renegotiation and subcontracting behavior by firm. Nine firms in the industry carried out more than half of all projects, constituting approximately 76% of the total value of projects, whereas 53 fringe firms undertook the remainder.[6] Further evidence of market concentration is that one firm undertook nearly one-fourth of all projects worth 36% of contracts. The average experience of engineers is higher for projects awarded to top firms. In the econometric analysis, we use a binary variable identifying top firms and a continuous variable capturing firm experience.[7] A top firm designation is based on having assets in the top decile of the distribution the year prior to the bid letting. By employing the threshold, we are able to separate firms into groups similar to those shown in Table 3.2 and to assign a similar proportion of top firms as in Bajari *et al.* (2014). Larger and more experienced contractors are more likely to undertake

[6] An additional 30 firms bid on projects during the period but did not win any projects.

[7] Firms' assets are disclosed each year prior to the renegotiation process. This information is omitted in prior estimation results in the literature because it is often proprietary. We explored other variables connected to firm heterogeneity, such as an indicator for those firms that won a disproportionate number of contracts in Vermont, an indicator for firms with Vermont headquarters, and variables reflecting the distance from the firms' headquarters to the project. Those results were very similar to the results for the "top firm" designation we use in this paper and are available upon request.

more projects due to their finances and range of capabilities. We expect that they are likely to submit more change orders as their knowledge and experience could help their chances of renegotiation with the state government.

We measure the degree of competition in the market by using the expected number of bidders.[8] We have no priors about the expected number of bidders or the type of project. It is possible that greater competition might lead firms to either ask for more or fewer change orders after winning the contract. In order to test whether certain types of projects are more susceptible to change orders, we use three binary indicators (road construction, bridge construction and miscellaneous projects). We also include two controls for changes in the business environment - the unemployment rate and the logarithm of the real value of all projects auctioned off in a month. These may affect renegotiation behavior if firms submit change orders more or less aggressively as the business environment changes.

A final control that we employ relates to the experience of the state engineers managing the project. In practice, the resident engineer and the project manager assigned to the project have the primary responsibility dealing with renegotiation. We measure the engineer's experience by counting in how many projects an engineer has been involved over the sample period. We then average across the resident engineer's and the project manager's experience. Across all projects, the average experience of the resident engineer and project manager is approximately 16 projects.

[8] Due to the concern of endogenous entry, we use the expected number of bidders instead of the actual number of bidders in this analysis, considering whether the plan-holders' identities are publicly announced prior to the letting. It is calculated using information over the past twelve months for each bidder and planholder on the list. We construct the probability of submitting bids conditional on being a plan-holder. For an auction at time t, the expected number of bidders is the summation of the participation probabilities. Then, we multiply a dummy variable by the expected number of bidders in order to identify auctions in which there are more than three qualified plan-holders on the plan-holder list. The state releases information on plan-holders' identities only when there are more than three qualified plan-holders.

3.3 Model and Estimation Method

In the section, we discuss the model and estimation method. N firms are observed in our sample. A total of P_t projects are procured in period t with $t \in \{1, 2, ..., T\}$) using a low price sealed bid auction format. A firm that is awarded a project can subcontract part of the work to another firm from the pool of available contractors who form a potential subcontracting network. We describe firms' subcontracting networks by the adjacency link matrix. An adjacency link matrix $Link_{pt}$ is an $N \times N$ matrix, whose elements depict the subcontracting status between each pair of firms in project p in period t. We say that firm i forms a link with firm j if the prime contractor i wins the project and subcontracts part of it to subcontractor j. In Vermont, it is typical that these subcontracting decisions are made after the contract is awarded. We define $Link_{ijpt} = 1$ $(i \in \{1, 2, ..., N\}, j \in \{1, 2, ..., N\}, i \neq j, p \in \{1, ..., P_t\}, t \in \{1, 2, ..., T\})$, where $Link_{ijpt}$ is the ith and jth element of the link matrix $Link_{pt}$. If i and j do not form a link, $Link_{ijpt} = 0$. Since subcontracting is a directional relationship (i subcontracting to j and j subcontracting to i are different), the subcontracting networks between firms are directional as well. In addition, we define $Link_{iipt} = 0$ since firm i cannot subcontract to itself. We also define $Link_t$ as the aggregation of $Link_{pt}$ across all projects in period t and $Link$ as the aggregation of $Link_t$ across all time periods.

In each project, we begin estimation after the state has awarded the project to the lowest bidder, and thus all potential subcontractors can connect to a single firm. The contractor on the project, denoted by i, then needs to determine which if any subcontractors it will hire from the available pool, S_t, which includes all firms that served as a subcontractor in Vermont in the year prior to the letting and those that are hired in the 3 months following the project let date. To better capture all firms' subcontracting relationships, we use a 12-month moving window to track firms' subcontracting network. Define $Network_t$ as an $N \times N$ matrix, whose ith and jth element $Network_{ijt} = max\{Link_{ijp\tau} : i, j \in \{1, ..., N\}, p \in$

$\{1, ..., P_t\}, \tau \in \{t, ..., t-12\}\}$. $Network_t$ indicates whether each pair of firms has formed a link before the current period but within the last 12-months.

Following the Bayesian estimation method first appearing in Christakis *et al.* (2010) and further developed by He and Kosmopoulou (2020), we assume that each pair of potential prime contractors and subcontractors meet once to decide whether i forms a link with j for all relevant projects during each period t according to some meeting order (MO_t), which will be determined endogenously in the Bayesian estimation. Our structure considers decisions made sequentially, as opposed to simultaneously. The sequential nature of the model allows for interdependence between the individual subcontracting decisions, creating better predictions in our framework, while also making a less strict assumption about how decision makers act. We then aggregate the individual decisions to arrive at a predicted project level of subcontracting that can then be used as an IV for the number of subcontractors on a project.

A project procured in period t is relevant to potential prime contractor i if firm i submits a bid in the project. Since a firm can be a bidder for one project and a subcontractor for another project, the potential primes and subcontractors may include the same set of firms. We also assume that the outcome of each meeting is known to all firms immediately after the meeting takes place, so firms make their decisions in subsequent meetings based upon what has already happened in the same period. We then define MO as the aggregation of MO_t across all time periods.

The contractor i who is maximizing expected profit $E_i(\pi^j_{ipt})$ $j = 1, ..., N$ at the time of bidding will subsequently hire subcontractor j at a meeting on project p at time t if $E_i(\pi^j_{ipt}) - E_i(\pi^{-j}_{ipt}) \geq 0$, where $E_i(\pi^{-j}_{ipt})$ indicates the profit made by firm i if it chooses not to hire subcontractor j and instead complete the project by itself or with previously hired subcontractors. Likewise, subcontractor j will form a subcontracting agreement if $E_j(\pi^i_{jpt}) \geq 0$, where π^i_{jpt} is the profit for firm j if it links with firm i. We assumes that utility is perfectly transferable between the prime contractor and a subcontractor.[9] Implicitly, this means that if a contractor has a high positive expected profit from a link, while the subcontractor has a slightly negative expected profit, the contractor can simply pay the subcontractor more money to make the profit of the link greater than 0 for both parties so that a link can be formed ($E_j(\pi^j_{ipt}) - E_j(\pi^{-j}_{ipt}) + E_i(\pi^i_{jpt})) \geq 0$). Note that implicit in this expected profit function are characteristics of the contractor-subcontractor relationship and regulatory provisions that affect the likelihood of contract renegotiation as well as their monetary consequences.

A bidder who intends to subcontract part of a project at the time of bidding faces uncertainty about the specifications of the subcontracted tasks and the size of the transfer. Thus the probability of a change order is higher, and more expensive for subcontracted work (Miller 2014).[10] Furthermore, subcontractors often have more specialized knowledge on the tasks that they undertake. Finally, the existence of the aforementioned 10% premium on subcontracted work for new items added may also create incentives for primes to petition for change orders with the intent of employing subcontractors on the added task.

We use a two-stage model to estimate the effect of subcontracting on contract renegotiation. In the first stage, we predict the probabilities of the prime contractor on a project hiring each potential subcontractor. The model's first stage is Bayesian so that the meeting order of firms can vary while still making the problem mathematically tractable. Note that, the number of potential meeting orders for a project is $S_t!$. The normalized value of the winning bidder hiring a subcontractor (hereafter referred to as a link) on a project is estimated

[9] Christakis *et al.* (2010) use a different model for friendship link formation where both individuals must have a positive value of friendship to create a link, but also lay out a perfectly transferable utility model, as well as a partially transferable utility model.

[10] Miller takes the change order and its amount as given in his model. He estimates separate itemized bid functions based on whether a subcontractor or contractor carries out a particular function (which must be declared ex ante in his California sample), and then backs out cost estimates to conclude that subcontractors are associated with higher renegotiation costs. Our approach instead endogenizes both the contracting choice and the contract renegotiation.

as:

$$\log(\Pr(link_{ijpt} = 1)/(1 - \Pr(link_{ijpt} = 1))) = \\ \alpha \cdot edge_{ijpt} + \beta \cdot \mathcal{N}_{ijpt} + \gamma \cdot N_{ipt} + \delta \cdot N_{jpt} + \theta \cdot I_{ijpt} + \eta \cdot X_{ipt} + \epsilon_{ijpt} \quad (3.1)$$

where $edge_{ijpt}$ is a dummy indicating if the prime contractor i worked with subcontractor j in the previous 12 months prior to the letting of project p at time t. $\mathcal{N}_{ijpt}$ is a vector of information about the links formed on the current project including the number of subcontractors already hired, a dummy to indicate at least one subcontractor has been hired, the number of items previous subs have experience on, and a dummy to indicate if the subcontractor has experience with an item neither the winning bidder nor previously hired subcontractors has had experience with. The inclusion of the dummy for a least one subcontractor hired is to allow for a fixed cost that must be born for hiring any number of subcontractors.

Other variables included are, a vector of prime contractor network characteristics (N_{ipt}), a vector of potential subcontractor network characteristics (N_{jpt}), a vector of prime contractor and subcontractor item characteristics (I_{ijpt}) and a vector of project and contractor characteristics (X_{ipt}) to be included in the second stage as well. All the variables and their descriptions are listed in Table A3.1.1 in the Appendix. Finally, an error term following a type II extreme error distribution ϵ_{ijpt} is included, leading to a logit model.

Notice that the model is not forward looking, as firms do not directly take future subcontractor meetings into consideration while making current decisions. This assumption is necessary to make the model tractable and is not uncommon in network models (see Jackson and Watts (2001), Badev (2013), and Mele (2013)). The data provide some indirect measures of the outside options of the firms with the total number of firms in the market and the network variables.

Since the model is Bayesian in nature it requires a prior distribution for all parameters and the meeting order. For both, we assume an uninformed prior. The parameters have a prior which is normally distributed with a mean of 0 and standard deviation of 100, while the meeting order has a uniform prior.

We use a Gibbs sampler to generate the posterior distribution of the parameters, updating parameters one at a time. For each parameter a new potential sample of the posterior is drawn from a normal distribution centered with a mean equal to the current value.[11] The potential value is accepted if the following condition is true:

$$\alpha \leq \min(1, (\Pr(D|MO_k, \mathcal{N}, X; \theta) \cdot p(\theta))/(\Pr(D|MO_k, \mathcal{N}, X; \theta_k) \cdot p(\theta_k))) \tag{3.2}$$

where α is a randomly drawn number between 0 and 1, D is the observed subcontracting outcomes, MO_k is the current meeting order, $\mathcal{N}$ is the network information at the current meeting order, X represents the other variables, θ is the proposed parameter set, θ_k is the previous parameter set, and $p(\theta)$ is the likelihood of θ in the prior distribution. After calculating equation (2) for all parameters, then the estimator proposes a new meeting order. To help prevent the estimator from attempting many unlikely meeting orders, new meeting orders are generated by reordering 1% of the subcontractors. As above, the proposed meeting order is accepted if the following is true:

$$\alpha \leq \min(1, \Pr(D|MO_p, \mathcal{N}, X; \theta_k)/\Pr(D|MO_k, \mathcal{N}, X; \theta_k)) \tag{3.3}$$

where MO_p is the proposed meeting order.[12] After the new meeting order is either accepted or rejected, the process starts over with a new proposed value for the first parameter.

To arrive at a sufficient sample for the posterior distribution, we run four parallel chains

[11] The standard deviation for each parameter is different so as to increase the efficiency of the sampler because some parameters have less informed posteriors.

[12] There is no prior distribution for the meeting order in the equation since the meeting order is assumed to be uniform and thus all configurations are equally likely.

of 10,000 samples, thinned every 40 iterations and a burn-in period of 20,000 iterations.[13] The individual subcontractor hiring decisions are then simulated many times using draws from the posterior distribution of parameters and the meeting order. These decisions are then aggregated up to the project level to arrive at the predicted level of subcontracting on the project such that:

$$\hat{sub}_{ipt} = (1/A) \cdot \sum_{a=1}^{A} \sum_{j=1}^{S_t} \hat{link}_{aijpt} \tag{3.4}$$

where $\hat{link}_{aijpt}$ is the a$^{\text{th}}$ predicted link between contractor i to subcontractor j on project p at time t. The predicted level of subcontracting incorporates data on the prime contractor's and subcontractors' experiences and networks. The key variables used to estimate the instrument are the network connections between individual firms, and their complementarities across tasks.

In the second stage, the number of change orders is estimated using a Poisson count model:

$$y_{ipt} = \exp(\alpha \cdot sub_{ipt} + \beta \cdot X_{ipt}) + \epsilon_{ipt} \tag{3.5}$$

The number of change orders (y_{ipt}) are function of the number of subcontractors on project p used by contractor i at time t, (sub_{ipt}), a vector of other project and contractor characteristics (X_{ipt}), and an additive error term ($\epsilon_i pt$). X_{ipt} is assumed to be uncorrelated with the error term, but sub_{ipt} may be correlated to unobserved heterogeneity. We then use the level of predicted subcontracting from the sequential Bayesian process described above as an IV for actual subcontracting.

The instrumental variable thus is the predicted number of subcontractors, and the exogenous variables identifying it principally consist of contractor and subcontractor network

[13] Despite these efforts the effective sample size of some parameters is rather low due to autocorrelation, especially on the variables affected by the meeting order. This is due to meeting order having a major effect on the potential values these variables can take at a point in time, slowing movement through the posterior distribution.

variables. These variables are orthogonal to project complexity, conditional on the included covariates, because firms' subcontractor networks depend upon many idiosyncratic factors, such as cross-firm personnel relationships. It could be argued that large firms are more likely to have large subcontractor networks and are also more likely to win bids on complex projects. For that reason, we include firm size as a covariate in each stage of our estimation procedure. Thus, the resulting predicted number of subcontractors is orthogonal to this influence. Furthermore, much of the predictive power is from subcontractor-centered network measures, rather than prime contractor-centered network measures (see the discussion of Table 3.3 that follows). In our dataset, the network density of individual subcontractors is strongly influenced by local market structure, which is driven at least in part by fixed costs and entry barriers. An example noted by VTrans engineers is the fact that in Vermont there are only three firms that conduct work on guardrails, which is not an item especially associated with project complexity. The subcontractors conducting guardrail work have indegree and authority centrality measures 4 times that of other subcontractors (For indegree 7.56 vs 1.99 and for authority 0.024 vs 0.005). In a similar vein, the edge variable, capturing whether firms were linked together in the last year, also represents connections to specialized subcontractors responsible for non-complex task, such as guardrails, flagging, or line painting. For each of these reasons, we believe there is no relationship between the instrumental variable and unobserved complexity.

3.4 Empirical Analysis

The first step in our econometric investigation is to predict the individual subcontracting decisions as described in Equation 3.1. These results can be seen in Table 3.3. In addition to the sequential Bayesian model presented in Column 1, two simultaneous specifications are shown - a traditional maximum likelihood logit model in Column 2, and a Bayesian logit model in Column 3. Both assume each subcontracting decision is made independently. A total of 28,678 potential subcontractor options across 273 projects are used as data. The first four variables appear only in the sequential model, as they indicate how the next subcontracting decision depends upon previous ones. It is immediately evident that there are interdependencies among subcontracting decisions as evidenced by the first four point estimates. First, contractors are more reluctant to hire additional subcontractors the more subcontractors they have already hired. There is a divergence of the pattern with an increased likelihood of hiring a second subcontractor after the first. This change, after the first subcontractor is hired, is dramatic. Evaluating the model at the means, the probability that a particular subcontractor is hired is 0.5% when no others have previously been hired. After the first subcontractor is hired though the probability rises to 4% for the second. It may be more costly for firms to hire the first subcontractor than subsequent ones, perhaps because of a fixed cost of subcontracting management that is spread across all subcontractors on a project. Additionally, the range of jobs previously hired subcontractors can perform decreases the likelihood of the next subcontractor being hired, while a subcontractor that is able to fill a gap in the project is more likely to be hired. Together the sequential assumption and the additional variables lead to a substantial improvement of the model over the two simultaneous specifications. The simulated pseudo R^2 is 0.388 in the sequential model compared to 0.350 in the maximum likelihood model.[14] The increased predictive power comes from improved predictions by the sequential model of the number of subcontractors used in larger projects. As the sequential model includes additional control variables it more closely replicates the observed patterns of subcontracting making it a more efficient instrument

[14] Simulated log likelihood and pseudo R^2 is calculated by simulating 16,000 different outcomes using 800 parameter sets and meeting orders from the posterior distribution, and taking the average. The simulated log likelihood is then calculated as $\sum_{i=1}^{N} y_{ipt} \cdot \log((1/A) \cdot \sum_{a=1}^{A} \hat{y}_{aipt}) + (1 - y_{ipt}) \cdot \log(1 - (1/A) \cdot \sum_{a=1}^{A} \hat{y}_{aipt})$, where y_{ipt} is the realized subcontracting outcome, $\hat{y}_{aipt}$ is a simulated outcome, and A is the total number of simulations. The simulated pseudo R^2 is calculated by taking the difference between simulated log likelihood and a the log likelihood for a constant-only model and dividing it by the log likelihood for a constant-only model.

overall.

In both the sequential and simultaneous models, the variables describing contractor-subcontractor networks are important predictors of linkages. Specifically, the outdegree, indegree and authority network measures are all statistically significant with similar magnitudes across all models. Well connected subcontractors, those with high indegree and authority centrality, are more likely to be hired. The extension of a prime's network, represented by their outdegree centrality, reduces the probability that any given subcontractor will be hired, which is logical given that those primes with large networks have a greater number of attractive options. Not surprisingly, given the regulatory requirements, the DBE status of a subcontractor increases the probability that they are hired.[15] The results also support the hypothesis that the number of items a subcontractor has experience with increases the likelihood that they are hired, but as the significance and magnitude of the quadratic term indicates, this effect rapidly tails off.

Most shared parameters between the simulations and sequential models have similar signs and magnitudes, but three have a substantial difference, that can be attributed to the model. First, the log number of subcontractors in the market is insignificant in the sequential model but negative and significant in the simultaneous models. With previously hired subcontractors included in the sequential model, available subcontractors become unimportant. Second, subcontractors that fill a gap in the prime contractor's skill set are more likely to be hired in the simultaneous model and less likely in the sequential model. This is because of the addition, in the sequential model, of the dummy indicating that a subcontractor fills a gap in both the contractor and previously hired subs skill sets. Thus, in the sequential model the interpretation of the coefficient is different, as it signals that the subcontractor may have skills that were previously been contracted for. Third, in the sequential model the coefficient

[15] VTrans is required to meet annual goals for DBE usage, but it does not set specific requirements at the project level.

of top firms although smaller, becomes statistically significant at the 1% level because its standard error falls dramatically. This is likely due to the inclusion of the additional variables in the sequential model that permit a more precise estimation of the effect of top firms.

As mentioned before, the sequential model offers an improved prediction for the individual subcontracting decisions, but equally important is how it predicts the number of subcontractors on a project. Figure 3.6 illustrates how the different models' predicted distributions compare with the observed distribution of subcontracting. Neither simultaneous model captures the behavior near 0 and has subcontractor usage fall off more slowly past the peak. The sequential model does a superior job on both fronts. The model features a spike at zero before dropping off, rising and then falling off quickly again. The model is still imperfect - it overpredicts no subcontractor use, and underpredicts a single used contractor but offers an improvement at the project level.

We use these estimations of the link probabilities to construct $\hat{sub}$, as noted in equation 4. That variable is then included in the estimation of the actual level of subcontracting, from which we derive the instrument. It is clear that the sequential model also performs well predicting subcontractor usage for individual projects, seen in Table 3.4. All three models provide information left out by the other control variables and are significant at the 1% level. Still, the sequential model outperforms the other two with a coefficient close to 1 in the specifications where predictive subcontracting enters on its own (Columns 1, 3, and 5). In the univariate model, the sequentially predicted subcontracting explains 58.2% of the variation in actual subcontractor use, better than the 54.9% from the simultaneous models. The only control variables with statistically significant coefficients (at the ten percent level or better) are the project's number of items and the top firm dummy.[16]

[16] An alternative specification to Table 3.4, that uses the percentage of the project value subcontracted as a dependent variable is presented in Table A3.4.1 in the appendix. In this specification, we use a quadratic form for the predicted number of subcontracts, because the marginal subcontractor is used less than the average. The results show a strong quadratic relationship with each additional subcontractor hired doing a smaller portion of the work than the previous one.

Next, we examine how subcontracting affects the number of change orders. The results, presented in Table 3.5, are obtained using the generalized method of moments (GMM) estimator. The first column presents a Poisson regression with no instrument for the number of subcontractors. Here, an increase in the number of subcontractors increases the likelihood of additional change orders, but the finding cannot be interpreted as causal because the number of subcontractors may be correlated with unobserved project complexity not captured by other controls. As such, we instrument for it in Column 2 using the predicted level of subcontracting from Table 3.4, Column 2. The coefficient on the number of subcontractors increases in magnitude and remains statistically significant. One might expect that the coefficient would become smaller because unobserved complexity was introducing a positive bias on the subcontracting coefficient in Column 1. However, coefficients of some control variables are sensitive to the inclusion of the IV especially the log of the engineering cost estimate and the number of items. This suggested that prior to the inclusion of the IV the coefficients of those variables reflected confounding effects.[17] Evaluated at the mean level of the control variables, a project with 5 subcontractors will have 2.52 change orders, but increasing the number of subcontractors to 6 will lead to a 0.45 increase in change orders.[18] This amounts to an elasticity of 0.89 at the means. We also use predicted subcontractors, from Table 3.3 Column 1, as a proxy variable for subcontractors in Column 3 and find similar results.[19]

Other observable characteristics also raise the likelihood of renegotiation. The project's duration, number of items, and engineers estimate all have positive signs in Column 1,

[17]It is not uncommon for 2SLS estimates to be larger than OLS even when selection pressures would suggest the OLS estimate is overestimated. For example, larger effects have recently been found in a study of the impact of air pollution on traffic accidents (Sager 2019).

[18]One additional subcontractor on a project with 2 and another with 8 subcontractors will lead to an additional 0.38 and 1.04 change orders respectively.

[19]We also run a normalized version of these regressions in Table A3.4.2. To do this we divide the number of change orders by the number of items since that is the level of renegotiation. We find that each additional subcontractor leads to an extra 1.8% of items to be renegotiated.

which is unsurprising as all three are related to the complexity of the project. As expected, the elevation of the project's location is a significant predictor of renegotiation, though the effect fades as the elevation squared has a negative effect. None of the other variables have statistically significant coefficients, including the dummy designating large firms and experience of either the firm or the engineers. [20]

Recall that, change orders may either be for new added items that were not included in the original plans, or merely for adjustments in the quantities of items that were in the plans. It is plausible that change orders consisting of quantity adjustments, are more likely caused by the coordination costs between a contractor and its subcontractors than change orders which add brand new items to a project. Following this line of reasoning, we estimate our specification in a subsample of projects that only have quantity adjustments. These results are displayed in Columns 4 through 6 of Table 3.5. The coefficient on the number of subcontractors is of similar magnitude as in the full sample and is statistically significant at the 1% level. The fact that the coeffient on the restricted sample, without "new items added", is similar in magnitude to that in the full sample, supports the view that coordination costs, rather than the special 10% premium on subcontracted new items, is ultimately driving the result. Again evaluating the marginal increase from 5 subcontractors to 6, for a project at the means of the controls leads to an increase of 0.429 additional change orders.[21]

Lastly, we estimate the factors influencing the costliness of change orders. In Table 3.6, we present the ordinary least squares and IV regression estimates with the dependent variable being the dollar value of change order costs. The costs measured here are those that appear on the invoice. Because firms are likely to add premia to their bids in anticipation

[20] We also used a propensity score method to test for differences between the likelihood of renegotiation between large and small firms as the two groups may win different types of projects. Matching on expected duration, number of items, engineers' cost estimates, all factors encompassing uncertainty, and engineer experience, we found no significant difference in the number of change orders. Those results are available upon request.

[21] A marginal increase from 2 to 3 subcontractors adds 0.29 change orders, while a change from 8 to 9 lead to an additional 0.64 change orders.

of possible adaptation costs that might occur as a result of change orders, the change order invoice contains elements of "direct" and "adaptation" costs.

Our estimation of the determinants of cost produces results that are similar to those of the count models. As with change orders, the number of subcontractors is a significant predictor of cost overruns, albeit at the 10% level. With the inclusion of the IV, the point estimate rises and remains significant. The results in Column 2 of Table 3.6 suggest that each additional subcontractor on a project adds $48,000 in readjustment costs.[22] Other important determinants of the renegotiation costs are the project duration, the engineer's cost estimate and the paving project dummy.[23] We also run the same regressions on renegotiation costs normalized by the engineer's estimate and log dollar value renegotiated.[24] These regressions again suggest that the number of subcontractors leads to more costly renegotiations, though the coefficient is not statistically significant in the log regression.[25] For the normalized regression the results suggest that each additional subcontractor raises costs by 1.8% of the engineer's estimate, which for the average project size of $1.9 million would be $34,000. The lower effect size in these two specification may be because subcontracting disproportionately affects smaller projects, while the log and normalized specifications imply the opposite. State regulations dictate that change orders should be implemented only if the unanticipated costs exceed 5% of the project's value, so small projects are more likely to require renegotiation.

Finally, one potential area of concern is that firms with large subcontractor networks may systematically choose projects that are more prone to change orders. If that is the case, subcontracting networks may affect the incidence of change orders through a channel other than

[22]We carry out a Hausman test that the point estimates in OLS and the IV are equal, and we reject that hypothesis at the 10% level.

[23]Paving projects have an automatic readjustment mechanism for asphalt costs caused by fluctuations in the price of oil, one of its major inputs.

[24]For regressions normalized by the engineer's estimate we do not include the engineer's estimate as a control variable. For regressions with log dollar value renegotiated, 6 projects have a negative value of renegotiation those observations are lost because of the log transformation.

[25]The marginal impact at 2, 5, and 8 subcontractors is $515, $4,694, and $42,700 respectively.

the network's influence on the number of subcontractors employed. As an additional check, we estimate the number of change orders, and the renegotiation amount in a specification that includes both the instrument and the network variables entered independently in addition to the other controls. We find that the coefficients on these network variables are small and statistically insignificant which we interpret as evidence that the network variables are only important for change orders through their influence on the number of subcontractors. We offer evidence in Appendix A3.3, Table A3.3.1.

3.5 Conclusion

Our analysis demonstrates that the number of subcontractors on a project is a powerful predictor of the likelihood of contract renegotiation and their financial importance. We estimate that each subcontractor on a project leads to 0.45 additional change orders and adds $48,000 to costs. We employ an instrumental variable - the predicted number of subcontractors - that depends on network variables. These network variables, conditional on control variables that we include such as firm size, are orthogonal to unobserved project complexity, and are therefore crucial for establishing the validity of our IV. As a consequence, our estimates of the effect of subcontractors on change orders are of a direct causal impact. Therefore, our paper provides new evidence in support of the hypothesis that coordination costs and other transaction costs associated with subcontracting can lead to contract renegotiations (Masten *et al.* 1991; Miller 2014).

Our conversations with Vermont Agency of Transportation officials offer important context for our results. It is often the case the prime contractors limit the information about the project that they share with subcontractors, and that this has the potential to lead to miscommunication and coordination failures. A possible policy implication of our finding is that the Transportation Agency could mandate more complete information sharing up front.

This could preempt coordination problems to a degree and obviate the need for some change orders. Nevertheless, prime contractors may be reluctant to share full information with subcontractors because it is costly to do so. It also could be the case that prime contractors feel that more extensive information sharing could reveal private information about their costs or capabilities that could compromise their competitive position. Given that many subcontractors are also prime contractors in their own right, or deal with other prime contractors as well, this is a very real concern. Agencies may wish to conduct experiments with different information-sharing protocols in order to determine the extent of any unintended negative consequences. Finally, letting agencies might debrief separately subcontractors and prime contractors ex post on projects that result in unusually large numbers of change orders. This could permit the identification of specific sources of coordination problems and possible remedies.

Bibliography

Agnello, R.J. and Pierce, R.K., 1996. Financial Returns, Price Determinants, and Genre Effects in American Art Investment, *Journal of Cultural Economics*, 20 (4), 359–383.

Anastasopoulos, P.C., Labi, S., Bhargava, A., Bordat, C., and Mannering, F.L., 2010. Frequency of Change Orders in Highway Construction Using Alternate Count-Data Modeling Methods, *Journal of Construction Engineering and Management*, 136 (8), 886–893.

Aral, S. and Walker, D., 2012. Identifying Influential and Susceptible Members of Social Networks, *Science*, 337 (6092), 337–341.

Aral, S. and Walker, D., 2014. Tie Strength, Embeddedness, and Social Influence: A Large-scale Networked Experiment, *Management Science*, 60 (6), 1352–1370.

Arellano, M., Blundell, R., and Bonhomme, S., 2017. Earnings and Consumption Dynamics: A Nonlinear Panel Data Framework, *Econometrica*, 85 (3), 693–734.

Ashenfelter, O. and Graddy, K., 2006. Art Auctions, *Handbook of the Economics of Art and Culture*, 1, 909–945.

Badev, A., 2013. Discrete Games in Endogenous Networks: Theory and Policy, *University of Pennslvania*.

Bajari, P., Houghton, S., and Tadelis, S., 2014. Bidding for Incompete Contracts, *The American Economic Review*, 104 (4), 1288–1319.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., and Jackson, M.O., 2013. The Diffusion of Microfinance, *Science*, 341 (6144).

Black, J. and De Meza, D., 1992. Systematic Price Differences between Successive Auctions are No Anomaly, *Journal of Economics & Management Strategy*, 1 (4), 607–628.

Bloch, F., Jackson, M.O., and Tebaldi, P., 2019. Centrality Measures in Networks, *Available at SSRN 2749124*.

Bordat, C., McCullouch, B., and Sinha, K., 2004. An Analysis of cost Overruns and Time Delays of INDOT Projects, *Technical Rep. Prepared for INDOT-FHWA-JTRP*, Indiana Department of Transportation, Indianapolis.

Börsch-Supan, A. and Hajivassiliou, V.A., 1993. Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models, *Journal of Econometrics*, 58 (3), 347–368.

Branzoli, N. and Decarolis, F., 2015. Entry and Subcontracting in Public Procurement Auctions, *Management Science*, 61 (12), 2945–2962.

Campos, N.F. and Barbosa, R.L., 2009. Paintings and numbers: an econometric investigation of sales rates, prices, and returns in latin american art auctions, *Oxford Economic Papers*, 61 (1), 28–51.

Christakis, N.A., Fowler, J.H., Imbens, G.W., and Kalyanaraman, K., 2010. An empirical model for strategic network formation., *No. w16039. National Bureau of Economic Research.*

De Silva, D.G., Dunne, T., Kosmopoulou, G., and Lamarche, C., 2012. Disadvantaged Business Enterprise Goals in Government Procurement Contracting: An Analysis of Bidding Behavior and Costs, *International Journal of Industrial Organization*, 30 (4), 377–388.

De Silva, D.G., Gertsberg, M., Kosmopoulou, G., and Pownall, R.A., 2020a. Dealer Networks in the World of Art, *Available at SSRN 3050848.*

De Silva, D.G., Kosmopoulou, G., and Lamarche, C., 2017. Subcontracting and the Survival of Plants in the Road Construction Industry: A Panel Quantile Regression Analysis, *Journal of Economic Behavior & Organization*, 137, 113–131.

De Silva, D.G., Kosmopoulou, G., Pownall, R., and Press, R., 2020b. Trading Patterns and the "Death Effect" on Artwork Prices.

Deltas, G. and Kosmopoulou, G., 2004. 'catalogue'vs 'order-of-sale'effects in sequential auctions: theory and evidence from a rare book sale, *The Economic Journal*, 114 (492), 28–54.

Ekelund, R.B., Ressler, R.W., and Watson, J.K., 2000. The "death-effect" in art prices: A demand-side exploration., *Journal of Cultural Economics*, 24 (4), 283–300.

Etro, F. and Stepanova, E., 2015. The Market for Paintings in Paris between Rococo and Romanticism, *Kyklos*, 68 (1), 28–50.

Fafchamps, M. and Lund, S., 2003. Risk-sharing Networks in Rural Philippines, *Journal of Development Economics*, 71 (2), 261–287.

Fouss, F., Saerens, M., and Shimbo, M., 2016. *Algorithms and Models for Network Data and Link Analysis*, Cambridge University Press.

Fraiberger, S.P., Sinatra, R., Resch, M., Riedl, C., and Barabási, A.L., 2018. Quantifying reputation and success in art., *Science*, 362 (6416), 825–829.

Gaonkar, S. and Mele, A., 2018. A structural model of firm collaborations with unobserved heterogeneity., *Available at SSRN 3267047*.

Geweke, J., 1991. Efficient Simulation from the Multivariate Normal and Student-t Distributions Subject to Linear Constraints and the Evaluation of Constraint Probabilities, *in: Computing science and statistics: Proceedings of the 23rd symposium on the interface*, Fairfax, Virginia: Interface Foundation of North America, Inc, 571–578.

Ginsburgh, V., 1998. Absentee Bidders and the Declining Price Anomaly in Wine Auctions, *Journal of Political Economy*, 106 (6), 1302–1319.

Ginsburgh, V. and Van Ours, J.C., 2007. On organizing a sequential auction: results from a natural experiment by christie's, *Oxford Economic Papers*, 59 (1), 1–15.

Goeree, K. and Offerman, T., 2002. Efficiency in Auctions with Private and Common Values: An Experimental Study, *American Economic Review*, 92 (3), 625–643.

Goetzmann, W.N., 1993. Accounting for Taste: Art and the Financial Markets over Three Centuries, *The American Economic Review*, 83 (5), 1370–1376.

Granovetter, M., 1977. The Strength of Weak Ties, *Social Networks*, 347–367.

Grant, D., 2010. Is an Artist Only Appreciated After He Dies?".

Graves, A., 1918. *Art Sales from Early in the Eighteenth Century to Early in the Twentieth Century:(mostly Old Master and Early English Pictures)*, vol. 1, A. Graves.

Haile, P.A., 2001. Auctions with Resale Markets: An Application to US Forest Service Timber Sales, *American Economic Review*, 91 (3), 399–427.

He, L. and Kosmopoulou, G., 2020. Subcontracting Network Formation among US Airline Carriers, *Available at SSRN 3308105*.

He, L., Kosmopoulou, G., and Zhou, X., 2020. Network Effects, Competition and Survival of Small and Minority-Owned Firms in Public Procurement.

Heckman, J.J., 1979. Sample Selection Bias as a Specification Error, *Econometrica: Journal of the Econometric Society*, 153–161.

Hsieh, T.y., Lu, S.t., and Wu, C.h., 2004. Statistical Analysis of Causes for Change Orders in Metropolitan Public Works, *International Journal of Project Management*, 22 (8), 679–686.

Iossa, E., Spagnolo, G., and Vellez, M., 2007. Contract Design in Public-Private Partnerships, Washinton, D.C., World Bank.

Jackson, M.O. and Watts, A., 2001. The Existence of Pairwise Stable Networks, *Seoul Journal of Economics*, 14 (3), 299–321.

Ji, L. and Li, T., 2008. Multi-round Procurement Auctions with Secret Reserve Prices: Theory and Evidence, *Journal of Applied Econometrics*, 23 (7), 897–923.

Jofre-Bonet, M. and Pesendorfer, M., 2000. Bidding Behavior in a Repeated Procurement Auction: A Summary, *European Economic Review*, 44 (4-6), 1006–1020.

Jung, H., Kosmopoulou, G., Lamarche, C., and Sicotte, R., 2019. Strategic Bidding and Contract Renegotiation, *International Economic Review,* Forthcoming.

Jung, H., Kosmopoulou, G., Press, R., and Sicotte, R., 2020. Subcontracting and the Incidence of Change Orders in Procurement Contracts.

Kagel, J.H., Harstad, R.M., and Levin, D., 1987. Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study, *Econometrica: Journal of the Econometric Society*, 1275–1304.

Karlan, D., Mobius, M., Rosenblat, T., and Szeidl, A., 2009. Trust and Social Collateral, *The Quarterly Journal of Economics*, 124 (3), 1307–1361.

Keane, M.P., 1994. A Computationally Practical Simulation Estimator for Panel Data, *Econometrica: Journal of the Econometric Society*, 95–116.

Krasnokutskaya, E. and Seim, K., 2011. Bid Preference Programs and Participation in Highway Procurement Auctions, *American Economic Review*, 101 (6), 2653–86.

Kvaløy, O. and Olsen, T.E., 2009. Endogenous Verifiability and Relational Ccontracting, *American Economic Review*, 99 (5), 2193–2208.

Li, T. and Zhang, B., 2010. Testing for Affiliation in First-Price Auctions Using Entry Behavior, *International Economic Review*, 51 (3), 837–850.

Li, T. and Zhang, B., 2015. Affiliation and Entry in First-Price Auctions with Heterogeneous Bidders: An Analysis of Merger Effects, *American Economic Journal: Microeconomics*, 7 (2), 188–214.

Maddison, D. and Jul Pedersen, A., 2008. The Death Eeffect in Art Prices: Evidence from Denmark, *Applied Economics*, 40 (14), 1789–1793.

Marion, J., 2009. How Costly is Affirmative Action? Government Contracting and California's Proposition 209, *The Review of Economics and Statistics*, 91 (3), 503–522.

Marion, J., 2015. Sourcing from the Enemy: Horizontal Subcontracting in Highway Procurement, *The Journal of Industrial Economics*, 63 (1), 100–128.

Masten, S.E., Meehan Jr, J.W., and Snyder, E.A., 1991. The Costs of Organization, *JL Econ. & Org.*, 7, 1.

Matheson, V.A. and Baade, R.A., 2004. 'Death Effect'on Collectible Prices, *Applied Economics*, 36 (11), 1151–1155.

Mei, J. and Moses, M., 2002. Art as an Investment and the Underperformance of Masterpieces, *American Economic Review*, 92 (5), 1656–1668.

Mele, A., 2013. A Structural Model of Segregation in Social Networks, *Available at SSRN 2294957*.

Milgrom, P.R. and Weber, R.J., 1982. A Theory of Auctions and Competitive Bidding, *Econometrica: Journal of the Econometric Society*, 1089–1122.

Miller, D.P., 2014. Subcontracting and Competitive Bidding on Incomplete Procurement Contracts, *The RAND Journal of Economics*, 45 (4), 705–746.

Mitali, B. and Ingram, P.L., 2018. Fame as an Illusion of Creativity: Evidence from the Pioneers of Aabstract Art, *HEC Paris Research Paper No. SPE-2018-1305*, 18–74.

Montogomery, J., 1991. Social Networks and Labor Market Outcomes, *American Economic Review*, 8 (5), 1408–1418.

Nakabayashi, J., 2013. Small Business Set-Asides in Procurement Auctions: An Empirical Analysis, *Journal of Public Economics*, 100, 28–44.

Oestreicher-Singer, G. and Sundararajan, A., 2012. The Visible Hand? Demand Effects of Recommendation Networks in Electronic Markets, *Management Science*, 58 (11), 1963–1981.

Oudot, J.M., 2006. Renegotiation of Defense Procurement Contracts, *Working Paper*, ATOM.

Pesando, J.E., 1993. Art as an Investment: The Market for Modern Prints, *The American Economic Review*, 1075–1089.

Pinkse, J. and Tan, G., 2005. The Affiliation Effect in First-Price Auctions, *Econometrica*, 73 (1), 263–277.

Rosa, B.V., 2019. Resident Bid Preference, Affiliation, and Procurement Competition: Evidence from New Mexico, *The Journal of Industrial Economics*, 67 (2), 161–208.

Sager, L., 2019. Estimating the Effect of Air Pollution on Road Safety Using Atmospheric Temperature Inversions, *Journal of Environmental Economics and Management*, 98, 102250.

Schilling, M.A. and Phelps, C.C., 2007. Interfirm Collaboration Networks: The Impact of Large-scale Network Structure on Firm Innovation, *Management Science*, 53 (7), 1113–1126.

Schrager, A., 2013. High-End Art is One of the Most Manipulated Markets in the World.

Townsend, R.M., 1994. Risk and Insurance in Village India, *Econometrica: Journal of the Econometric Society*, 539–591.

Train, K.E., 2009. *Discrete Choice Methods with Simulation*, Cambridge University Press.

Trusov, M., Bucklin, R.E., and Pauwels, K., 2009. Effects of Word-of-mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site, *Journal of Marketing*, 73 (5), 90–102.

Twain, M., 2003. *Is He Dead?: A Comedy in Three Acts*, vol. 1, Univ of California Press.

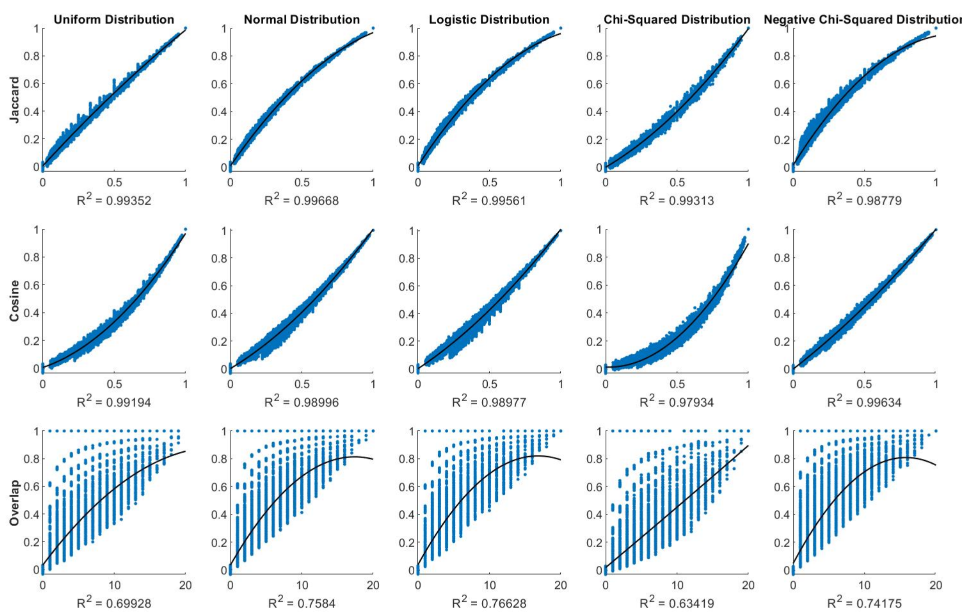
Ursprung, H.W. and Wiermann, C., 2011. Reputation, Price, and Death: An Empirical Analysis of Art Price Formation, *Economic Inquiry*, 49 (3), 697–715.

Ursprung, H.W. and Zigova, K., 2020. Diff-in-Diff in Death: Estimating and Explaining Artist-Specific Death Effects.

Figures

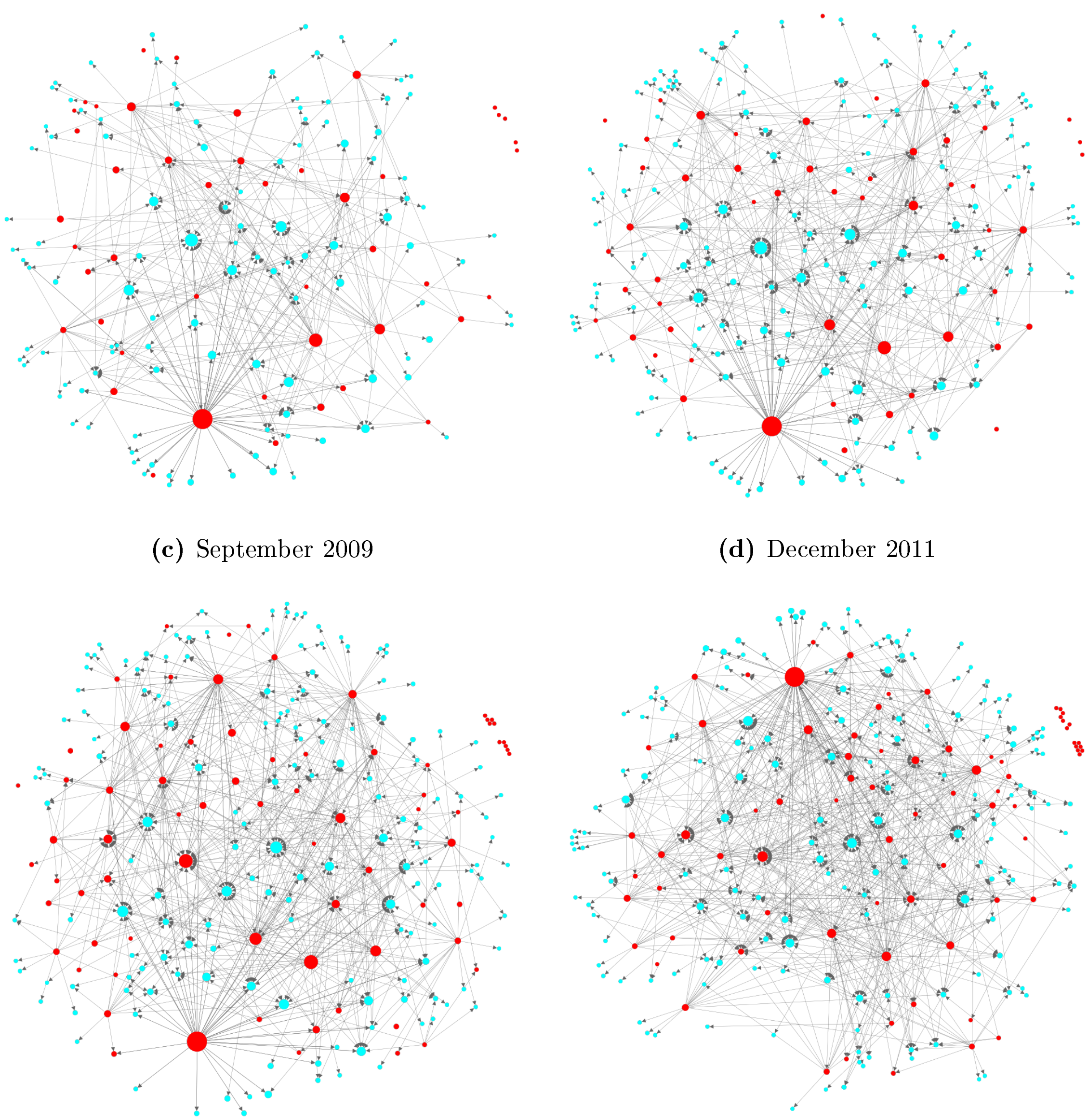
Chapter 1 Figures

Figure 1.1: Monte Carlo Simulation with Overlapping Subcontractors and Symmetric Means



Panels show the relationship between a measure of similarity and the correlation between the private values of 2 contractors. The top row uses jaccard similarity, the middle uses cosine similarity, and the bottom uses the overlap count. Each column uses a different underlying distribution for the subcontractors. From left to right they are a uniform distribution, normal distribution, logistic distribution, chi-squared distribution, and negative chi-Squared distribution. R^2 values of a quadratic fit line are shown below each panel.

Figure 1.2: Contractor-Subcontractor Network: Four Slices



(a) January 2005

(b) April 2007

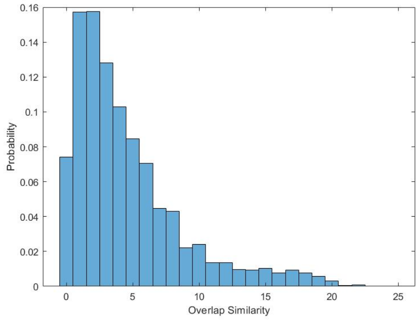
(c) September 2009

(d) December 2011

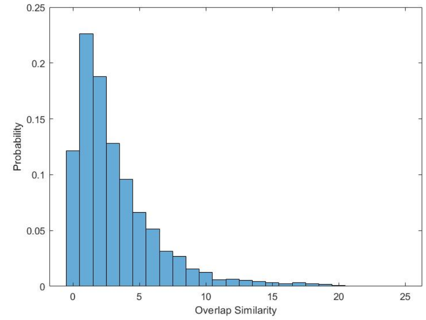
Potential Bidders are shown in red. Subcontractors that were never potential bidders are shown in light blue. Node location is constant in all 4 slices. The links are directed from potential bidders to subcontractors, using information on subcontracting from the prior 12 months. Node size varies based on the maximum of hub and authority centrality at that time. All images are constructed using Gephi.

Figure 1.3: Subcontractor Network Similarity Histograms

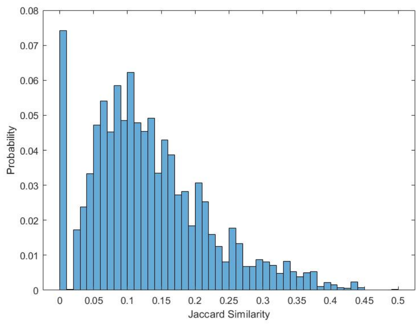
(a) Planholder Pair: Overlap



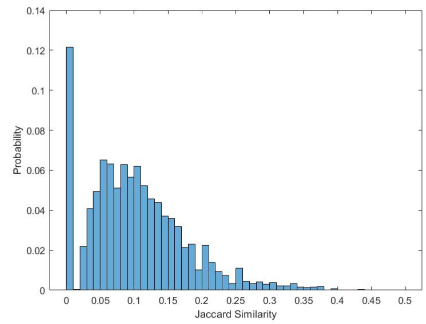
(b) Potential Planholder Pair: Overlap



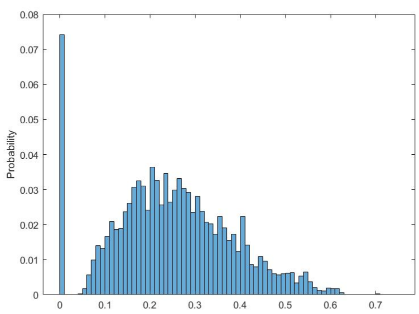
(c) Planholder Pair: Jaccard Similarity



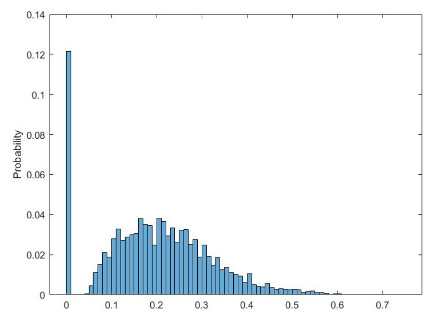
(d) Potential Planholder Pair: Jaccard Similarity



(e) Planholder Pair: Cosine Similarity



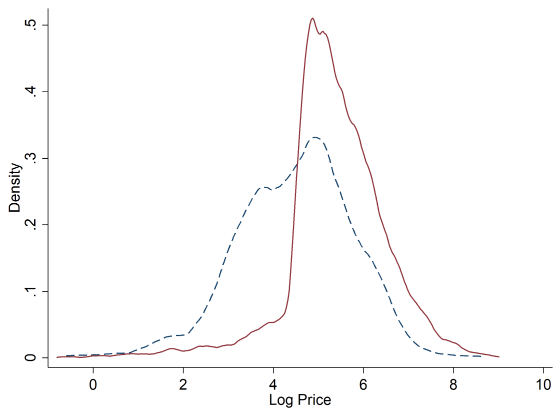
(f) Potential Planholder Pair: Cosine Similarity



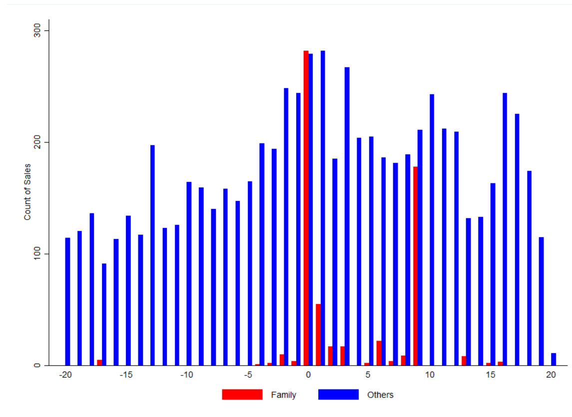
Chapter 2 Figures

Figure 2.1: Family Sales

(a) Price Density by Seller Identification



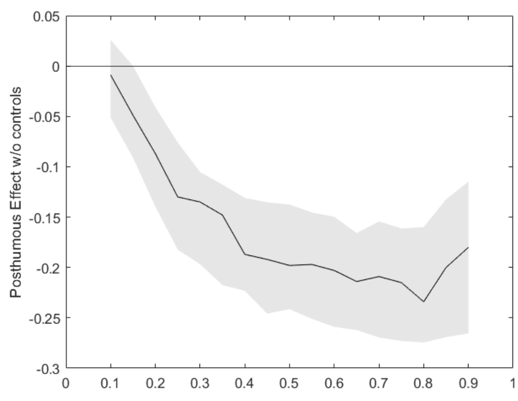
(b) Count of Sales by Seller Identification



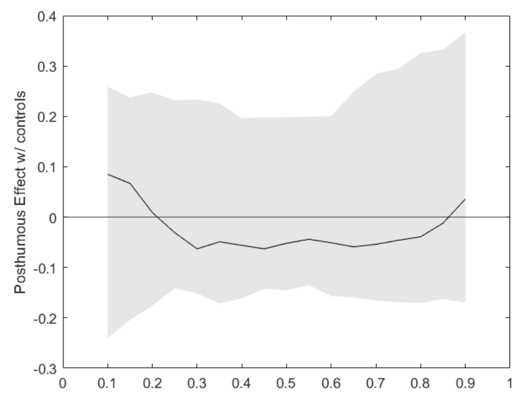
In Panel A, The blue dashed line represents the price density of pieces sold by sellers who's names match the artist's. The solid red line represents pieces sold by all other sellers. In Panel B, the red bars represent pieces sold by family sellers in a given year, while the blue bars represent those works sold by others.

Figure 2.2: Distributional Posthumous Effect on Log Price

(a) Unconditional Effect



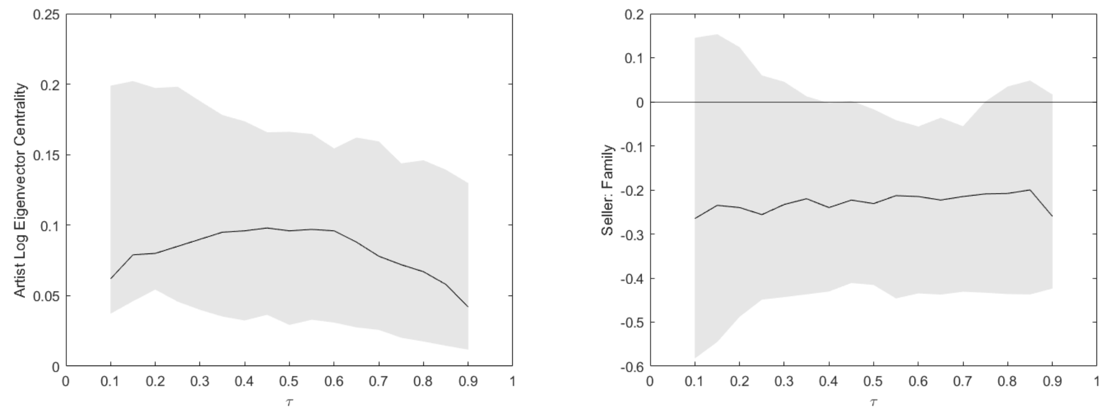
(b) Conditional Effect



Panel A captures distributional posthumous effects on log price corresponding to estimates in Panel A of Table 3. Panel B captures distributional posthumous effects corresponding to estimates in Panel B of Table 3. The solid lines are the point estimate for each quanitle. The shaded regions represent the bootstrapped 95% confidence interval from 1000 repetitions.

Figure 2.3: All Quantiles: Network Effects

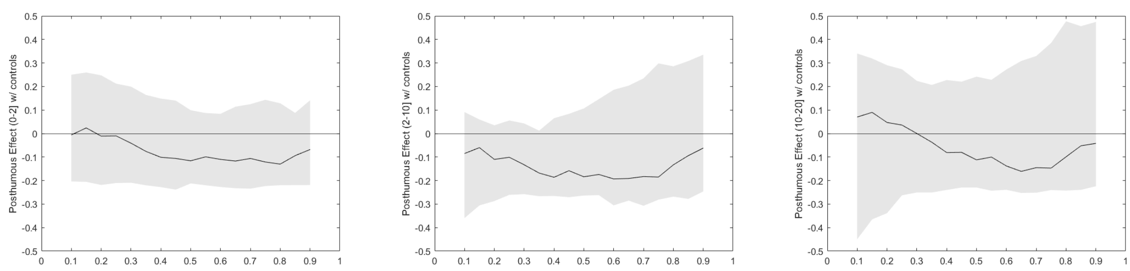
(a) Artist: Log Egienvector Centrality **(b)** Seller: Family



Panel A captures the artist's log eigenvector centrality effects corresponding to estimates in Panel B of Table 3. Panel B captures the effect of family sales corresponding to estimates in Panel B of Table 3. The solid lines are the point estimate for each quanitle. The shaded regions represent the bootstrapped 95% confidence interval from 1000 repetitions.

Figure 2.4: All Quantiles: Prices changes after death

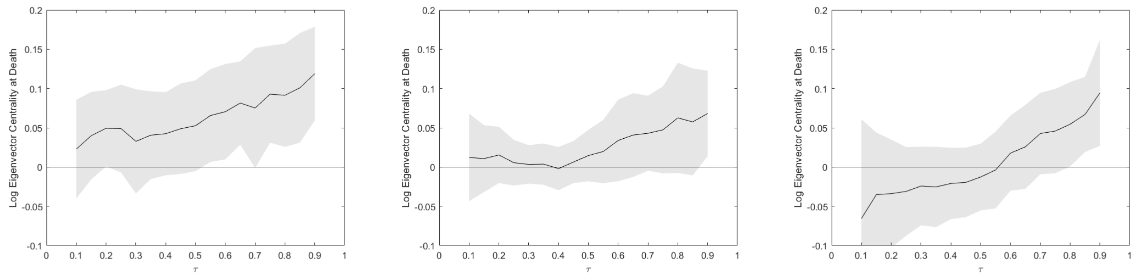
(a) ≤ 2 Years after Death **(b)** 2-10 Years after Death **(c)** 10-20 Years after Death



Panels A, B and C capture price change in three bins following death, instead of using a continuous time trend. Panel A includes works sold between 0 and 2 years after death, B includes works sold 2 to 10 years after death and C includes works sold 10 to 20 years after death. The solid lines are the point estimate for each quantile. The shaded regions represent the bootstrapped 95% confidence interval.

Figure 2.5: All Quantiles: Network at Death

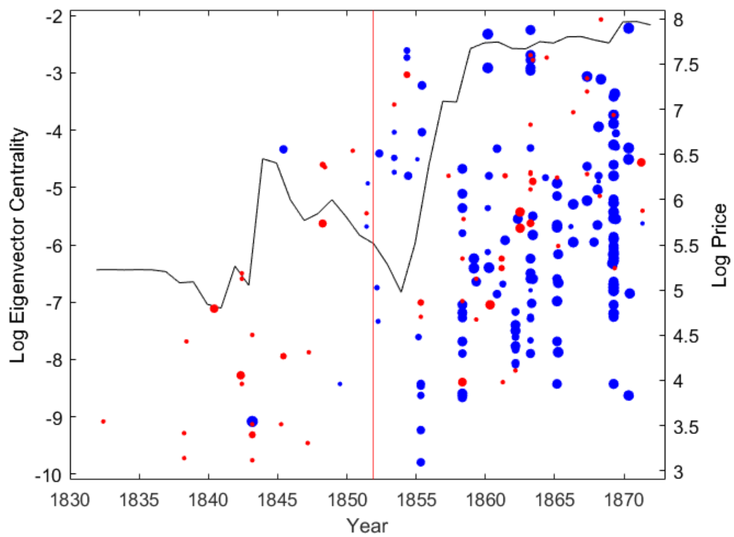
(a) $\leq$ 2 Years after Death **(b)** 2-10 Years after Death **(c)** 10-20 Years after Death



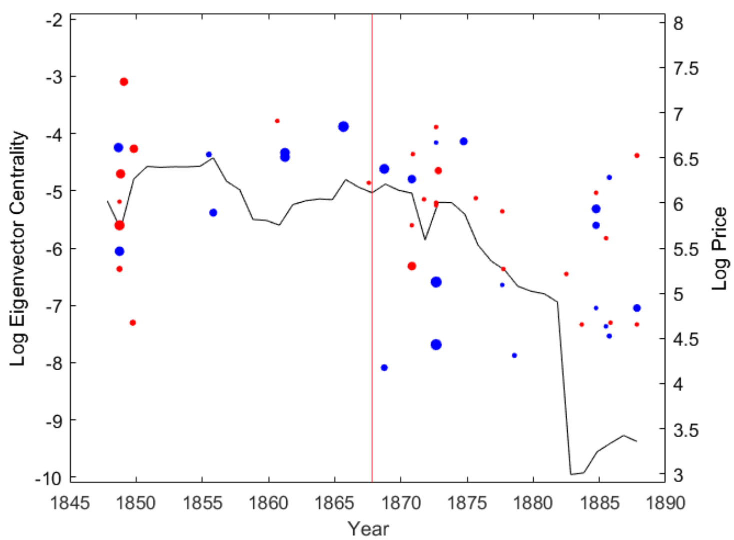
Panels A, B and C capture log eigenvector centrality effects corresponding to estimates in Panels A, B and C of Table 4 respectively. The solid lines are the point estimate for each quanitle. The shaded regions represent the 95% confidence interval.

Figure 2.6: Artist comparison

(a) J.M.W. Turner



(b) Horatio McCulloch



The black line shows the log eigenvector centrality of each artist from 20 year before his death, to 20 years after. The vertical red line indicates the year each artist died. The dots show log prices of pieces sold. The blue dots are pieces bought by dealers and the red dots those bought by others. The dots are scaled to the square root of the buyers eigenvector centrality.

Chapter 3 Figures

Figure 3.1: Histograms of the Number of Change Orders and the Cost of Change Order

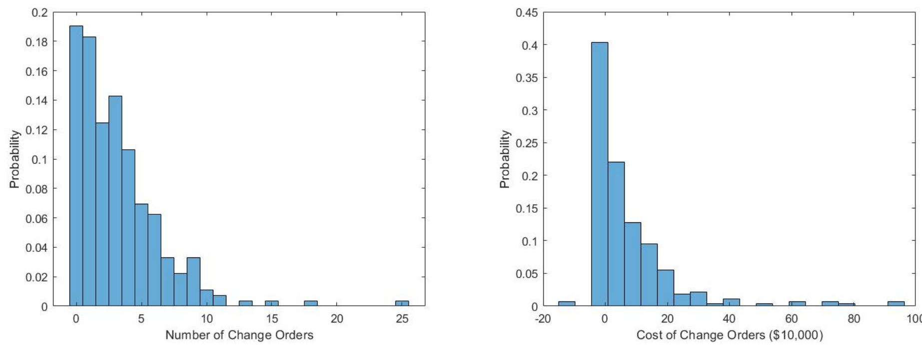


Figure 3.2: Number of Subcontractors by Project

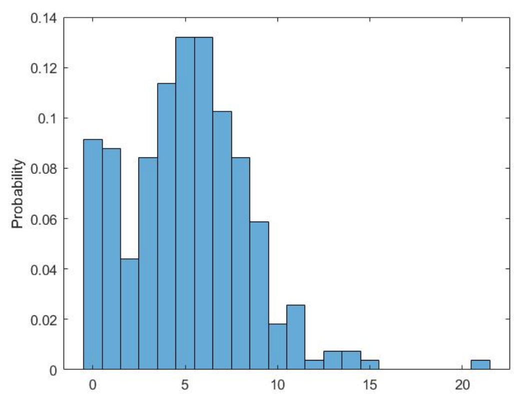


Figure 3.3: Histograms of the Subcontractor Items and Percentage of Winning Bid completed by Subcontractors

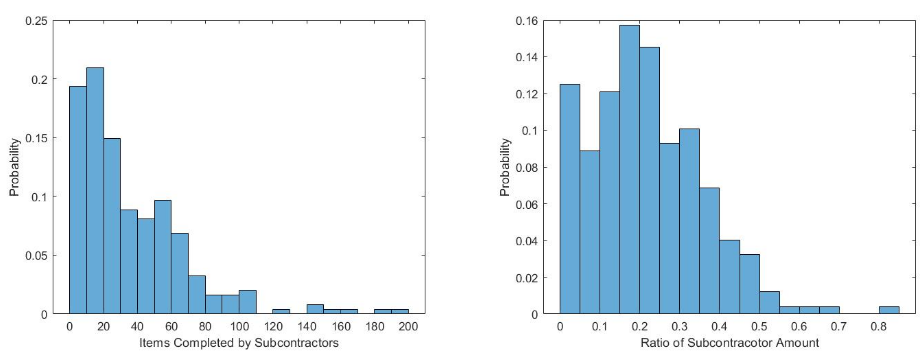


Figure 3.4: Contractor-Subcontractor Network

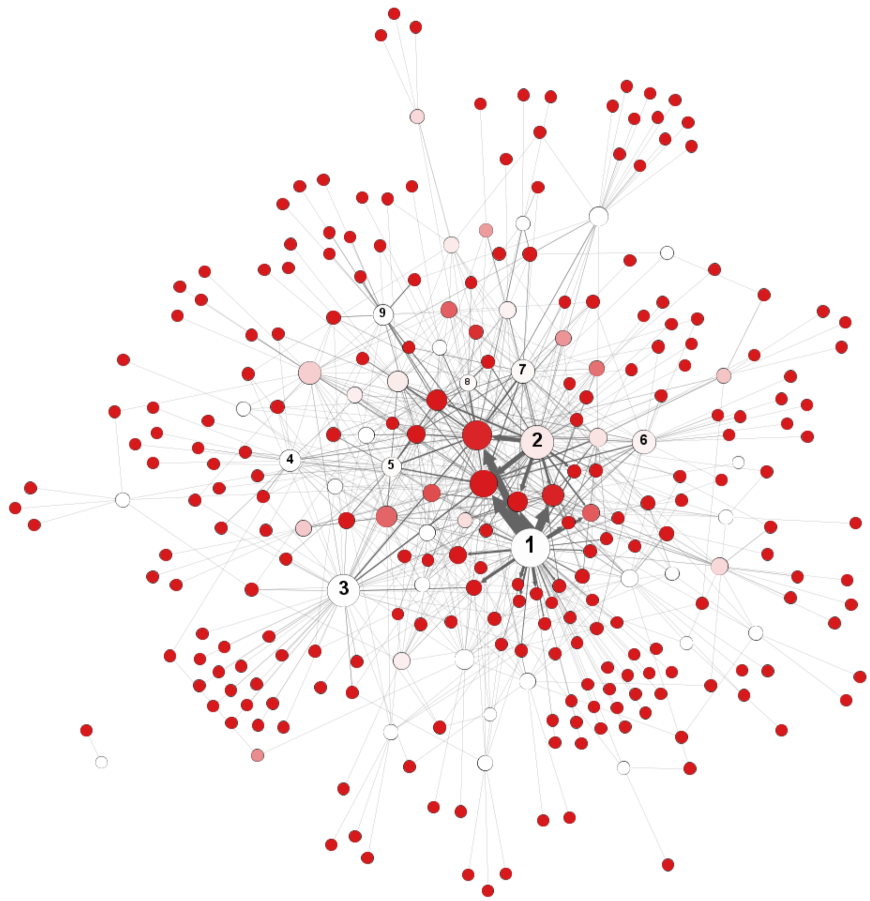


Figure 3.5: Project Locations and Change Orders in the Vermont Highway Construction Industry

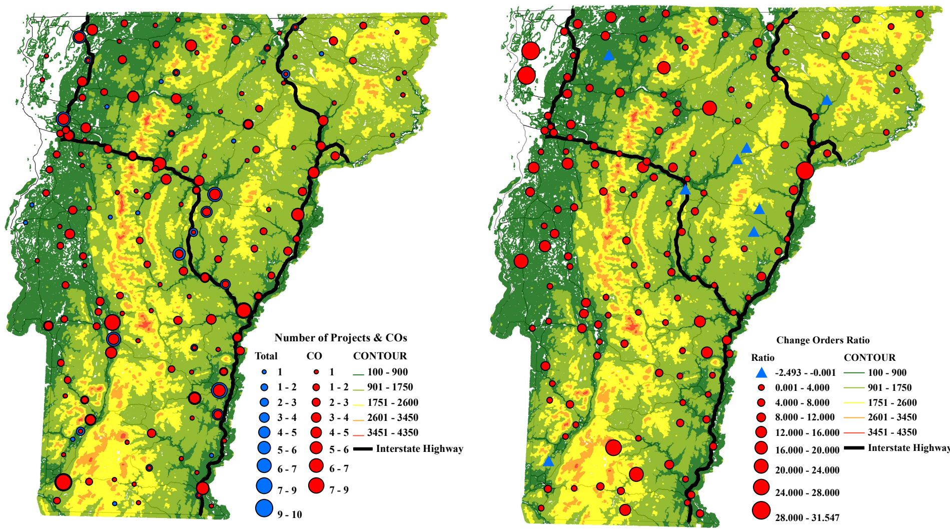
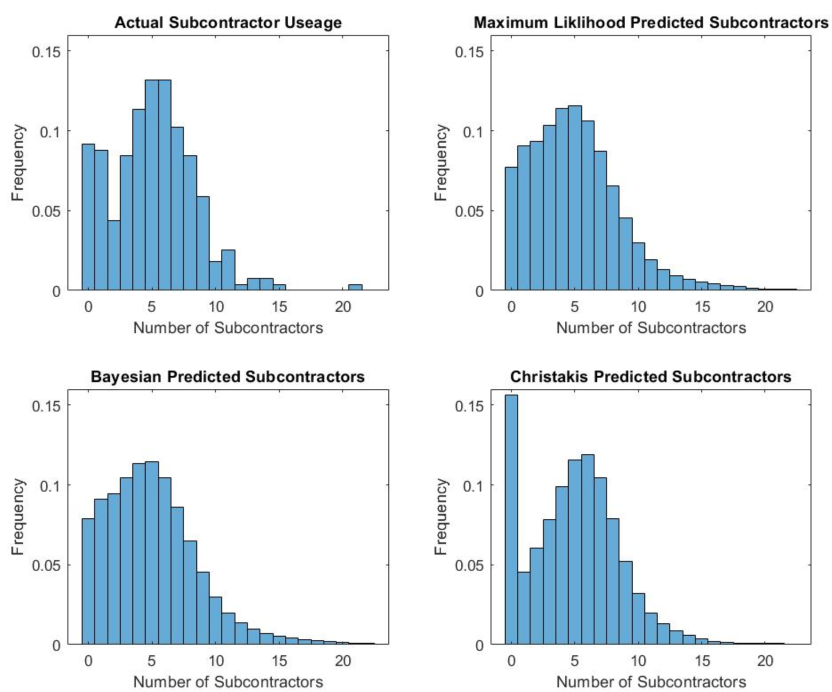


Figure 3.6: Number of Subcontractors by Project



Tables

Chapter 1 Tables

Table 1.1: Auction Variable: Summary Statistics

Auction Variables	Mean	Median	Std dev
Total Bidder	4.31	4	2.141
Total Planholders	7.19	7	3.04
Total Potential Planholders	23.66	24	8.114
Plan Cost	22.3	11.9	25.6
Engineer's Estimate ($1000)	1,136	529	1,625
Contract Days	140	120	61.8
Project Items	45.7	35	28.4
DBE Goal (%)	2.74	3	2.80
OK Unemployment Rate	5.15	4.6	1.23
Observations		516	

The Oklahoma Unemployment Rate is taken from the Bureau of Labor Statistics. All other data comes from ODOT bridge and approach contracts from 2005 to 2011.

Table 1.2: Potential Bidder: Summary Statistics

	Planholders			Potential Planholders		
	Mean	Median	Std dev	Mean	Median	Std dev
Bidder	0.621	1	0.485	0.202	0	0.401
Planholder	1	1	0	0.325	0	0.468
Distance from job site (mi)	91.58	78.11	67.35	129.5	112.6	88.61
Backlog ($1000)	767.4	428.4	894.8	760.8	350.0	982.4
Outdegree Centrality	18.33	16	11.94	16.03	14	11.20
Hub Centrality	0.025	0.020	0.018	0.021	0.016	0.016
Horizontal Subcontractor	0.499	0	0.500	0.512	1	0.500
Observations		3,093			9,524	

All data comes from ODOT bridge and approach contracts from 2005 to 2011. Firms with no subcontracting connections are dropped.

Table 1.3: Potential Bidder Pair: Summary Statistics

	Planholder Pair			Potential Planholder Pair		
	Mean	Median	Std Dev	Mean	Median	Std Dev
Subcontractor Overlap	4.557	3	4.147	3.253	2	3.346
Jaccard Similarity	0.132	0.116	0.089	0.103	0.091	0.078
Cosine Similarity	0.250	0.243	0.134	0.201	0.199	0.124
Observations		9,471			91,497	

All data comes from ODOT bridge and approach contracts from 2005 to 2011. Firms with no subcontracting connections are dropped. Each observation is a potential bidder pair in an auction.

Table 1.4: Planholder Bid Decision

	Standard (1)	Constant (2)	Jaccard (3)	Cosine (4)	Overlap (5)
ρ_1			0.024	0.069	0.001
			(0.207)	(0.135)	(0.005)
ρ_0		-0.016	-0.019	-0.033	-0.022
		(0.016)	(0.032)	(0.037)	(0.027)
Potential Bidders	-0.048***	-0.048***	-0.048***	-0.048***	-0.048***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log Estimate	-0.105	-0.105	-0.106	-0.108	-0.107
	(0.069)	(0.067)	(0.067)	(0.067)	(0.067)
Log Working Days	0.131	0.135	0.136	0.138	0.137
	(0.103)	(0.100)	(0.100)	(0.100)	(0.100)
Log Items	-0.253**	-0.254**	-0.253**	-0.250**	-0.252**
	(0.115)	(0.112)	(0.112)	(0.112)	(0.112)
DBE Goal	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.009)	(0.009)	(0.009)	(0.009)	(0.09)
Time Trend	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
OK Unemployment	0.115***	0.116***	0.116***	0.116***	0.116***
	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)
Distance (100 mi)	-0.224***	-0.223***	-0.222***	-0.222***	-0.222***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Backlog ($mill)	-0.026	-0.029	-0.029	-0.028	-0.028
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Outdegree Centrality	-0.008	-0.008	-0.008	-0.007	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Hub Centrality (X100)	0.153***	0.151***	0.151***	0.151***	0.151***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Horizontal Sub	-0.058	-0.056	-0.056	-0.056	-0.057
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Log Likelihood	-1962.6	-1962.2	-1962.2	-1962.0	-1962.1
Pseudo R^2	0.044	0.044	0.044	0.044	0.044

A standard probit regression is shown in Column 1. The results of the replication of Li and Zhang (2010) on ODOT data are seen in Column 2. Columns 3, 4, and 5 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Columns 2 through 4 use 400 simulation and finite differences to estimate derivatives. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.5: Potential Planholder Buy Decision

	Standard (1)	Constant (2)	Jaccard (3)	Cosine (4)	Overlap (5)
ρ_1			0.462***	0.348***	0.006***
			(0.080)	(0.054)	(0.002)
ρ_0		0.031***	-0.014	-0.034***	0.013
		(0.008)	(0.011)	(0.013)	(0.010)
Potential Bidders	-0.030***	-0.031***	-0.030***	-0.030***	-0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log Plan Cost	0.113***	0.112**	0.111**	0.111**	0.105**
	(0.040)	(0.045)	(0.046)	(0.046)	(0.046)
Log Working Days	0.328***	0.332***	0.310***	0.302***	0.318***
	(0.056)	(0.064)	(0.065)	(0.066)	(0.065)
Log Items	-0.388***	-0.386***	-0.369***	-0.364***	-0.384***
	(0.071)	(0.081)	(0.082)	(0.083)	(0.081)
DBE Goal	-0.009	-0.008	-0.010	-0.010	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Time Trend	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
OK Unemployment	0.157***	0.158***	0.142***	0.138***	0.146***
	(0.019)	(0.021)	(0.021)	(0.022)	(0.022)
Distance (100 mi)	-0.630***	-0.639***	-0.626***	-0.623***	-0.636***
	(0.022)	(0.022)	(0.022)	(0.023)	(0.022)
Backlog ($ mill)	-0.106***	-0.105***	-0.103***	-0.100***	-0.103***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Outdegree Centrality	-0.015***	-0.017***	-0.017***	-0.016***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Hub Centrality (X100)	0.238***	0.247***	0.246***	0.240***	0.247***
	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)
Horizontal Sub	-0.066**	-0.071**	-0.076***	-0.076***	-0.074**
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Log Likelihood	-5230.5	-5221.1	-5204.5	-5199.5	-5217.0
Pseudo R^2	0.129	0.130	0.133	0.134	0.131

A standard probit regression is shown in Column 1. The results of the replication of Li and Zhang (2010) on ODOT data are seen in Column 2. Columns 3, 4, and 5 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Columns 2 through 4 use 700 simulation and finite differences are used to estimate derivatives. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.6: Bidding Behavior

	Standard (1)	Constant (2)	Jaccard (3)	Cosine (4)	Overlap (5)
ρ_1			0.377***	0.329***	0.013***
			(0.132)	(0.087)	(0.003)
ρ_0		0.166***	0.373***	0.341***	0.365***
		(0.003)	(0.030)	(0.033)	(0.027)
Potential Bidders	-0.012***	-0.013***	-0.014***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Log Engineer's Estimate	0.921***	0.920***	0.921***	0.921***	0.920***
	(0.010)	(0.011)	(0.014)	(0.014)	(0.014)
Log Working Days	0.079***	0.084***	0.092***	0.092***	0.093 ***
	(0.015)	(0.017)	(0.022)	(0.022)	(0.022)
Log Items	0.128***	0.123***	0.114***	0.114***	0.115***
	(0.017)	(0.019)	(0.024)	(0.024)	(0.024)
DBE Goal	-0.001	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Time Trend	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OK Unemployment	-0.053***	-0.052***	-0.051***	-0.051***	-0.051***
	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
Distance (100 mi)	0.039***	0.035***	0.032***	0.032***	0.032***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Backlog ($ mill)	-0.017***	-0.014***	-0.012***	-0.012***	-0.011***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Outdegree Centrality	0.002	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hub Centrality	-1.114*	-1.008*	-0.893*	-0.881*	-0.991**
	(0.588)	(0.531)	(0.489)	(0.484)	(0.483)
Horizontal Sub	0.008	0.008	0.009	0.009	0.008
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Pseudo R^2	0.970	0.975	0.977	0.977	0.977

The results use a Bayesian method to capture affiliation between bids. A Standard regression is done in Column 1. General affiliation is tested for in Column 2. Columns 3, 4, and 5 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Posterior distribution standard deviations are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.7: Planholder Bid Decision: Windows

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
Panel A: 6-month window				
ρ_1		-0.245	-0.070	-0.013**
		(0.245)	(0.149)	(0.007)
ρ_0	-0.009	0.020	0.006	0.032
	(0.018)	(0.035)	(0.038)	(0.029)
Log Likelihood	-1863.7	-1863.2	-1863.6	-1861.9
Pseudo R^2	0.038	0.038	0.038	0.039
Panel B: 18-month window				
ρ_1		-0.166	-0.100	-0.002
		(0.186)	(0.125)	(0.003)
ρ_0	-0.025*	-0.002	0.001	-0.016
	(0.015)	(0.030)	(0.036)	(0.025)
Log Likelihood	-1949.7	-1949.3	-1949.4	-1949.6
Pseudo R^2	0.051	0.051	0.051	0.051

The results use the same regressors and methods as Table 1.4. Panel A has 560 auctions, 2,945 planholders, and 7,803 planholder pairs. Panel B has 493 auctions, 3,087 planholders, and 9,846 planholder pairs. General affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.8: Potential Planholder Buy Decision: Windows

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
Panel A: 6-month window				
ρ_1		0.202**	0.158***	0.001
		(0.093)	(0.059)	(0.003)
ρ_0	0.035***	0.016	0.007	0.033***
	(0.009)	(0.013)	(0.014)	(0.012)
Log Likelihood	-4815.6	-4813.1	-4811.8	-4815.5
Pseudo R^2	0.137	0.137	0.137	0.137
Panel B: 18-month window				
ρ_1		0.451***	0.358***	0.005***
		(0.078)	(0.054)	(0.002)
ρ_0	0.028***	-0.017	-0.041***	0.008
	(0.008)	(0.011)	(0.012)	(0.010)
Log Likelihood	-5329.1	-5312.4	-5305.9	-5323.6
Pseudo R^2	0.129	0.132	0.133	0.130

The results use all the same regressors and methods as Table 1.5. Panel A has 562 auctions, 8,722 potential planholders, and 69,552 potential planholder pairs. Panel B has 494 auctions, 9,836 potential planholders, and 101,901 potential planholder pairs. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.9: Planholder Bid Decision: No Network

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.035	0.069	0.001
		(0.206)	(0.135)	(0.004)
ρ_2		-0.040	-0.027	-0.040
		(0.063)	(0.066)	(0.060)
ρ_3		0.005**	0.005**	0.005**
		(0.002)	(0.002)	(0.002)
ρ_4		0.162*	0.175*	0.163*
		(0.095)	(0.097)	(0.093)
ρ_0	0.002	-0.023	-0.035	-0.023
	(0.014)	(0.032)	(0.037)	(0.026)
Log Likelihood	-2357.0	-2352.5	-2352.4	-2352.5
Pseudo R^2	0.056	0.057	0.058	0.057

The expands the results of Table 1.4 to incorporate firms with no observed network. This leads to an increased sample size of 516 auctions, 3,709 planholders, and 13,861 planholder pairs. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. The number of simulations used increases to 450. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.10: Potential Planholder Buy Decision: No Network

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.546***	0.418***	0.008***
		(0.077)	(0.054)	(0.002)
ρ_2		0.038**	0.062***	0.005
		(0.019)	(0.019)	(0.017)
ρ_3		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
ρ_4		0.104***	0.126***	0.075***
		(0.027)	(0.027)	(0.026)
ρ_0	0.030***	-0.026**	-0.049***	0.004
	(0.007)	(0.011)	(0.012)	(0.010)
Log Likelihood	-6624.0	-6597.1	-6589.8	-6613.8
Pseudo R^2	0.116	0.120	0.121	0.118

The expands the results of Table 1.5 to incorporate firms with no observed network. This leads to an increased sample size of 516 auctions, 12,209 potential planholders, and 155,286 potential planholder pairs. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. The number of simulations used increases to 800. Standard errors are shown in parenthesis.* indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.11: Planholder Bid Decision: Weighted Network

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.295	0.105	-0.012
		(0.426)	(0.222)	(0.040)
ρ_0	-0.016	-0.025	-0.024	-0.013
	(0.016)	(0.021)	(0.024)	(0.019)
Outdegree ($mil)	0.014**	0.014**	0.014**	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)
Hub Centrality	-1.237	-1.265	-1.265	-1.216
	(0.980)	(0.982)	(0.982)	(0.982)
Log Likelihood	-1985.6	-1985.4	-1985.5	-1985.6
Pseudo R^2	0.032	0.033	0.033	0.033

The expands the results of Table 1.4 to dollar weights to firm's network. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 1.12: Potential Planholder Buy Decision: Weighted Network

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.468***	0.505***	0.010
		(0.104)	(0.073)	(0.010)
ρ_0	0.025***	0.013	-0.004	0.023
	(0.008)	(0.008)	(0.009)	(0.008)
Outdegree ($mil)	-0.002	-0.002	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Hub Centrality	-0.652	-0.647	-0.663	-0.628
	(0.553)	(0.559)	(0.561)	(0.556)
Log Liklihood	-5346.2	-5338.1	-5324.5	-5345.7
Pseudo R^2	0.110	0.111	0.113	0.110

The expands the results of Table 1.5 to dollar weights to firm's network. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Chapter 2 Tables

Table 2.1: Descriptive Statistics

	Before Death		After Death	
Varriable	Mean / Count	STD	Mean / Count	STD
Number of Pieces Sold	3,127		4,633	
Number of Unique Artists	160		160	
Number of Unique Buyers	647		946	
Number of Unique Sellers	716		929	
Number of Unknown Sales	381		516	
Price	381.7	508.1	355.2	596.0
Average Number of Bidders in an Auction	40.19	19.56	42.11	20.92
Artist: Eigenvector Centrality	0.005	0.006	0.011	0.018
Artist: Number of Art Sold	30.59	33.07	43.04	42.4
Buyer: Eigenvector Centrality	0.024	0.038	0.024	0.038
Buyer: Capacity	11,095	16154	12000	17,974
Buyer: Dealer	0.664	0.473	0.627	0.484
Artist-Buyer Link	0.481	0.500	0.511	0.500
Seller: Family	0.007	0.084	0.129	0.336
Seller's Past Volume	3.82	14.68	3.176	12.51
Unknown Seller	0.122	0.327	0.111	0.315
Christie's Dummy	0.967	0.179	0.942	0.233

Before Death includes pieces sold at auction from 20 years prior to death. After Death includes pieces sold at auction till 20 years after death. Source: Authors' calculation.

Table 2.2: Buyer Likelihood to Purchase Artwork at Auction

	Dealers	Others	All
Variable of Interest	(1)	(2)	(3)
Posthumous	-0.008	-0.001	0.018
	(0.050)	(0.054)	(0.037)
Artist: Log Eigenvector Centrality	-0.003	-0.020***	-0.009*
	(0.006)	(0.006)	(0.004)
Artist: Log # of Art Sold	-0.036**	0.028*	-0.011
	(0.015)	(0.016)	(0.011)
Buyer: Log Eigenvector Centrality	0.078***	-0.005	0.043***
	(0.005)	(0.004)	(0.003)
Buyer: Log Capacity	0.039***	0.043***	0.059***
	(0.008)	(0.006)	(0.005)
Artist-Buyer Link	0.566***	0.530***	0.572***
	(0.019)	(0.029)	(0.015)
Seller: Family	-0.001	0.038	-0.004
	(0.037)	(0.037)	(0.026)
Seller: Unknown	-0.108***	0.137***	-0.012
	(0.025)	(0.025)	(0.018)
Seller: Log Past Sales	-0.025*	0.038**	0.000
	(0.013)	(0.015)	(0.010)
Max Rival: Log Eigenvector	-0.188***	0.002	-0.129***
	(0.015)	(0.013)	(0.019)
Max Rival: Log Capacity	-0.115***	0.004	-0.109***
	(0.020)	(0.019)	(0.013)
Mean Rival: Artist-Buyer Link	-0.658***	-0.399***	-0.551***
	(0.116)	(0.129)	(0.086)
Artist: Contemporary British	0.043*	-0.041	0.004
	(0.022)	(0.025)	(0.016)
Observations	110,217	206,295	316,512
Other Controls	Yes	Yes	Yes
Pseudo R^2	0.147	0.068	0.137

Each observation is a bidder at an auction who may buy a painting. Column 1 includes only the bidders who were art dealers. Column 2 includes only the bidders who were not art dealers. Column 3 looks at the full sample. All columns incorporates other control variables as well, including log number of buyers, log number of painting for sale, a dealers capacity, dummies for an artwork's medium and genre. Source: Authors' calculation.

Table 2.3: Distributional Posthumous Effect on Log Price

Variables of Interest	Mean	Quantiles(τ) 0.1	0.25	0.5	0.75	0.9
Panel A. Without Controls						
Posthumous	-0.120***	-0.009	-0.130***	-0.198***	-0.215***	-0.180***
	(0.026)	(0.021)	(0.027)	(0.028)	(0.027)	(0.038)
Controls	No	No	No	No	No	No
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. With Controls and Sample Selection						
Posthumous	-0.007	0.085	-0.031	-0.052	-0.046	0.036
	(0.047)	(0.130)	(0.105)	(0.087)	(0.115)	(0.145)
Artist: Log Eigenvector	0.084***	0.062**	0.085***	0.096***	0.072***	0.042***
Centrality	(0.012)	(0.042)	(0.034)	(0.032)	(0.030)	(0.032)
Artist: No Network	-0.981***	-0.684**	-0.917***	-1.116***	-0.944**	-0.636**
	(0.147)	(0.439)	(0.343)	(0.330)	(0.364)	(0.444)
Artist: Log Number of	-0.050**	0.008	-0.017	-0.095*	-0.095**	-0.090*
Art Sold	(0.027)	(0.095)	(0.070)	(0.058)	(0.058)	(0.069)
Buyer: Log Eigenvector	-0.054***	-0.022	-0.034	-0.033	-0.053	-0.067
Centrality	(0.008)	(0.064)	(0.049)	(0.045)	(0.044)	(0.061)
Buyer: No Network	0.731***	0.404	0.544*	0.536**	0.671**	0.705**
	(0.079)	(0.504)	(0.389)	(0.313)	(0.359)	(0.429)
Buyer: Log Capacity	0.269***	0.158***	0.186***	0.215***	0.272**	0.302**
	(0.014)	(0.047)	(0.038)	(0.038)	(0.058)	(0.086)
Buyer: Dealer	-0.194***	-0.165	-0.132	-0.195	-0.176*	-0.207*
	(0.031)	(0.202)	(0.166)	(0.148)	(0.101)	(0.143)
Artist-Buyer Link	-0.079	0.014	-0.013	-0.020	-0.031	-0.053
	(0.050)	(0.335)	(0.298)	(0.290)	(0.373)	(0.429)
Seller: Family	-0.307***	-0.265	-0.256	-0.231*	-0.209**	-0.260*
	(0.060)	(0.166)	(0.120)	(0.098)	(0.108)	(0.125)
Log Seller's	0.003	0.008	-0.003	-0.020	-0.016	-0.008
past volume	(0.019)	(0.058)	(0.042)	(0.032)	(0.034)	(0.042)
Unknown Seller	-0.137***	-0.078*	-0.116**	-0.125**	-0.142**	-0.167*
	(0.028)	(0.084)	(0.073)	(0.058)	(0.073)	(0.100)
Christie's Dummy	0.463***	1.252***	0.621***	0.356*	0.251	0.179
	(0.077)	(0.497)	(0.450)	(0.331)	(0.272)	(0.254)
$\hat{\rho}$	-0.025			-0.060		
	(0.103)			(0.444)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Total number of observations is 7,760 for all columns. Sample selection on the mean uses the method of Heckman (1979) while for the quantiles Arellano, Blundell, and Bonhomme (2017) is used. Other control variables include a cubic time trend, log number of buyers, a quadratic in the age of the artist, a dummy for if the art was part of a collection, as well as seller type dummies, medium dummies, and genre dummies. The standard errors are calculated using 1000 bootstrap repetitions. * indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level. Source: Authors' calculation.

Table 2.4: Network at Death on Prices distribution

		Quantiles(τ)			
Variables of Interest	Mean	0.25	0.50	0.75	0.90
Panel A: Less than 2 years after death					
Artist: Log Eigenvector	0.060*	0.041	0.053*	0.091**	0.119***
Centrality at Death	(0.033)	(0.029)	(0.028)	(0.036)	(0.030)
Artist: Log Number	0.060	0.095	0.047	-0.036	0.000
of Art Sold	(0.067)	(0.074)	(0.063)	(0.076)	(0.063)
Seller: Family	-0.543***	-0.269*	-0.481***	-0.529***	-0.755***
	(0.154)	(0.145)	(0.123)	(0.154)	(0.130)
Seller: Log Past Volume	-0.063	-0.025	-0.010	0.011	-0.075
	(0.077)	(0.084)	(0.057)	(0.080)	(0.071)
R^2	0.311	0.278	0.290	0.262	0.168
Panel B: Between 2 and 10 years after death					
Artist: Log Eigenvector	0.022	0.006	0.015	0.047*	0.068**
Centrality at Death	(0.022)	(0.015)	(0.017)	(0.028)	(0.028)
Artist: Log Number	-0.119	-0.112	-0.026	0.049	0.128**
of Art Sold	(0.115)	(0.121)	(0.117)	(0.108)	(0.052)
Seller: Family	-0.813*	-1.137***	-0.555	-0.492	0.034
	(0.465)	(0.415)	(0.575)	(0.330)	(0.317)
Seller: Log Past Volume	-0.056	-0.044	-0.062***	-0.095**	-0.149***
	(0.039)	(0.035)	(0.040)	(0.042)	(0.055)
R^2	0.246	0.232	0.227	0.173	0.117
Panel C: Between 10 and 20 years after death					
Artist: Log Eigenvector	-0.021	-0.031	-0.013	0.046*	0.094***
Centrality at Death	(0.028)	(0.029)	(0.022)	(0.027)	(0.034)
Artist: Log Number	0.042	0.044	0.079	0.115*	0.141**
of Art Sold	(0.081)	(0.065)	(0.063)	(0.068)	(0.070)
Seller: Family	0.226	0.060	0.769*	0.723***	0.240
	(0.697)	(1.179)	(0.436)	(0.258)	(0.195)
Seller: Log Past Volume	-0.040	-0.040	-0.020	-0.034	-0.037
	(0.035)	(0.028)	(0.060)	(0.056)	(0.066)
R^2	0.379	0.362	0.367	0.325	0.266

Total number of observations is 902 in Panel A, 1,876 in Panel B and 1,855 in Panel C. R^2 for quantile regressions is actually pseudo R^2. Other control variables include a cubic time trend, log number of buyers, a quadratic in the age of the artist, A dummy if sold at Christie's, a dummy for if the art was part of a collection, as well as seller type dummies, medium dummies, and genre dummies. Robust standard errors shown in parenthesis. * indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level. Source: Authors' calculation.

Chapter 3 Tables

Table 3.1: Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max	Number of Observations
Number of Change Orders	4.272	4.245	1	35	254
Change Order Amount (thousands of dollars)	105.02	185.10	-116.85	1421.65	254
Change Order Percentage	7.173	9.525	-17.28	61.89	254
Number of Subcontractors	5.093	3.291	0	21	312
Number of Items Subcontracted	31.87	32.15	0	191	312
Percentage Subcontracted	19.79	14.43	0	82.11	312
Engineering Cost Estimate (millions of dollars)	1.910	2.432	0.026	24.551	312
Expected Duration (days)	191.619	124.562	14	813	312
Number of Items	60.228	35.346	2	245	312
Elevation (hundreds of feet)	7.164	3.704	1	22.5	312
Engineer Experience (projects)	16.032	11.820	1	41.5	312
Firm Experience (years)	66.017	45.171	3	140	303
Expected Number of Bidders	2.516	2.743	0	11.524	281
Unemployment Rate	4.637	1.431	3.3	7.3	312
Real Volume of Projects (millions of dollars)	3.049	2.678	0.038	13.979	312
Number of Subcontractors in the Market	98.385	25.957	15	128	312
Contractor Outdegree Centrality	8.978	10.774	0	38	312
Contractor Hub Centrality	0.045	0.069	0	0.226	312
Contractor Past Item Experience (percentage)	0.646	0.338	0	1	312
Subcontractors Hired	0.052	0.222	0	1	30696
Contractor-Subcontractor link	0.091	0.288	0	1	30696
Subcontractor Indegree Centrality	1.658	2.479	0	24	30696
Subcontractor Authority Centrality	0.004	0.010	0	0.082	30696
Horizontal Subcontractor	0.080	0.272	0	1	30696
DBE Subcontractor	0.292	0.455	0	1	30696
Subcontractor Item Experience (percent)	0.128	0.217	0	1	30696
Subcontractor Unique Item Dummy	0.243	0.429	0	1	30696

Table 3.2: Bidding and renegotiation activities of 92 firms

Firm ID	(A)	(B)	(C)	(D)	(E)	(F)	(G)
(1)	71	35.954	65	6.894	3.775	6.45	0.266
(2)	33	12.204	30	8.374	3.970	6.21	0.254
(3)	9	10.147	8	4.408	8.889	9.11	0.235
(4)	8	4.976	6	7.118	2.625	4.25	0.214
(5)	9	3.697	9	3.183	6.333	7.00	0.143
(6)	8	3.359	7	10.550	5.125	6.25	0.190
(7)	12	2.417	10	6.016	3.583	5.42	0.210
(8)	8	1.956	8	2.714	3.250	5.88	0.211
(9)	8	1.781	7	5.877	3.125	6.38	0.136
(Remaining 83 Firms)	146	23.509	104	4.874	2.692	3.66	0.177
All Firms	312	100.000	254	5.859	3.478	5.09	0.225

(A): Number of Wins
(B): Value of Winning Projects/Value of Procured
(C): Number of Contracts Renegotiated
(D): Average Value of Change Orders/Winning Bid on Project (%)
(E): Average Number of Change Orders per Project
(F): Average Number of Subcontractors Used
(F): Percentage of Bid Completed by Subcontractors

Table 3.3: Link Prediction

	(1) Sequential	(2) Simultaneous	(3)
		ML	Bayesian
Project Subs Hired	-0.149***		
	(0.032)		
At Least 1 Sub Hired	2.250***		
	(0.276)		
Rival Sub: Items %	-0.794**		
	(0.356)		
Unique Item: Prime and Rival	2.296***		
	(0.238)		
Edge	2.492***	2.281***	2.288***
	(0.112)	(0.101)	(0.101)
Log Available Subs	0.100	-0.462**	-0.463**
	(0.262)	(0.210)	(0.211)
Prime: Outdegree	-0.033***	-0.029***	-0.029***
	(0.009)	(0.008)	(0.008)
Prime: Log Hub	-0.007	-0.017	-0.015
	(0.053)	(0.044)	(0.044)
Prime: Item %	-6.185***	-4.969***	-4.984***
	(0.562)	(0.473)	(0.479)
Prime: Item % sqr	4.169***	3.127***	3.135***
	(0.570)	(0.486)	(0.491)
Sub: Indegree	0.198***	0.169***	0.170***
	(0.013)	(0.011)	(0.011)
Sub: Log Authority	0.253***	0.254***	0.255***
	(0.031)	(0.029)	(0.029)
Sub: DBE	0.499***	0.498***	0.498***
	(0.090)	(0.083)	(0.084)
Sub: Horizontal Sub	-0.254*	-0.221*	-0.221*
	(0.140)	(0.127)	(0.128)
Sub: Item %	1.988***	2.027***	2.038***
	(0.587)	(0.543)	(0.542)
Sub: Item % sqr	-2.968***	-2.589***	-2.615***
	(0.710)	(0.664)	(0.665)
Unique Item: Prime	-1.095***	0.506***	0.508***
	(0.211)	(0.092)	(0.092)
Prime: Top Firm	0.121***	0.167	0.168
	(0.034)	(0.114)	(0.112)
Observations	28,678	28,678	28,678
Simulated Log Likelihood	-3412.2	-3621.7	-3629.9
Simulated Pseudo R^2	0.388	0.350	0.349

*** Denotes statistical significance at the 1% level, ** denotes significance at the 5% and * denotes significance at the 10% level. Standard deviation of posterior in parenthesis for Columns 1 and 3. Standard errors in parenthesis for Column 2. Additional control variables include Log Project Duration, Number of Items, Log Engineer's Estimate, Elevation and its square, a Top Firm Dummy, Engineer's Experience, Firm's Experience, Expected Number of Bidders, Unemployment Rate, Log Volume, and Dummies for Project Type. Full Results available upon request.

Table 3.4: Predicting Actual Subcontractor use

	(1)	(2)	(3)	(4)	(5)	(6)
	Sequential		Simultaneous			
			ML		Bayesian	
$\hat{sub}$	0.815***	0.295***	0.744***	0.249***	0.743***	0.249***
	(0.049)	(0.095)	(0.045)	(0.074)	(0.045)	(0.074)
Log of Expected Duration		-0.253		-0.272		-0.270
		(0.272)		(0.266)		(0.266)
Number of Items		0.048***		0.050***		0.050***
		(0.008)		(0.007)		(0.007)
Log of Engineer's Estimate		0.230		0.262		0.262
		(0.172)		(0.168)		(0.168)
Elevation (hundreds of feet)		-0.027		-0.033		-0.033
		(0.091)		(0.091)		(0.091)
Elevation squared		0.003		0.003		0.003
		(0.004)		(0.004)		(0.004)
Top Firm		0.796*		0.868**		0.864**
		(0.416)		(0.402)		(0.402)
Engineer Experience (projects)		0.052		0.035		0.037
		(0.233)		(0.234)		(0.234)
Firm Experience (years)		-0.005		-0.005		-0.005
		(0.004)		(0.004)		(0.004)
Expected Number of Bidders		0.036		0.037		0.037
		(0.050)		(0.050)		(0.050)
Unemployment Rate		0.044		0.048		0.047
		(0.079)		(0.080)		(0.080)
Log Volume		-0.079		-0.091		-0.090
		(0.128)		(0.128)		(0.128)
Asphalt Project		0.277		0.335		0.332
		(0.478)		(0.465)		(0.465)
Bridge Project		0.214		0.295		0.294
		(0.504)		(0.489)		(0.489)
Observations	273	273	273	273	273	273
R^2	0.582	0.673	0.549	0.673	0.549	0.673

*** Denotes statistical significance at the 1% level, ** denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors in parenthesis. $\hat{sub}$ is the predicted level of subcontracting from 16,000 simulations of results.

Table 3.5: Number of Change Orders

	Full Sample			Subsample		
	GMM	GMM IV	GMM Proxy	GMM	GMM	GMM Proxy
Number of Subcontractors	0.053***	0.165**		0.045***	0.133***	
	(0.020)	(0.073)		(0.017)	(0.043)	
$\hat{sub}$			0.071***			0.075***
			(0.025)			(0.023)
Log Duration	0.243**	0.290**	0.235*	0.194	0.236**	0.197*
	(0.122)	(0.115)	(0.121)	(0.119)	(0.111)	(0.117)
Number of Items	0.004*	-0.004	0.003	0.005***	-0.001	0.002
	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)
Log of Engineer Estimate	0.172**	0.103	0.172**	-0.028	-0.090	-0.020
	(0.079)	(0.096)	(0.083)	(0.078)	(0.087)	(0.080)
Elevation (hundreds of feet)	0.081*	0.078*	0.082**	0.087**	0.080**	0.080**
	(0.042)	(0.041)	(0.041)	(0.035)	(0.036)	(0.035)
Elevation squared	-0.003*	-0.003*	-0.003*	-0.004**	-0.004**	-0.003**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Top Firm	0.054	-0.064	0.024	0.076	-0.046	0.053
	(0.151)	(0.185)	(0.151)	(0.155)	(0.185)	(0.154)
Engineer Experience (projects)	-0.110	-0.088	-0.121	-0.170*	-0.150	-0.189**
	(0.094)	(0.100)	(0.095)	(0.089)	(0.094)	(0.089)
Firm Experience (years)	0.001	0.003	0.002	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Expected Number of Bidders	0.003	-0.006	0.003	-0.032	-0.042*	-0.030
	(0.023)	(0.025)	(0.023)	(0.021)	(0.022)	(0.021)
Unemployment Rate	0.007	-0.003	-0.001	0.036	0.025	0.025
	(0.033)	(0.034)	(0.033)	(0.033)	(0.036)	(0.032)
Log Volume	-0.047	-0.017	-0.046	-0.082**	-0.058	-0.078*
	(0.047)	(0.056)	(0.046)	(0.041)	(0.047)	(0.040)
Asphalt Project	-0.047	-0.151	-0.047	0.227	0.130	0.191
	(0.243)	(0.275)	(0.235)	(0.282)	(0.310)	(0.275)
Bridge Project	-0.076	-0.133	-0.084	0.093	0.001	0.057
	(0.231)	(0.249)	(0.228)	(0.282)	(0.301)	(0.280)
Observations	273	273	273	173	173	173

*** Denotes statistical significance at the 1% level, ** denotes significance at the 5% and * denotes significance at the 10% level. Clustered standard errors are in parentheses.

Table 3.6: Value of Contract Renegotiation

	Value of Change Orders ($10,000)		(Change Orders / Estimate) X100		Log(Value of Change Orders +1)	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Number of Subcontractors	1.336*	4.823*	0.619**	1.785*	0.151	0.736
	(0.726)	(2.671)	(0.259)	(0.997)	(0.114)	(0.651)
Log of Engineer Estimate	4.030***	2.828*			0.958**	0.766*
	(1.441)	(1.576)			(0.386)	(0.432)
Log Duration	4.707	5.978*	2.589*	2.826*	1.628**	1.842***
	(3.289)	(3.392)	(1.557)	(1.550)	(0.662)	(0.712)
Number of Items	-0.050	-0.285	-0.080**	-0.166**	0.003	-0.036
	(0.076)	(0.186)	(0.032)	(0.079)	(0.014)	(0.047)
Elevation (hundreds of feet)	0.387	0.539	-0.268	-0.228	0.075	0.082
	(0.686)	(0.821)	(0.421)	(0.439)	(0.234)	(0.233)
Elevation squared	-0.030	-0.042	0.000	-0.003	-0.005	-0.007
	(0.033)	(0.042)	(0.019)	(0.020)	(0.011)	(0.011)
Top Firm	-3.513	-7.570	-0.819	-2.305	-0.375	-1.034
	(3.992)	(5.940)	(1.559)	(2.164)	(0.903)	(1.133)
Engineer Experience (projects)	-1.359	-1.537	-0.493	-0.707	0.385	0.264
	(1.996)	(2.118)	(0.923)	(0.939)	(0.460)	(0.481)
Firm Experience (years)	0.019	0.042	0.021	0.028	0.019*	0.024**
	(0.050)	(0.060)	(0.021)	(0.023)	(0.010)	(0.011)
Expected Number of Bidders	-0.167	-0.339	0.201	0.150	0.239**	0.207*
	(0.319)	(0.379)	(0.250)	(0.251)	(0.115)	(0.117)
Unemployment Rate	0.701	0.475	0.197	0.100	-0.059	-0.099
	(0.628)	(0.642)	(0.369)	(0.361)	(0.176)	(0.182)
Log Volume	-0.130	0.278	0.266	0.372	0.195	0.256
	(0.785)	(0.765)	(0.600)	(0.597)	(0.214)	(0.223)
Asphalt Project	4.719**	3.203	2.806*	2.290	-0.738	-1.099
	(2.344)	(3.002)	(1.629)	(1.746)	(0.896)	(1.001)
Bridge Project	-1.637	-3.034	2.623	2.189	-0.977	-1.360
	(2.646)	(3.348)	(1.816)	(1.893)	(0.897)	(1.045)
Observations	273	273	273	273	257	257
R^2	0.205	0.059	0.069	0.001	0.310	0.250

*** Denotes statistical significance at the 1% level, ** denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors are in parentheses.

Appendix

Chapter 1 Appendixes

A1.1 Potential Planholder's Decision to Bid

Table A1.1.1: Potential Planholder Bid Decision: Windows

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
Panel A: 6-month window				
ρ_1		-0.143	-0.017	-0.010***
		(0.107)	(0.067)	(0.003)
ρ_0	0.000	0.015	0.003	0.029**
	(0.009)	(0.015)	(0.016)	(0.014)
Log Likelihood	-3938.7	-3937.8	-3938.7	-3934.2
Pseudo R^2	0.129	0.130	0.129	0.130
Panel B: 18-month window				
ρ_1		0.108	0.154**	-0.001
		(0.090)	(0.060)	(0.002)
ρ_0	-0.002	-0.015	-0.037**	0.003
	(0.008)	(0.013)	(0.015)	(0.011)
Log Likelihood	-4160.5	-4159.7	-4157.1	-4160.3
Pseudo R^2	0.139	0.140	0.140	0.139

The results use all the same regressors and methods as Table A1.1.2. Panel A has 562 auctions, 8,722 potential planholders, and 69,552 potential planholder pairs. Panel B has 494 auctions, 9,836 potential planholders, and 101,901 potential planholder pairs. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A1.1.2: Potential Planholder Bid Decision

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.123	0.150**	-0.001
		(0.094)	(0.061)	(0.002)
ρ_0	-0.001	-0.015	-0.034**	0.003
	(0.008)	(0.013)	(0.015)	(0.012)
Potential Bidders	-0.030***	-0.030***	-0.030***	-0.030***
	(0.003)	(0.003)	(0.003)	(0.003)
Log PlanCost	0.080*	0.078*	0.077*	0.081*
	(0.044)	(0.044)	(0.044)	(0.044)
Log Working Days	0.315***	0.312***	0.309***	0.316***
	(0.063)	(0.063)	(0.063)	(0.063)
Log Items	-0.501***	-0.495***	-0.492***	-0.502***
	(0.080)	(0.080)	(0.080)	(0.080)
DBE Goal	-0.009	-0.010	-0.010*	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
Time Trend	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
OK Unemployment	0.169***	0.166***	0.163***	0.170***
	(0.021)	(0.021)	(0.021)	(0.021)
Distance (100 mi)	-0.690***	-0.687***	-0.684***	-0.691***
	(0.028)	(0.029)	(0.029)	(0.028)
Backlog ($mill)	-0.087***	-0.086***	-0.085***	-0.087***
	(0.020)	(0.020)	(0.020)	(0.020)
Outdegree Centrality	-0.020***	-0.019***	-0.019***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.004)
Hub Centrality	27.486***	27.361***	27.126***	27.524***
	(2.693)	(2.715)	(2.720)	(2.688)
Horizontal Sub	-0.084***	-0.086***	-0.086***	-0.084***
	(0.032)	(0.032)	(0.032)	(0.032)
Log Likelihood	-4137.6	-4136.7	-4134.5	-4137.5
Pseudo R^2	0.136	0.136	0.137	0.136

The results of the replication of Li and Zhang (2010) on ODOT data are seen in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. All columns use 700 simulation. Finite differences are used to estimate derivatives. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A1.1.3: Potential Planholder Bid Decision: No Network

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.159*	0.177***	0.000
		(0.093)	(0.061)	(0.002)
ρ_2		0.015	0.035	-0.002
		(0.026)	(0.026)	(0.025)
ρ_3		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
ρ_4		0.108***	0.128***	0.090**
		(0.039)	(0.040)	(0.038)
ρ_0	0.002	-0.024*	-0.044***	-0.006
	(0.007)	(0.013)	(0.015)	(0.011)
Log Likelihood	-5011.3	-5005.8	-5002.9	-5007.3
Pseudo R^2	0.136	0.137	0.137	0.136

The expands the results of Table A1.1.2 to incorporate firms with no observed network. This leads to an increased sample size of 516 auctions, 12,209 potential planholders, and 155,286 potential planholder pairs. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. The number of simulations used increases to 800. Standard errors are shown in parenthesis.* indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A1.1.4: Potential Planholder Bid Decision: Weighted Network

	Constant (1)	Jaccard (2)	Cosine (3)	Overlap (4)
ρ_1		0.383***	0.370***	0.002
		(0.130)	(0.088)	(0.012)
ρ_0	-0.005	-0.016*	-0.031***	-0.005
	(0.008)	(0.008)	(0.010)	(0.008)
Outdegree ($mil)	-0.001	0.000	0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Hub Centrality	-0.969	-1.002	-1.045	-0.969
	(0.633)	(0.638)	(0.640)	(0.634)
Log Liklihood	-4265.6	-4261.8	-4257.1	-4265.6
Pseudo R^2	0.109	0.110	0.111	0.109

The expands the results of Table A1.1.2 to dollar weights to firm's network. General Affiliation is tested for in Column 1. Columns 2, 3, and 4 allow affiliation between firms to vary according to their jaccard similarities, cosine similarities and number of overlapping subcontractors respectively. Standard errors are shown in parenthesis. * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Chapter 2 Appendix

A2.1 Variable Definitions

Table A2.1.1: Variable Definitions

Variable	Definition
Price	The hammer price of a work sold in an English auction recorded in pounds.
Average Number of Bidders	Number of unique seller who purchased artwork in the auction house on the day a artwork was sold
Posthumous	Dummy variable indicating if an artwork is sold follow the artist's death.
Artist Eigenvector Centrality	Eigenvector centrality of an artist in the 10 years prior to the sale date. Eigenvector centrality measures the relative influence of nodes (in this case an artist) in a network by calculating the primary eigenvector of the network adjacency matrix. The variable is continuous on the interval [0,1]
Artist Eigenvector Centrality at Death	Eigenvector centrality of an artist calculated in the window from 10 years before an artist death till their death. The variable is continuous on the interval [0,1]
Artist Log Number of Art Sold	Number of pieces by an artist sold at auction in the 10 years prior to the sale date.
Buyer Eigenvector Centrality	Eigenvector centrality of a buyer in the 10 years prior to the sale date. The variable is continuous on the interval [0,1]
Buyer Capacity	Highest amount ever spent by a buyer in the past.
Artist-Buyer link	Dummy indicating a buyer has purchased an artwork by the artist in the 10 years prior to the sale date.
Seller: Family	Dummy indicating the seller's name and artist's name in Graves's records match
Seller: Past Volume	Number of pieces sold by the seller in the 10 years prior to the sale date.
Seller: Unknown	Dummy indicating the seller is listed as Unknown in Grave's records
Christie's	Dummy indicating a work was sold at Christie's auction house
Max Rival Eigenvector Centrality	Highest eigenvector centrality of the other bidders at auction
Max Rival Capacity	Highest Capacity of the other bidders at auction
Mean Rival Artist-Buyer Link	Percentage of other bidders which have previously purchased an artist's work.
Medium	Medium of an artwork. Can be a painting, drawing, sculpture, engraving, or copy
Genre	Genre of an artwork. Can be animal, landscape, still life, history, religion, mythology, genre, portrait, marine, or other.
School	Art school of an artwork. Either contemporary British or contemporary continental.

Chapter 3 Appendix

A3.1 Variable Description

Table A3.1.1: Variable Description

Variable	Description
Edge	Contractor has hired the potential subcontractor in the previous 12 months
Number of Subcontractors	Number of subcontractors hired by the contractor for a project
$\hat{sub}$	Number of predicted subcontractors from the sequential Bayesian model
$\mathcal{N}_{ijpt}$	
Project Subs Hired	Number of subcontractors hired on a project prior to current subcontractor
At Least 1 Sub Hired	Dummy indicating at least 1 subcontractors hired prior to current subcontractor
Rival Sub: Item %	Percentage of item types previously hired subcontractors have experience with
Unique: Item: Prime and Rival	Dummy indicating the potential subcontractor has experience with an item which neither the contractor or previously hired subcontractors have experience with
N_{ipt}	
Log Available Subs	Natural logarithm of the number of subcontractors active in the market
Prime: Outdegree Centrality	The number of unique subcontractor the contractor has worked with in the previous 12 months
Prime: Log Hub Centrality	The natural logarithm of contractors hub centrality in the network of contractors and subcontractors in the previous 12 months
Prime: Missing Network	Dummy indicating the contractor has not hired a subcontractor in the previous 12 months
N_{jpt}	
Sub: Indegree Centrality	The number of unique contractors the potential subcontractor has worked with in the previous 12 months
Sub: Log Authority Centrality	The natural logarithm of potential subcontractors authority centrality in the network of contractors and subcontractors in the previous 12 months
Sub: Missing Network	Dummy indicating the potential subcontractor has not worked as a subcontractor in the previous 12 months
Sub: DBE	Dummy indicating the potential subcontractor is a disadvantage business enterprise
Sub: Horizontal Sub	Dummy indicating the potential subcontractor performed work as a contractor in the previous 12 months
I_{ijpt}	
Prime Item %	Number of items the contractor has experience performing
Sub: Item %	Number of items the potential subcontractor has experience performing
Unique Item: Prime	Dummy indicating the potential subcontractor has experience with an item which the contractor does not have experience with
X_{ipt}	
Log of Expected Duration	Natural logarithm of expected project length in days
Number of Items	Number of unique items required for a project
Log of Engineer's Estimate	Natural logarithm of engineer's cost estimate
Elevation	Number of feet above sea level the project is located
Top Firm	Dummy indicating a firm is in the top 10% in terms of assets
Log Engineer's Experience	Natural logarithm of number of projects the engineer worked on during the sample
Firm Experience	Number of years the firm has been active in the market
Expected Number of Bidders	Expected Number of Bidders based on publicly available information at the time of letting
Log Volume	Natural logarithm of the dollar value of projects in Vermont during the month the project was let
Asphalt Project	Dummy indicating the project is a repaving project
Bridge Project	Dummy indicating the project is a bridge project

A3.2 Network Example

To explain the hub and authority measures more fully, we created a simple stylized network, example presented in Figure A3.2.1. It consists of four contractors, labeled A through D, and eight subcontractors, labeled 1 through 8. The network is laid out in a similar way as in Figure 3.4, with contractors represented by white nodes and subcontractors by red nodes. The nodes are sized according to their hub (for contractors) and authority (for subcontractors) centrality values. The values of the centrality measures can also be found in Table A3.2.1.

This network example helps reveal how the ranking of hub (authority) centrality does not always align with outdegree (indegree) centrality. Contractor A has a higher outdegree centrality than contractor D, but since four of A's five connections are to peripheral subcontractors, while all three of D's connections are to central subcontractors, D has a higher hub centrality. This same intuition follows when comparing contractors B and C. While C has more connections it is less centrally located in the network, compared to B leading to lower hub centrality.

With the subcontractors, the authority centrality does not overturn the ordering based on indegree centrality, though in theory it could. The example highlights how subcontractors with the same number of connections can have different levels of authority centrality. Subcontractors 1 and 2 both are linked to three of four contractors, but since 2 is linked to the more centrally connected A, as compared with C, it has the higher authority centrality. This pattern is repeated with the subcontractors 3, 5, 6, 7, and 8 located in the periphery. Since by the measure of hub centrality A is more central than C, its subcontractors end up with higher authority centrality.

To calculate hub and authority centrality we use eigenvector theory and the adjacency matrix of the network, which stores all links of the network in an $N \times N$ matrix. The authority centrality is calculated as:

$$a = A \cdot h$$

where a is an $N \times 1$ vector of authority centralities, A is the adjacency matrix, and h is an $N \times 1$ vector of hub centralities. Similarly hub centrality is calculated as:

$$h = A' \cdot a$$

For small networks the centrality measures can be calculated analytically, but for larger networks they are calculated by beginning with a constant vector and repeatedly iterating the measures until a steady state is reached. For more information on hub, authority, outdegree and indegree centrality measures see Bloch *et al.* (2019).

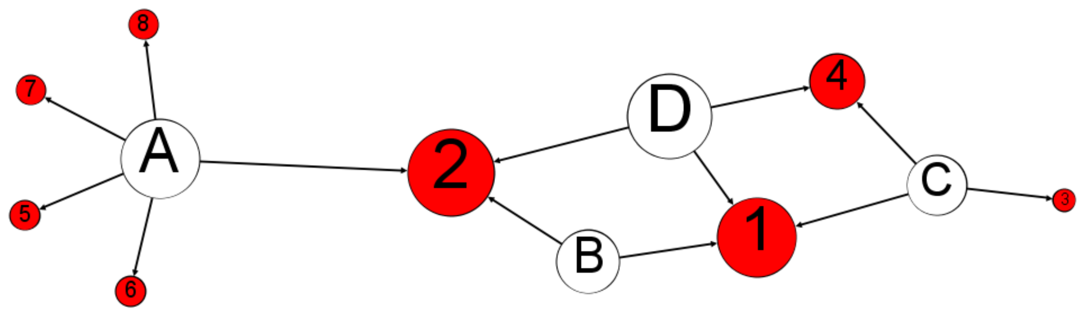


Figure A3.2.1: Example Network

Table A3.2.1: Centrality Measures

Contractor	Outdegree	Hub
A	5	0.547
B	2	0.437
C	3	0.414
D	3	0.582
Subcontractor	**Indegree**	**Authority**
1	3	0.547
2	3	0.598
3	1	0.158
4	2	0.380
5	1	0.209
6	1	0.209
7	1	0.209
8	1	0.209

A3.3 Direct Network Effects on Renegotiation

One potential area of concern is that firms with large networks may systematically choose more complex projects, thus violating the exclusion restriction for the instrumental variable. In order to provide additional evidence that there is no such correlated complexity, we provide regressions with additional control variables, namely the winning contractors outdegree and hub centralities, and the subcontractor averages for indegree and authority centrality, for use in Table A3.3.1. Whether only outdegree and indegree centrality (Columns 1 and 4), hub and authority centrality (Columns 2 and 5), or all 4 are included (Columns 3 and 6) the network variables are always statistically insignificant and the point estimates on the effect of the number of subcontractors changes little. When considering the number of change orders the effect remains statistically significant, though for the value of change orders it is not. These results provide evidence that contractor networks affect change orders only indirectly through their impact on the number of subcontractors used in a project.

Table A3.3.1: Correlated Unobserved Complexity across Projects

	Number of Change Orders			Value of Change Orders		
	GMM IV	GMM IV	GMM IV	2SLS	2SLS	2SLS
Number of Subcontractors	0.162**	0.163**	0.159**	4.744	4.387	4.305
	(0.068)	(0.071)	(0.066)	(2.907)	(2.935)	(2.791)
Prime: Outdegree	0.003		0.006	0.127		0.098
	(0.008)		(0.009)	(0.194)		(0.208)
Sub Average: Indegree	0.016		0.013	0.204		0.299
	(0.027)		(0.035)	(0.497)		(0.855)
Prime: Log Hub		-0.029	-0.048		0.029	-0.291
		(0.056)	(0.058)		(1.034)	(1.042)
Sub Average: Log Authority		0.081	0.034		0.700	-0.041
		(0.101)	(0.094)		(1.218)	(1.931)
Observations	248	248	248	248	248	248

*** Denotes statistical significance at the 1% level, ** denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors are in parentheses. All regressions include the other control variables found in Tables 3.5 and 3.6.

A3.4 Further Normalizations

Table A3.4.1: Percentage of Contract Subcontracted

	(1)	(2)
$\hat{sub}$	4.099***	2.657***
	(0.513)	(0.794)
$\hat{sub}$ squared	-0.203***	-0.160***
	(0.033)	(0.037)
Log of Expected Duration		0.553
		(1.745)
Number of Items		0.044
		(0.058)
Elevation (hundreds of feet)		0.468
		(0.691)
Elevation squared		-0.043
		(0.030)
Top Firm		5.190*
		(2.665)
Engineer Experience (projects)		0.549
		(1.491)
Firm Experience (years)		0.019
		(0.031)
Expected Number of Bidders		0.465
		(0.392)
Unemployment Rate		0.379
		(0.563)
Log Volume		-1.118
		(0.792)
Asphalt Project		5.299
		(3.403)
Bridge Project		-0.610
		(3.405)
Observations	273	273
R^2	0.174	0.275

*** Denotes statistical significance at the 1% level, denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors are in parentheses.

Table A3.4.2: Percentage of Items Renegotated

	(1) OLS	(2) 2SLS
Number of Subcontractors	0.350**	1.809**
	(0.139)	(0.756)
Log Expected Duration	2.001**	2.532***
	(0.839)	(0.929)
Number of Items	-0.060***	-0.158***
	(0.020)	(0.059)
Log of Engineer Estimate	0.165	-0.338
	(0.588)	(0.641)
Elevation (hundreds of feet)	0.398	0.461
	(0.301)	(0.330)
Elevation squared	-0.017	-0.023
	(0.013)	(0.015)
Top Firm	0.712	-0.984
	(1.036)	(1.303)
Engineer Experience (projects)	-1.435	-1.510
	(1.009)	(1.013)
Firm Experience (years)	0.004	0.014
	(0.011)	(0.013)
Expected Number of Bidders	-0.106	-0.178
	(0.194)	(0.212)
Unemployment Rate	-0.102	-0.196
	(0.285)	(0.316)
Log Volume	0.235	0.406
	(0.339)	(0.382)
Asphalt Project	-0.536	-1.170
	(1.776)	(1.849)
Bridge Project	-0.511	-1.095
	(2.105)	(2.137)
Observations	273	273

*** Denotes statistical significance at the 1% level, ** denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors are in parentheses.