THREE ESSAYS ON AIRLINE PRICING AND ENTREPRENEURIAL VENTURES

A dissertation presented

By

Pinshuo Wang

to
The Department of Economics

In partial fulfillment of the requirements for the degree of
Doctor of Philosophy

in the field of

Economics

Northeastern University
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March, 2018

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ABSTRACT OF DISSERTATION

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Abstract

This dissertation consists of three chapters in applied microeconomics. Airline prices vary over time because of demand shocks, which could be for the flight or for substitute flights, and because of intertemporal price discrimination. In the first chapter, using flight level data collected by purchase day from an online travel agency, I find flights departing on the same day or within nearby departure dates are highly substitutable. I also find that passengers who purchase closer to the departure day or on weekdays are less price sensitive and value substitutes less. In the counterfactual analysis, I show that airlines benefit from subsitution.

Bundling practice of ancillary service plays a crucial role in determining product price. The second chapter examines the impact of airlines' unbundling of checked bag service on price. I find that a carrier's unbundling decreases its fare but increases rival's fare. Specifically, when a carrier unbundles, its fare drops immediately and is followed by a series of small drops in the following periods, while its rival's fare increases immediately but the hike disappears over time. I also extend a simple Hotelling model, which shows that unbundling deters passengers from checking bags, and diverts bag checking passengers to its bundled rivals, which in turn increases rival's cost, and thus increases rival's fare. The model also predicts that unbundling decreases one's own fare.

Does having student loans negatively impact recent graduates' likelihood of creating high-impact entrepreneurial ventures? The third chapter answers this question by utilizing "no-loans" financial aid policies by universities as a natural experiment. We empirically examine whether graduates of universities that replace loans with grants in financial aid packages are more likely to become entrepreneurs and are eventually successful in raising venture capital (VC) financing. In particular, we test whether such a policy impacts cohorts that are already enrolled in college prior to the implementation of such policies (to eliminate potentially confounding effects through enrollment choice). We find that graduates from universities that establish no-loans financial aid policies are more likely to start entrepreneurial ventures and these ventures are more likely to get subsequent VC backing and more VC dollars. Further, ventures started by graduates of universities that establish no-loans financial aid policies are backed by high reputation venture capitalists, which is indicative of a higher likelihood of subsequent success. Moreover, such ventures have larger

levels of sales and employment five years after founding. Our results are stronger for high-tuition universities, universities that have a greater extent of R&D activity, and that grant a greater number of doctoral degrees. Overall, our results document a significant adverse effect of student loans on a crucial engine of economic growth - high impact, venture capital backed startups - highlighting a major policy-relevant concern related to student loans.

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Chapter 1

Airline Pricing with Departure Time Substitution

1.1 Introduction

When consumers purchase an airline ticket, they search for flights departing on a particular date, but they may end up booking a flight that departs on a different date. While anecdotal evidence shows that consumers substitute across departure dates, it has not been evaluated systematically by economists. Substitution plays an important role in understanding airline pricing and influences the way we interpret observed price patterns.

Airline revenue management is interestingly complicated. First, airlines sell "perishable" seats over a finite time horizon under capacity constraints. Second, travelers purchase tickets at different points in time. Business travelers learn about their meetings last minute and tend to purchase close to departure days. Third, airlines face demand uncertainty. Airlines set prices in advance according to their expectations. Realized demand can be higher or lower than expected demand.

The literature has focused on explaining the price variation by intertemporal price discrimination and by dynamic price adjustment after a demand shock by changing the price of demand-shocked flight. Intertemporal price discrimination gives an airline the latitude to charge business travelers who tend to purchase closer to the departure days higher fares, and leisure travelers who purchase in advance lower fares. For example, Lazarev (2013) and Liu (2015) focus on the role of intertemporal price discrimination in airline markets, and find it explains a large portion of price variation. They also both allow consumers search and wait to purchase the tickets in their demand models. Although fare has an increasing trend overall as departure day approaches, it fluctuates as realized demands are unexpected high or low. That is, fare is dynamically adjusted to demand shocks. Escobari (2012) finds that dynamic adjustment plays a substantial role in airline pricing. Williams (2013) examines both intertemporal price discrimination and dynamic adjustment and finds they are complements in airline industry.

However, one feature that has been largely ignored in the economics literature is that consumers substitute across departure times and dates. As mentioned earlier, when consumers purchase tickets, they usually search for a flight of a particular departure date, but they may end up purchasing a flight that departs on a different date.[1] This substitution influences prices. An airline is a multi-product firm that sells tickets of flights that depart at different points in time at a given purchase time. If flights depart at different times are substitutable, the airline will price so that profit is maximized across flights.

For analysis, I first estimate demand in a nested logit framework. I then use my demand estimation to construct conterfactual for firm analysis.

In my demand model, a consumer is free to choose any flight that departs on the following 42 days. Different from prior literature, it allows consumers to substitute across flights at different departure times, and therefore captures consumers' substitution patterns. My demand model also allows consumers' tastes for price to vary depending on how many days they purchase in advance. It reflects the feature of airline industry that there are two distinct types of consumers, namely business travelers and leisure travelers (e.g. Berry and Jia, 2010; Berry, Carnall, and Spiller, 2006.) Business travelers have higher reservation prices. They are uncertain or do not learn about their travel plans until it gets closer to the departure day, and therefore purchase late. Leisure travelers have lower reservation prices, plan ahead, and purchase in advance. Therefore, the share of business travelers is expected to increase over time (towards departure date.) By allowing consumers' tastes for price to vary with advance purchase days, my demand model reflects the representative consumer changes from a leisure traveler to a business traveler as the departure day approaches.

My demand results are consistent with expectations. First, I find flights depart on the same

[1]Some travel sites show substitute options. For example, Expedia shows the cheapest flights found in the last 48 hours for similar trips that depart on different days that are close to the passenger's search.

day or within nearby departure dates are highly substitutable. In other words, when the price of one flight is higher, consumers are likely to switch to another substitute flight. Second, I find consumers who purchase closer to the departure days or on weekdays are less price sensitive and value substitution less. This is evidence that the share of business travelers is rising as it gets closer to the departure day and that business travelers tend to purchase on weekdays. Lastly, I simulate counterfactuals where the firm faces demand uncertainty and naively ignores it in the first place. I show that the firm benefit from substitution.

This paper contributes to the literature by measuring the extent of consumers' substitution across flights and its role in airline pricing. It indicates that the airline price variation that we observe does not only come from intertemporal price discrimination and adjustment to the demand shock of a particular flight, but also comes from adjustment to the demand shocks of substitute flights. One paper that is closely related to this study is Escobari (2017). His primary focus is on substitution patterns in various demand systems.[2] This study examines both substitution across both departure times and dates, and provides evidence on the role of substitution in pricing.

The remainder of the paper proceeds as follows. Section 2 describes data. Section 3 presents demand model and estimation. Section 4 discusses firm model and counterfactual. Section 5 concludes.

1.2 Data

I collected a panel dataset of flights for 111 domestic directional airport pairs. My routes are selected using DB1B data according to the following criteria (Williams, 2017; Liu, 2015). First, I selected highly concentrated markets (HHI $>$ 0.9). All routes in my sample have only one carrier that sells and operates direct flights. Focusing on monopoly routes simplifies the analysis of market structure. Second, I selected routes where over 70% of passengers travel between the two cities as origin and destination for their trips. High direct traffic means the routes are likely to be a complete flight rather than as a leg of a longer flight. It mitigates the need to control for the different pricing pattern of feeder routes from the main routes. Third, over 70% of passengers travel

[2] Three substitution patterns including airports, carriers, and departure times within a departure date.

nonstop between the two cities. It minimizes competition with indirect flights. Lastly, quarterly number of passengers are between 3,000 and 30,000. This corresponds to 30 to 300 daily passengers. The median route distance in my sample is 784 miles, which is comparable to the overall DB1B sample. Daily number of flights ranges from one to three.

For each route selected above, I collected information on fare and seat map for all direct flights between the two airport pairs. Airlines set prices in advance, but only actively adjust prices within a certain window of departures. Prices of domestic flights are most volatile within the last 21 days of flight departures. Meanwhile, travel websites[3] suggest that prices tend to be on the higher side 90 days in advance compared to the 21 to 90 days. To ensure that my data represents an airline's active revenue management, I collected information for the following 42 days before the flight departs. Few tickets are sold earlier than the 42-day window (Lazarev, 2013.) The data was collected at the flight level daily between July 16, 2016 and September 16, 2016 from an online travel agency. The data on number of seats sold and remaining is not directly observable from the website, but I recover them from daily seat map that is also available to consumers.

Table 1 shows the summary statistics of the sample. The average fare is \$204.41, which is comparable to the average fare of the complete DB1B database. Daily sales are low but expected. Number of tickets sold daily is 0.72 on average. 58% of the flights in my sample have zero daily ticket sales. Mean load factor is 63%. The fact that the load factor 50% at the 25th percentile and 79% at the 75th percentile suggests that more seats are sold on advance purchase days versus on the days that are closer to the departure. Figure 1 shows that fare (at mean) has an increasing trend as departure approaches. Also, fare jumps at 7, 14, and 21 days, which is consistent with conventional view of advance purchase discounts at these days.

1.3 Demand

1.3.1 Consumer Choice

A market is defined by a unique combination of origin, destination, and purchase date. Every consumer enters the market with a choice set of all the flights on the following 42 departure dates

[3]e.g. CheapAir, https://www.cheapair.com/blog/the-cheapest-flights-are-found-54-days-out-with-one-big-caveat/

on a particular route. For simplicity, I assume consumers myopic. That is, consumers either purchase or exit the market. As shown in Figure 1, if consumers anticipate fare to be higher as they wait, there is little incentive for them to wait unless the uncertainty of traveling is high.[4] In my model, the only uncertainty of traveling is when to depart. Consumers enter the market either purchase a good in the choice set, or purchase an outside good. An outside good is an option other than air travel, such as bus or car. A consumer i's utility of product j is given by:

$$u_{ij} = \boldsymbol{X_j}\beta - (\alpha + \gamma AD_j)p_j + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \tag{1.1}$$

where $\boldsymbol{X_j}$ is a vector of product characteristics that includes advance purchase day, whether the flight arrives in the morning, flight duration (in log of minutes), distance between the two cities (in log of miles), departure day of the week fixed effects, and purchase day of the week fixed effects.

Consumers' price preferences vary depending on the product characteristic of advance purchase day. This is reflected in the coefficient γ on the interaction of advance purchase day AD_j and price p_j. γ is expected to be positive, indicating that the consumer who purchase more in advance is more price sensitive. This is a representative consumer model. The representative consumer changes from a leisure traveler to a business traveler as the departure day approaches. Note that under the assumptions of my model, consumers are homogeneous, and α does not vary across consumers. I capture the difference in consumers' tastes for price by allowing a consumer's price preference to be different across products. It significantly simplifies the estimation process, yet captures the feature of airline industry.

ξ_j is the unobservable product characteristics (to researchers). Consumer's idiosyncratic tastes of product j are represented by $(1-\sigma)\epsilon_{ij}$. ζ_{ig} is the common taste shock to all flights within a nest. A nest is defined by every consecutive Monday to Thursday, or Friday to Sunday. For example, a flight that departs on Monday, August 15 is in the same nest as a flight departs on Thursday August 18, but a different nest as a flight departs on Saturday August 20. The idea of my nest definition is simple. A consumer who searches for a flight departing on Tuesday is more likely to

[4]If consumers are forward-looking, the elasticities are likely to be overstated under the myopic assumption. The myopic assumption treats all no-buy consumers as if they choose an outside option while they may come back and purchase on another day.

switch among Monday to Thursday versus Friday to Sunday, because it is likely to be for business reasons, and therefore on weekdays. On the other hand, tourist travelers are likely to choose among weekends in order to avoid asking for leave.

Assume ϵ_{ij} follows type I extreme value distribution, then $(1-\sigma)\epsilon_{ij} + \zeta_{ig}$ also follows type I extreme value distribution (Cardell 1997). σ is between zero and one. As it approaches one, the within group correlation gets larger, and as it approaches zero, the within group correlation disappears.

Setting mean utility $\delta_j = \boldsymbol{X_j}\beta - (\alpha + \gamma AD_j)p_j + \xi_j$, I solve for the market share. Inside share (share within a nest) and group share are respectively

$$s_{j/g} = \frac{e^{\delta_j/(1-\sigma)}}{D_g} \tag{1.2}$$

$$s_g = \frac{D_g^{(1-\sigma)}}{1 + \sum_g D_g^{(1-\sigma)}} \tag{1.3}$$

where $D_g = \sum_{j \in J_g} e^{\delta_j/(1-\sigma)}$. Then, the market share for product j is given by

$$s_j = \frac{e^{\delta_j/(1-\sigma)}}{D_g^{\sigma}(1 + \sum_g D_g^{(1-\sigma)})} \tag{1.4}$$

Following Berry (1994), setting the mean utility of outside good to zero, I derive the analytic form

$$ln(s_j) - ln(s_0) = \boldsymbol{X_j}\beta - (\alpha + \gamma AD_j)p_j + \sigma ln(s_{j/g}) + \xi_j \tag{1.5}$$

Then, the price elasticites will be:

$$\eta_{jk} = \frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j} = \begin{cases} -(\alpha + \gamma AD_j)p_j(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma}s_{j/g} - s_j), & \text{if k=j} \\ (\alpha + \gamma AD_j)p_k s_k(\frac{\sigma}{1-\sigma}\frac{s_{j/g}}{s_j} + 1), & \text{if k and j are in the same nest} \\ (\alpha + \gamma AD_j)s_k p_k, & \text{otherwise} \end{cases} \tag{1.6}$$

1.3.2 Estimation

To estimate the demand model above, I need instruments for fare and inside share, as unobservable product characteristics affect both price and demand. It will also affect inside share by construction. I use supply shock as the instrument for price. Taking capacity as exogenous, airline has fixed capacity. Current seat supply is then determined by realized past demands. Therefore, I construct supply shocks from past demand shocks. If demand was realized more than airline expected in the past, it would result in a negative supply shock for current period. For this instrument to be valid, I make the assumption that demand shocks are not serially correlated. In other words, past demand shock does not predict future demand shock. The construction of the instrument is reported in Table 2 Column (1). I regress quantity sold on fare and other product characteristics. Then I define supply shock for day t as the accumulated residuals of past five booking days. Table 2 Column (2) shows first stage regression in a logit model. A positive supply shock results in a fare decrease as expected.[5]

For nested logit estimation, I also need instrument for inside share. I use average number of seats remaining on all other flights within a nest[6]. A valid IV for inside share should satisfy the condition that it affects inside share, but not the unconditional share. Literature suggests using characteristics of other firms in the group or number of products in the group[7] (e.g. Berry 1994, Reimers 2017). In my setting the number of flights does not change within a nest over time, and only varies across markets. Therefore, I use average number of seats remaining on all other flights within a nest as the IV. This proxies for the product competition within a nest.

Results for demand estimation are reported in Table 2. Column (3) shows the logit IV regression results. The coefficient on fare predicts a mean elasticity of -19.11. Column (4) shows the logit IV results with the interaction term indicating price preference changes across advance purchase days, which is consistent with the share of tourist travelers is high for advance purchase. It shows people who purchase in advance are more price sensitive. Column (5) shows the nested logit results with the changing preference. Results are similar to logit IV. The coefficient on σ is 0.83, indicating

[5] The first stage F-stat is greater than ten and significant, indicating I do not have a weak instrument.
[6] It is log transformed.
[7] These are used as proxies for competition within a nest that not necessarily affect the right hand variable.

flights within a nest are highly substitutable. The positive coefficient on advance purchase day shows that tickets tend to sell more in advance. However, the fact that it is negative in Column (3) indicates it may have a non-linear relationship with sales.

Figure 2 and 3 show the own-elasticity and cross-elasticity calculated from demand estimation respectively. W represents week. For instance, $W3 - Sun$ refers to the Sunday of 3 weeks in advance of the departure date. First, passengers who purchase more in advance are more price sensitive and also more likely to substitute to other flights. Second, passengers who purchase on weekends are more price sensitive and are more likely to switch to other flights. These observations are consistent with expectations. Passengers who purchase in advance or on weekends are more likely to be leisure travelers who care more about price and are more flexible in terms of departure date compared to business travelers. Economically, a -200 elasticity indicates a reduction of 1.4 tickets in sale in the case of one percent increase in fare.

1.4 The Role of Substitution

Product substitution is important for various reasons. First, a demand model that ignores substitution is likely to attribute too much variation to elastic demand, and therefore over-estimating demand elasticities. Importantly, substitution has implications for airline pricing and subsequently welfare. I show the role of product substitution in counterfactual simulations.

Airline prices vary due to price discrimination and demand shocks. I assume an airline is a multi-product firm that sells tickets for the flights that depart on the following days[8]. Fixed cost is sunk and marginal cost to fly a passenger is zero, but the airline is capacity constrained. The airline chooses the optimal prices based the following profit maximization problem:

$$\pi = \sum_{i \in t} \sum_{j \in m} p_{ij} E\left[Q_{ij}(p_{i1}, p_{i2}, ..., p_{ij}, ..., p_{ik})\right] \quad s.t. \quad \sum_{i \in t} Q_{ij} \leq capacity\ of\ flight\ j \tag{1.7}$$

where i represents a shopping day, j represents a particular flight. m represents a market defined

[8]It was assumed 42 days in the demand estimation

as a unique combination origin, destination, and purchase day, which includes a set of departure days. t represents a set of shopping days prior to the departure of a flight. Consistent with flight substitution, demand is a function of flights departing at different times and days on a given shopping day.

The above problem includes price discrimination, demand uncertainty, and sophisticated firm behavior (i.e. taking demand uncertainty into consideration). There are two difficulties in solving the above problem numerically. First, my demand model assumes output quantity is observed instead of distinct consumer draws with noise. While my demand estimation provides clear evidence on product substitution, it does not involve or generate any uncertainty for the firm to formulate expectation. Second, solving this problem numerically is an overwhelming task for the computer as it involves too many parameters simultaneously. Therefore, I simulate counterfactuals under a simple behavior assumption to illustrate the implication of substitution.

I examine the role of substitution under demand uncertainty but the firm is naive. That is, the firm can adjust prices every period according to the realized demand, but it always sets prices as if the demand is certain. An airline takes initial capacity as given, and sets prices across flights and shopping days simultaneously to maximize profit.

To facilitate the simulation process, I restrict a market to all flights departing on the following 15 days on any particular shopping day. Subsequently, for each flight, the airline considers a maximum of 15 shopping days of prices. Note that this simulation only relies on the demand parameters from earlier estimation. The cost of capacity is simultaneously estimated from the capacity constraint. I first simulate the optimal prices according to my estimated cross elasticities. Then, I scale down cross elasticities to zeros to compare the price patterns.

I find prices are slightly lower on average when flights are substitutable, and profits are higher.[9] Airlines benefit from substitution by lowering prices of popular departure times so that passengers move from peak departure times to other departure times, which tend to equalize the costs of capacity across flights for airlines. Two sets of prices get closer as departure day approaches since last minute buyers value substitution less.

[9] The results of lower prices and higher profits hold regardless whether the capacity constraint binds or not.

1.5 Conclusion

Airline price variation occurs in response to demand shocks for the flight as well as for substitute flights, and occurs because of intertemporal price discrimination. Although recent literature has moved forward significantly by examining the role of intertemporal price discrimination and fare response to demand shocks for flights, the response to demand shocks for substitute flights has been largely ignored. Using flight level data collected by purchase day from an online travel agency, I find flights depart on the same day or within nearby departure dates are highly substitutable. I also find that passengers who purchase closer to the departure day or on weekdays are less price sensitive and value substitutes less. In the counterfactual analysis, I show that airlines benefit from subsitution.

Table 1.1: Summary Statistics

	Mean	Std.Dev.	1st Quartile	Median	3rd Quartile	Obs
Fare	204.41	104.76	132.10	174.10	254.60	174814
Daily Sales	0.72	2.98	0.00	0.00	1.00	174814
Load Factor	0.63	0.20	0.50	0.64	0.79	174814

Table 1.2: Demand Estimation

	(1) Shock Construction Quantity	(2) Logit IV First Fare	(3) Logit IV Diff Share	(4) Logit IV Diff Share	(5) Nested Logit IV Diff Share
Fare	-0.002***		-0.092***	-0.025***	-0.024***
	(0.000)		(0.007)	(0.008)	(0.006)
Fare*Advance Purchase Day				-0.003***	-0.003***
				(0.000)	(0.000)
σ					0.833**
					(0.355)
Advance Purchase Day	-0.007***	-4.566***	-0.411***	0.355***	0.359***
	(0.001)	(0.029)	(0.033)	(0.076)	(0.072)
Arrive AM	-0.083***	-10.400***	-0.934***	-1.001***	-0.957***
	(0.015)	(0.549)	(0.102)	(0.100)	(0.090)
ln(Flight Duration)	1.041***	271.696***	23.783***	25.545***	25.564***
	(0.072)	(3.441)	(1.998)	(1.974)	(1.727)
ln(Distance)	-0.334***	-141.953***	-12.499***	-12.834***	-13.212***
	(0.050)	(2.448)	(1.075)	(1.038)	(0.897)
Supply Shock		-1.803***			
		(0.100)			
Constant	-1.643***	-40.460***	-4.507***	-27.972***	-26.794***
	(0.147)	(3.959)	(0.601)	(2.676)	(2.708)
Departure DOW FE	Yes	Yes	Yes	Yes	Yes
Purchase DOW FE	Yes	Yes	Yes	Yes	Yes
R^2	0.010	0.323	.	.	.
Observations	174814	110415	110415	110415	106285

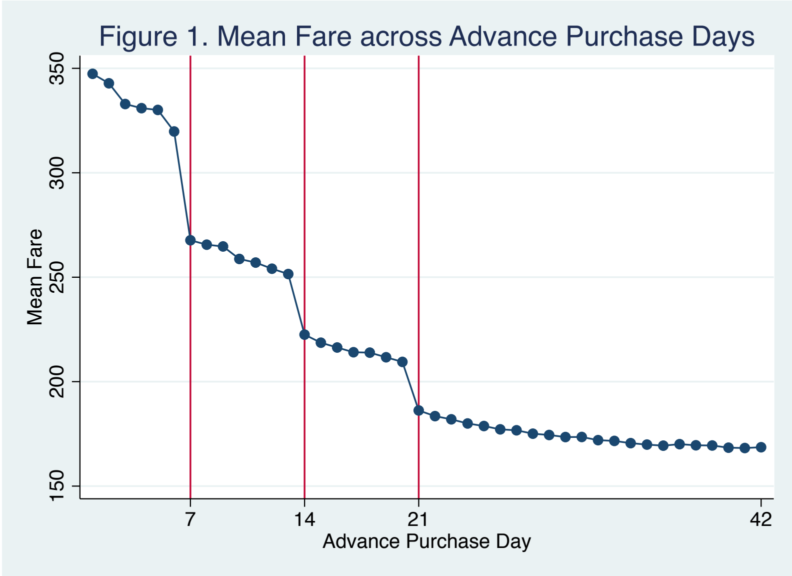
Figure 1. Mean Fare across Advance Purchase Days
Mean Fare
150
200
250
300
350
7
14
21
42
Advance Purchase Day

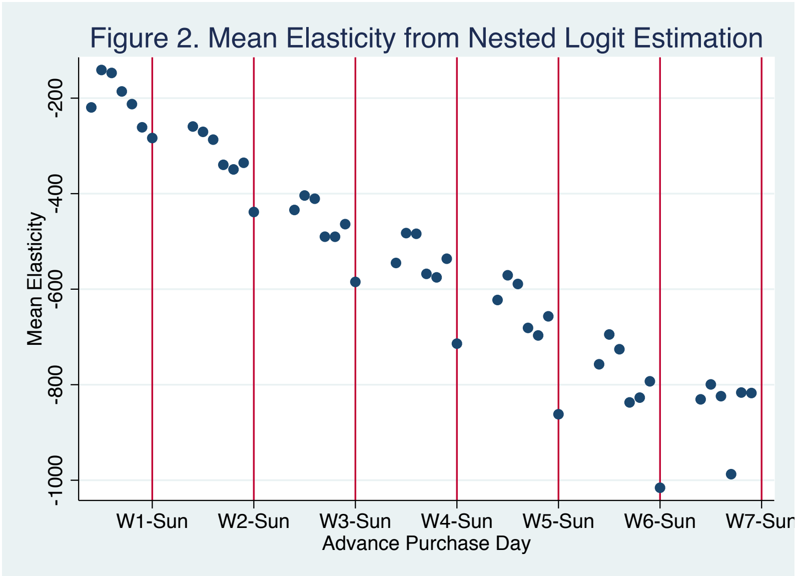
Figure 2. Mean Elasticity from Nested Logit Estimation
Mean Elasticity
-1000
-800
-600
-400
-200
W1-Sun
W2-Sun
W3-Sun
W4-Sun
W5-Sun
W6-Sun
W7-Sun
Advance Purchase Day

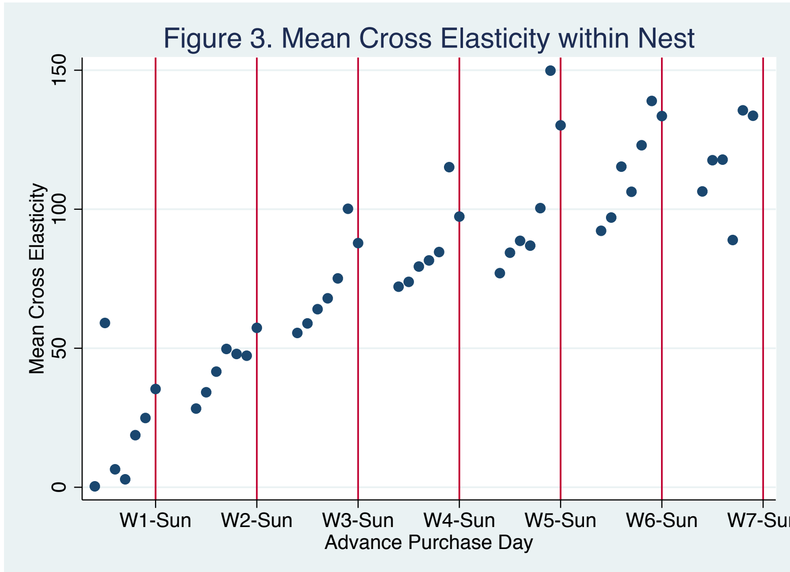
Figure 3. Mean Cross Elasticity within Nest
Mean Cross Elasticity
0
50
100
150
W1-Sun
W2-Sun
W3-Sun
W4-Sun
W5-Sun
W6-Sun
W7-Sun
Advance Purchase Day

Chapter 2

The Impact of Unbundling of Ancillary Service on Price in Airline Industry

2.1 Introduction

Offering ancillary service is a common practice in many industries. A hotel may provide phone or internet service to its consumers, and an airline may offer bag checking or meal service. However, there is no uniform strategy regarding whether to bundle ancillary service. Such bundling/unbundling practice of ancillary service plays a crucial role in determining product price, leading to interest in these practices by consumers, rivals, and government agencies.[1] Thus, it is important to understand the dynamics of such bundling/unbundling practice.

This paper examines the case of airline bag fees, an especially controversial case. Before 2008, most airlines allow passengers to check at least one bag without any charge in addition to the ticket price. However, in 2008, airlines began to institute first checked bag unbundling. By the end of 2009, almost all major carriers unbundled bag fees from base fares, except JetBlue and Southwest. JetBlue unbundled in 2015, and left Southwest as the only bundling carrier thus far.

This research examines airline industry's transition from the bundling of checked bag service to unbundling, in order to understand the impact of unbundling of ancillary service on fare from the following aspects. First, it examines the impact of an airline's unbundling on its own fare. Second,

[1]For example, Federal Trade Commission held a conference on economics of drip pricing that firms advertise only part of a products price and reveal other charges later as the customer goes through the buying process

it investigates changes of an airline's fare in response to its rival's unbundling. Third, it looks into whether these impacts last over time. Fourth, it analyzes how these impacts vary with market heterogeneities.

This research fits into the broad literature on bundling such as price discrimination (Adams and Yellen, 1976; Schmallensee, 1984) and efficiencies (Evans and Salinger, 2008; Bakos and Brynjolfsson 2000). It also relates to hidden surcharges (Bilotkach 2009) and add-on pricing (Ellison, 2005). There are three papers that are closely related to mine on airline unbundling. Brueckner et al. (2015) looked into the impact of bag fee introduction on airline's fare, and found that average fare falls due to bag fee, but it falls by a less amount than the bag fee itself. Scotti and Dresner (2015) examined the impact of bag fee on both demand and fare, and found that bag fee decreases fare and leads to less passenger loss compared to regular fare increase. Additionally, Schumann and Singh (2014) provides empirical evidence that such unbundling leads to market differentiation.

These papers mainly focus on the fare of the airline initiating the bag fee. An airline's price response to its rival's unbundling has been largely overlooked. This is important because of consumer heterogeneity: Consumers value checked bag service differently. Charging a bag fee will deter low valuation (of checked bag service) consumers from checking a bag, and also divert checked bag consumers to other carriers that do not charge bag fees. In this paper, I show a theoretical competition model that unbundling decreases one's own fare and increases rival's fare. My empirical findings are consistent with the model predictions. In the empirical analysis, I also show that unbundling leads to an immediate fare drop and is followed by a series of small drops in the following periods, while its rival's fare increases immediately but the hike disappears over time. This latter result suggests the possibility that a carrier initiating a bag fee effectively is raising the operating cost of its rival who absorbs diverted baggage-laden passenger traffic.

In Section 2, I discuss the theoretical model. Section 3 describes the data. Section 4 shows the empirical framework and results. Finally, I conclude the paper in Section 5.

2.2 Model

For the theoretical model, I show that unbundling deters consumers with low valuation of checked bag service from checking a bag, and also diverts checked bag consumers who are willing to check bags to the bundled carrier. Thus, the unbundled carrier gets a larger share of non-bag travelers, while the bundled carrier gets a larger share of costly bag travelers. Subsequently, the fare decreases for unbundled carrier, but increases for bundled carrier.

Consider a Hotelling model with two firms. Assume that two firms are symmetric in terms of marginal cost of transporting a passenger (c), marginal cost of transporting a bag (w), and air travel quality. A firm charges uniform and exogenous f ($f > w$) for a bag if unbundles.

Additionally, assume that consumers have identical unit transportation/time cost for reaching a firm (t). Also, consumers have identical high reservation value (V) for air travel. Thus, everyone travels with a firm.

Assume there are a total of N consumers in the market who are evenly distributed along the Hotelling line. A number of bN consumers are willing to check bags and value checked bag service at $\delta > 0$, which has the cumulative distribution function $F(.)$. And a number of $(1-b)N$ consumers who are not willing to check bags value checked bag service at 0. Thus, a consumer who is willing to check a bag will do so if his δ is greater than the bag fee f. And consumers who are not willing to check bags never check bags.

First, consider the case that both firms bundle. Each firm solves its profit maximization and sets price

$$P_1 = P_2 = t + c + bw \tag{2.1}$$

and each gets half of the market of both bag travelers and non-bag travelers. Next, consider the case that Firm 1 unbundles and Firm 2 bundles. Then,

$$P_1 = t + c + bw - \frac{1}{3}bf - \frac{2}{3}bwF(f) \tag{2.2}$$

$$P_2 = t + c + bw + \frac{1}{3}bf - \frac{1}{3}bwF(f). \tag{2.3}$$

Note that in Case 2 is the ticket price only of Firm 1. This is lower than the price in Case 1. However, it does not include checked bag service, whereas Case 1 does. In Case 2, the total price of Firm 1 for those who travel with bags is $P_1 + f$, which is actually higher than the total price in Case 1. Thus, the model indicates that fare decreases for non-bag travelers, but increases for bag travelers after unbundling. Firm 2's price in Case 2 is higher than it is in Case 1, indicating that Firm 1's unbundling increases Firm 2's fare. The model also demonstrates the rational that unbundling deters consumers with low from checking bags, and diverts some of the remaining bag consumers to Firm 2. Hence, Firm 2 gets more than a half of the total bag travelers, and less than a half of the non-bag travelers. Subsequently, the average cost of Firm 2 increases, and thus its fare rises.

Finally, when both firm unbundle, they set price

$$P_1 = P_2 = t + c + bw - bwF(f). \tag{2.4}$$

Compared to Case 1, it indicates that fare decreases, while the total price including a checked bag increases, and fewer consumers opt in for checked bag service.

Thus, the model shows that unbundling deters consumers from using the ancillary service, and diverts costly consumers to the bundled firm. Thus, the bundled carrier incurs higher average cost, and its fare rises.

2.3 Data

The main data utilized in this study comes from U.S. Airline Origin and Destination Survey (DB1B), which is a 10% quarterly sample of domestic airline tickets. It provides information on fare, number of passengers, and other route characteristics. I also collect the data of first checked baggage, such as airline's unbundling date and baggage fee amount, from news articles. For the analysis, I aggregate the data to directional route-carrier-quarter level.[2] The final dataset covers 2,731 routes, 8,055 carrier-route combinations, and contains 58,473 directional route-carrier-quarter observations

[2]Both directional and non-directional levels have been used in the literature. Since bag fee is charged when checking a bag for each directional flight, it is more appropriate to use directional level here.

spanning from 2007 to 2010.[3]

The main analysis variable is D(Bag Fee), which is a dummy variable indicating whether a carrier has unbundled in a given quarter. It is worth mentioning that bag fee unbundling is a corporate level decision, instead of market specific. For instance, when American Airline instituted unbundling in June 2008, it applied to all of its markets nationwide. Thus, bag fee variables vary by carrier across time, but not across routes. Also, when carriers first implemented the bag fee, they were uniformly (within the sample) $15.

Table 1 reports passenger weighted descriptive statistics for the data. The mean of D(Bag Fee) is 0.43, indicating that 43% of the passengers flew with carriers that charged bag fees during the sample period. The four-year mean fare is $167. The average number of passengers in a route-carrier-quarter is about 2,300, and decreases slightly over the course of sample years. The mean non-stop distance of sample routes is 856 miles. The geometric mean income and population of origin and destination MSAs are 45 million and four thousand, respectively.

2.4 Empirical Framework and Results

2.4.1 Identification

Checked bag unbundling was implemented over time by different carriers, which allows me to use these unbundling events in a Difference-in-Differences framework. One concern about the causal interpretation is the endogeneity of unbundling. For instance, carriers that chose to unbundle might have lower fares in the first place. The story is that lower fare carriers that are struggling with making a profit are more likely to unbundle so that they could earn profit by charging for checked bag service. This concern is mitigated for the following reasons. First, I control for carrier and time fixed effects, which addresses any carrier unobservable characteristics that do not change over time or time specific effects. Second, there is no particular pattern in the order of carriers' implementations of bag fees. During this sample period, it was started by United and followed by a well mix of carriers in terms of their finances. Third, since checked bag unbundling is implemented by each carrier nationwide to all of its markets, the endogeneity concern is lessened for any of its

[3]This analysis only includes non-stop trips and non-monopoly markets.

particular market, which is the analysis observation level of this study.

2.4.2 Impact of Unbundling on Fare

The first set of empirical tests aim to delineate the role of unbundling on fare. I use the following pooled OLS model as the base regression model:

$$ln(Fare_{irt}) = \beta_0 + \beta_1 D(BagFee)_{it} + \gamma X_{irt} + \mu_i + \delta_t + \epsilon_{irt} \tag{2.5}$$

where i represents carrier, r represents route, and t represents year-quarter. The dependent variable is the natural log of fare. The main explanatory variable is , which is a dummy variable indicating whether carrier i has unbundled in a year-quarter t. X_{irt} is a vector of control variables designed to capture market and carrier-market characteristics. I also include carrier and time fixed effects.

Column (2) in Table 2 shows the corresponding results of the specification in Equation (1). Column (1) reports the parsimonious specification where I only control for carrier and time fixed effects with no additional controls. This specification is designed to mitigate any endogeneity concerns of the control variables. Column (3) shows the results of a within estimator to better control for unobserved cross-sectional heterogeneity. Broadly, the results are similar across specifications and indicates a negative relationship between first checked bag unbundling and fare. This result is also economically significant. For instance, unbundling is associated with a 6% fare decrease, which corresponds to a \$10 fare decrease at mean fare \$167 (using Column (2)). An average \$10 fare decrease is smaller than a \$15-\$20 baggage fee. Thus, fare decreases for travelers who do not check bags, but increases for those who check bags. This finding is consistent with the model prediction.

2.4.3 Rival's Price Response to Unbundling

Table 3 shows the results of rival's price response to unbundling. I use Share of Rivals with Bag Fee as the measure of rival's unbundling, which is defined by the number of unbundled rivals divided by the number of all rivals of a carrier. For example, this variable is zero if non of the rivals on the route has unbundled; it equals to 0.5 if one of the two rivals on the route has unbundled. Column (1) shows the parsimonious specification where I only control for carrier and time fixed effects.

Column (2) shows the full specification. These results show that price increases with the share of unbundled rivals, which is consistent with the model prediction. Economically, it corresponds to 1.5% (Column (2)) price increase when share of unbundled rivals increases by 0.5, which is about $3 increase at mean fare $167.

2.4.4 Impacts of Short-run and Long-run

This section explores whether unbundling has a sustainable impact on price. I show in the model that unbundling effects are different during the market transition when there are both unbundled and bundled carriers and after the transition when all carriers unbundle. Specifically, unbundling increases rival's price during the transition, but rival's price falls after the transition. Thus, I expect that unbundling only has a temporary upward impact on rival's price. Additionally, unbundling does not necessarily lead to an immediate price hike or drop. In particular, information asymmetry may create lags for consumers to learn about carrier's unbundling. Such lags lead to delay in consumer response and price response. Thus, I expect price change takes place over time. Table 6 presents the results of the following regression model:

$$ln(Fare_{irt}) = \beta_0 + \beta_1 D(BagFee)_{it} + \sum_{j=1}^{j=n} \beta_j \Delta t + \gamma X_{irt} + \mu_i + \delta_t + \epsilon_{irt} \tag{2.6}$$

where Δt is the number of periods after carrier i unbundles, which is defined by zero before carrier i unbundles. As expected, unbundling is associated with an immediate drop of fare and followed by a series of small price drops over time. For the price response to rival's unbundling, represents the number of periods after carrier i first unbundled rival unbundles. The results show that although price increases immediately in response to rival's unbundling, it decreases gradually over time. Thus, the price hike brought by rival's unbundling is temporary and would disappear over time.

2.4.5 Market Heterogeneity

Although a carrier unbundles nationwide, its impact can be different across markets given market heterogeneity. For example, passengers on tourist routes are more likely to have checked bags than on heavily business routes. Therefore, I additionally conduct a series of interaction tests to understand the cross-sectional heterogeneity in the relationships between unbundling and fare shown above. Thus, I expect unbundling decreases fare more in tourism markets where airlines try to avoid losing tourism consumers. For the same reason, rivals should increase fare less. The results are reported in Column (1) and (2) of Table 4. Consistent with expectations, unbundling decreases fare in general, while it is associated with a larger magnitude of fare decrease of the unbundling carrier in tourism markets, and a smaller magnitude of fare increase of the rivals.

A second type of heterogeneity would involve passengers on short-hauls who also tend to have less luggage and are less likely to check bags. Thus, I expect unbundling decreases fare more on long-hauls where passengers tend to check bags, and increases rival's fare less. The results reported in Column (3) and (4) of Table 4 are consistent with expectations. In fact, Column (3) shows that fare barely change on short-hauls. This is not surprising since passengers are unlikely to need any checked bag service on very short routes.

Finally, Column (5) and (6) of Table 4 show that unbundling decreases fare less in more concentrated market, and increases rival's fare more. These results are consistent with expectation. The more market power a carrier has, the less it would decrease fare when unbundling. Similarly, the more a market is concentrated, the larger the fraction of passenger who check bags would switch to each rival. Therefore, it increases rival's fare more in such case.

2.5 Conclusion

In this paper, I examine the impact of airlines' unbundling of checked bag service on price. I establish a simple Hotelling competition model, which shows that bundling impacts both self and rival's price. In particular, unbundling deters passengers from checking bags, and diverts bag checking passengers to its bundling rivals, which in turn increases rival's cost. Thus, it increases rival's price. The model also predicts that unbundling decreases one's fare, however, increases the total price for passengers who check bags. The empirical findings are consistent with the predictions of the model.

Additionally, I find that rival's price response to unbundling is temporary and disappears over time. This is due to the unbundling transition of the market. As the model predicts, when all carriers unbundle, the cost asymmetry goes away, thus price falls. I also find that information asymmetry may create a lag in the price response. That is, unbundling carrier's fare drops immediately but followed by a few small drops in the following periods.

Finally, unbundling impacts fare differently across markets. It decreases fare more in markets where consumers are more likely to check bags, such as tourist markets and long-hauls. It also increases rival's fare less in these markets. Furthermore, it decreases fare less in more concentrated market, while increases rival's fare more.

Table 2.1: Summary Statistics

Panel A. D(Bag Fee)

	Mean	Std.Dev.	Obs
2007	0.00	0.00	15021
2008	0.34	0.47	14881
2009	0.70	0.46	13652
2010	0.74	0.44	14919
Total	0.43	0.49	58473

Panel B. Fare

	Mean	Std.Dev.	Min	Median	Max	Obs
2007	163.95	53.49	52.12	158.73	460.89	15021
2008	173.91	58.23	58.36	165.66	514.34	14881
2009	156.73	50.19	39.00	150.89	450.53	13652
2010	174.65	54.45	71.79	164.87	446.91	14919
Total	167.43	54.75	39.00	160.01	514.34	58473

Panel C. Passengers

	Mean	Std.Dev.	Min	Median	Max	Obs
2007	2,550.18	2,470.62	90	1859	12945	15021
2008	2,329.68	2,167.11	90	1702	10695	14881
2009	2,171.89	1,974.31	90	1600	10592	13652
2010	2,146.65	2,019.17	90	1562	12086	14919
Total	2,308.15	2,183.08	90	1682	12945	58473

Panel D. Other Variables

	Mean	Std.Dev.	Min	Median	Max	Obs
Distance	856.48	513.50	109.00	733.00	2,724.00	58473
Org-Dest Mean Income	45.70	5.21	27.44	45.24	62.71	58473
Org-Dest Mean Population	4.27	2.64	0.32	3.63	15.67	58473

Table 2.2: Fare and Bag Fee

	(1)	(2)	(3)
	ln(Fare)	ln(Fare)	ln(Fare)
D(Bag Fee)	-0.055***	-0.061***	-0.048***
	(0.015)	(0.014)	(0.005)
HHI		0.230***	0.070***
		(0.016)	(0.026)
Number of Legacy Carriers		0.033***	0.019***
		(0.004)	(0.003)
Number of LCCs		-0.068***	-0.066***
		(0.005)	(0.008)
D(Tour Destinations)		-0.095***	
		(0.007)	
ln(Distance)		0.325***	
		(0.008)	
ln(Org-Dest Mean Population)		0.033	0.429***
		(0.037)	(0.135)
ln(Org-Dest Mean Income)		-0.015***	-1.848***
		(0.004)	(0.278)
Constant	5.156***	2.670***	5.652***
	(0.022)	(0.129)	(0.694)
Time FE	Yes	Yes	Yes
Carrier FE	Yes	Yes	No
Carrier-Market FE	No	No	Yes
Clustered SE	Carrier-Time	Carrier-Time	Carrier-Market
R^2	0.287	0.665	0.916
Observations	58,473	58,473	58,473

Table 2.3: Fare and Rival's Bag Fee

	(1)	(2)
	ln(Fare)	ln(Fare)
D(Bag Fee)	-0.050***	-0.059***
	(0.015)	(0.013)
Share of Rivals with Bag Fee	0.108***	0.031**
	(0.018)	(0.012)
HHI		0.230***
		(0.016)
Number of Legacy Carriers		0.031***
		(0.004)
Number of LCCs		-0.063***
		(0.005)
D(Tour Destinations)		-0.095***
		(0.007)
ln(Distance)		0.325***
		(0.008)
ln(Org-Dest Mean Population)		0.035
		(0.038)
ln(Org-Dest Mean Income)		-0.016***
		(0.004)
Constant	5.152***	2.670***
	(0.021)	(0.131)
Time FE	Yes	Yes
Carrier FE	Yes	Yes
Clustered SE	Carrier-Time	Carrier-Time
R^2	0.295	0.666
Observations	58,473	58,473

Table 2.4: Fare and Bag Fee over Time

	(1) ln(Fare)	(2) ln(Fare)	(3) ln(Fare)
D(Bag Fee)	-0.045***	-0.059***	-0.045***
	(0.014)	(0.013)	(0.014)
Number of Quarters after Bag Fee	-0.006**		-0.005**
	(0.002)		(0.002)
Share of Rivals with Bag Fee		0.043***	0.041***
		(0.014)	(0.014)
Number of Quarters after First Rival's Bag Fee		-0.005***	-0.004***
		(0.001)	(0.002)
HHI	0.231***	0.226***	0.227***
	(0.016)	(0.015)	(0.015)
Number of Legacy Carriers	0.033***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)
Number of LCCs	-0.068***	-0.062***	-0.062***
	(0.005)	(0.005)	(0.005)
D(Tour Destinations)	-0.095***	-0.095***	-0.095***
	(0.007)	(0.007)	(0.007)
ln(Distance)	0.325***	0.325***	0.325***
	(0.008)	(0.008)	(0.008)
ln(Org-Dest Mean Population)	0.033	0.037	0.037
	(0.037)	(0.038)	(0.038)
ln(Org-Dest Mean Income)	-0.015***	-0.016***	-0.016***
	(0.004)	(0.004)	(0.004)
Constant	2.674***	2.657***	2.662***
	(0.129)	(0.131)	(0.131)
Time FE	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Clustered SE	Carrier-Time	Carrier-Time	Carrier-Time
R^2	0.666	0.666	0.667
Observations	58,473	58,473	58,473

Table 2.5: Fare and Bag Fee Interaction Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Fare)	ln(Fare)	ln(Fare)	ln(Fare)	ln(Fare)	ln(Fare)
D(Bag Fee)	-0.053***	-0.060***	0.124	-0.058***	-0.109***	-0.057***
	(0.013)	(0.013)	(0.094)	(0.013)	(0.021)	(0.013)
Share of Rivals with Bag Fee		0.034***		0.219*		-0.005
		(0.012)		(0.112)		(0.021)
D(Bag Fee)*D(Tour Destinations)	-0.087***					
	(0.013)					
Share of Rivals with Bag Fee*D(Tour Destinations)		-0.029*				
		(0.015)				
D(Bag Fee)*ln(Distance)			-0.028*			
			(0.015)			
Share of Rivals with Bag Fee*ln(Distance)				-0.029*		
				(0.017)		
D(Bag Fee)*HHI					0.090***	
					(0.028)	
Share of Rivals with Bag Fee*HHI						0.059*
						(0.032)
HHI	0.232***	0.230***	0.234***	0.230***	0.194***	0.199***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.019)	(0.024)
Number of Legacy Carriers	0.033***	0.031***	0.034***	0.031***	0.033***	0.031***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of LCCs	-0.068***	-0.063***	-0.068***	-0.064***	-0.067***	-0.063***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
D(Tour Destinations)	-0.061***	-0.081***	-0.096***	-0.095***	-0.096***	-0.095***
	(0.010)	(0.011)	(0.007)	(0.007)	(0.008)	(0.008)
ln(Distance)	0.325***	0.325***	0.336***	0.339***	0.325***	0.325***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.008)	(0.008)
ln(Org-Dest Mean Population)	0.035	0.034	0.034	0.029	0.029	0.034
	(0.037)	(0.038)	(0.037)	(0.037)	(0.037)	(0.038)
ln(Org-Dest Mean Income)	-0.015***	-0.017***	-0.016***	-0.016***	-0.014***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	2.659***	2.670***	2.592***	2.603***	2.707***	2.688***
	(0.127)	(0.131)	(0.131)	(0.149)	(0.127)	(0.133)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Carrier-Time	Carrier-Time	Carrier-Time	Carrier-Time	Carrier-Time	Carrier-Time
R^2	0.667	0.666	0.666	0.666	0.666	0.666
Observations	58,473	58,473	58,473	58,473	58,473	58,473

Chapter 3

The Impact of Student Debt on High Value Entrepreneurship and Venture Success: Evidence from No-Loans Financial Aid Policies

Joint work with Karthik Krishnan

3.1 Introduction

Student debt in the United States hit at a record high value of $1 Trillion in 2011 and has been steadily increasing ever since.[1] A significant chunk of this exposure is held by U.S. federal and state governments. Meanwhile, policymakers have also shown interest in the rate of entrepreneurship and start-up activity in the economy. Entrepreneurship, particularly in high-technology areas, has been a solid and reliable engine of economic growth and employment, making it a significant policy focus. For instance, a recent study released by the Kauffman Foundation reports that companies that are less than one year old with one to four employees have created, on average, more than 1 million jobs per year over the past three decades.[2]

This impetus on entrepreneurship has made the question of how student debt can affect high growth venture creation an important one.[3] Krishnan and Wang (2017) argue that college loans

[1]See, for instance, the *USA Today* article, "Student loan outstanding will exceed $1 trillion this year," by Dennis Cauchon, October 25, 2011.

[2]See, Kauffman Foundation Research Series: Firm Formation and Economic Growth, *The Return to Business Creation,* 2013, by Ian Hathaway, Jordan Bell-Masterson, and Dane Stangler.

[3]The President's Jobs Council recently released its recommendations for nurturing high growth enterprises that

and student debt make it costlier for individuals to enter uncertain entrepreneurship activities, given the significant costs of default on these loans in the case of business failure. Given that failure is the most common outcome of venture-backed startups (e.g., Hall and Woodward (2010)), this is a substantial cost to bear, even in expectation.[4] Another possibility is that student debt can make individuals more financially constrained, which in turn makes it harder to start-up a firm.

Policymakers already use this argument as a justification of important policy decisions. In fact, the Office of the President cited enhancement of entrepreneurship as one of the benefits of the executive actions by President Barack Obama to reduce student loan repayment burdens in 2011.[5] Further, media reports suggest that this issue is debated by a broader audience.[6] In spite of such actions at the highest levels of government, there is scant systematic evidence relating student debt to high growth, high impact entrepreneurship and entrepreneurial success. In this paper, we try to bridge this gap by analyzing the relation between student debt and high-impact entrepreneurship. In particular, for a sample of high technology companies, we study how entrepreneurs' student loans affect the likelihood of their ventures obtaining venture capital financing and the quality of venture capital backing for such firms. We also study eventual business outcomes like sales and assets for such firms.

Student loans can impact entrepreneurship rates through various mechanisms. In the context of individuals, for whom default and personal bankruptcy can be extremely costly, student loans can impose a significant cost of undertaking risky endeavors such as starting up businesses.[7] In particular, negative shocks to a startup's cash flows can reduce the payoff to the entrepreneur, which makes it hard for the entrepreneur to make student loan repayments and thus exacerbates the cost of student debt liabilities.[8] This cost of student debt, magnified by the high failure

create new jobs. See, http://files.jobs-council.com/jobscouncil/files/2011/10/JobsCouncil_InterimReport_Oct11.pdf for details. One of the recommendations from this council was to "reduce student loan burden."

[4]See also the *Wall Street Journal* article, "The Venture Capital Secret: 3 Out of 4 Startups Fail," by Deborah Gage, September 20, 2012.

[5]"Reducing Student Loan Burdens for America's Entrepreneurs," by Aneesh Chopra (U.S. Chief Technology Officer) and Jim Shelton (Assistant Deputy Secretary for Innovation and Improvement at the U.S. Department of Education), *Office of Science and Technology Policy, Executive Office of the President.*

[6]See, for instance, the *Wall Street Journal* article, "How Student Debt Harms the Economy," by Mitchell Daniels, January 27, 2014.

[7]For instance, Hall and Woodward (2010) show that venture capital backed entrepreneurial firms have a 75 percent failure rate.

[8]In the U.S., student debt is difficult to discharge through personal bankruptcy procedures. Further, defaulting

likelihood in high impact, venture capital backed entrepreneurship, reduces tolerance for failure and therefore, as shown by Manso (2011), stifles innovative entrepreneurship. We term this the "cost of business failure" effect of student debt. These effects are likely to be even stronger for venture backed startups. Innovative and riskier ventures typically seek venture capital (usually in the high technology space). Such ventures carry technology related risks and risks related to venturing into new markets. These risks, in addition to those related to any business start, make the cost of business failure effect outlined above even more severe for high impact ventures seeking venture capital financing.

Student debt may also be related to high-impact entrepreneurship through other mechanisms. One possibility is that student debt can make it harder to start-up a business (as opposed to making failure after startup more costly) due to difficulty in accessing financing. We term this the "startup financing constraint" effect. However, in recent years, this is a smaller concern for high-technology firms as technological advances like cloud computing and 3D printing have made it significantly cheaper to start high-technology ventures. Beyond alternative mechanisms, any analysis relating student debt to entrepreneurship has to consider endogeneity issues. In particular, student debt may reflect unobservable characteristics such as family wealth and socio-economic conditions. Our tests reveal the causal effect of student debt on high-impact entrepreneurship and the mechanisms driving such a relationship.

Two major hurdles in a study like ours are: finding a source of exogenous variation for student loans and creating a dataset that will allow us to relate high-impact venture backed entrepreneurship with student loans of entrepreneurs. We overcome the first hurdle by using "No-Loans" financial aid policies set up by various schools as our source of exogenous variation for student loans. Since 1998, over 70 universities in the U.S. have replaced loans with grants in their financial aid packages, at least for certain groups of students (e.g. low income families). This lowers student debt burdens of graduating students significantly. No-loans financial aid policies impacted the loan component

on student loans has tangible costs for borrowers. They can get penalized by facing garnishment of future wages and tax refunds, increases in loan balances due to the collection costs, movement of the loan to a third party collection agency, and lawsuits by the Department of Education. Beyond this, bankruptcy itself can be costly and can affect individual credit scores which in turn impacts ability to get employment, rental housing, and get credit (e.g., credit cards, mortgage, etc.).

of financial aid negatively, but not overall financial aid. However, these policies were not designed with entrepreneurship as the central focus, but rather financial affordability of higher education. Thus, we expect no-loans financial aid policies to increase high-impact entrepreneurship by reducing student debt burden. In these tests, we restrict the sample to students that were already enrolled in college prior to the policy change to eliminate any effect of the financial aid policy change affecting college choice. We note that such policies are implemented by wide variety of schools ranging from Princeton University to the College of Holy Cross, and so are not driven by university rankings. Moreover, all our regressions have university and state-year fixed effects to account for university-specific or state-year-specific effects. Furthermore, we utilize trend effect dummies in our regressions which do not indicate any prior trends in schools' trajectory of producing entrepreneurs prior to the implementation of no-loans financial aid policies. Additionally, our matching procedure creates a control group of universities that is similar to our treated group in terms of Carnegie Classification and pre-policy levels of entrepreneurial activity and growth by recent graduates.

The other significant hurdle in a study such as ours is getting data on individual entrepreneurial ventures and linking them to university loan policies of students' alma mater. We combine data from various sources to conduct our analyses. First, we obtain entrepreneur and venture specific data from Crunchbase, a source of data that contains details of entrepreneurs and ventures. We obtain data on financial aid policies and other variables for universities and alma mater of entrepreneurs from the Integrated Post-Secondary Education Database System (IPEDS) provided by the Department of Education. Data on venture backing is obtained from VentureXpert and firm-level performance variables like sales and employment are obtained from the NETS database. Our overall sample consists of 4293 entrepreneurs, 8093 matched entrepreneurial firms, and 111 universities for years between 1987 to 2012.

We start by providing evidence that our instrument for student loans, i.e., no-loans financial aid policies are associated with a statistically significant reduction in the fraction of students graduating from an institution with student loans. In particular, implementing such a policy at a school decreases the fraction of students graduating with loans by 3.3 percentage points. We also show that our results are unrelated to the total financial aid provided by an educational institution.

Thus, our results are consistent with no-loans financial aid policies reducing student loans without reducing total financial aid.

We find that no-loans financial aid policies are positively related to the propensity to start a (high-technology) firm and to receive venture backing within 3 (and 5) years after graduating from college. Economically, schools implementing no-loans financial aid policies have 1.43 more entrepreneurs (who start a venture within 5 years after graduation) after the policy change among cohorts that were already enrolled prior to the policy change. This is high relative to the unconditional mean of 0.56 entrepreneurs who start a firm within 5 years after graduation. Importantly, universities with no-loans policies have a post-policy change increase of 0.6 entrepreneurs (who start a venture within 5 years of graduation) whose ventures subsequently receive venture capital. This is large compared to the unconditional sample mean of 0.16 for this variable.

Graduates of schools that implement no-loans financial aid policies also receive significantly more venture capital dollars. Furthermore, graduates of no-loans financial aid policy schools that start a venture after graduation are also more likely to get backing from higher reputation venture capitalists. Higher reputation venture capitalists have been shown to select higher quality firms and create more value for their portfolio companies in the literature (see, e.g., Chemmanur, Krishnan, and Nandy, 2011; Sorensen, 2007). We show that our venture backing results hold for university-year level analysis as well as individual level analysis. The individual level analysis only includes entrepreneurs, and indicates that the increase in venture capital backing for graduating entrepreneurs after no-loans policies is not simply driven by the creation of more entrepreneurs after such policies are implemented.

We then examine when the impact of student loans on high-impact entrepreneurship is more important. For more expensive schools, we expect the impact of lower loan fractions in financial aid policies to be more important. Consistent with this expectation, we find that the positive relation between high technology entrepreneurship by college graduates and no-loans financial aid policies is stronger for universities with higher levels of in-state tuition cost. We also expect that universities with more research activity are more likely to have knowledge spill overs into entrepreneurial ventures (e.g., Jaffe, Trajtenberg, and Henderson, 1993). For such schools, the impact of student loans may be more important. Consistent with this expectation, we find that the positive relation between high technology entrepreneurship by college graduates and no-loans financial aid policies is stronger for universities with more R&D spending, universities that grant more doctoral degrees, and located in California and Massachusetts. Moreover, R&D activity also strengthens the positive impact of no-loans policies on venture capital backed entrepreneurship.

Finally, for the sample of ventures (founded by recent graduates) that survive for at least 5 years after founding, we show that firm sales is 89% higher and firm employment is 76% higher for ventures started by entrepreneurs graduating from no-loans institutions. Our results thus provide evidence indicating that such university policies can have a positive economic impact for the economy. In particular, no-loans financial aid policies of schools support more risk-taking by entrepreneurs graduating from these schools and can lead to higher impact entrepreneurship.

Our contribution is to highlight the impact of student loans on an important aspect of economic value creation, namely, the creation of high impact, high technology, and venture-backed startups. Prior literature (Krishnan and Wang, 2017; Ambrose, Cordell, and Ma, 2015) has analyzed entrepreneurship in a broad sense, and due to data limitations and limitations related to identification, does not delve deeply into the *type* of entrepreneurs impacted by student loans or their outcomes. We overcome this gap in the literature by creating a new dataset and utilizing a relatively new identification strategy. Moreover, our results have implications for policymakers and practitioners. First, our results indicate that university financial aid policies can have impact on the economy. Second, our results indicate that excessive dependence on student loans may end up stifling innovative ventures, which can be very harmful for the economy in the long run. Finally, since no-loans policies are geared more toward lower income groups, such policies may help in building long-term wealth and promoting risk-taking in this group, which may have implication for long-term income inequality.

3.2 Related Literature

We contribute to three distinct literatures. First, we contribute to the literature on entrepreneurship; particularly to the strand that analyzes how an entrepreneur's background and situation impacts her ability to build a successful enterprise. The phenomenon of entrepreneurship has received increasing interest in recent years, as growing evidence suggests that entrepreneurial activity is associated with economic growth (King and Levine, 1993; Jayaratne and Strahan, 1996; Aghion and Griffith, 2005). It has also been argued that entrepreneurship plays a central role in stimulating innovation and therefore drives the process of Schumpeterian "creative destruction," whereby new products and technologies continue to displace old ones, thus keeping the economy from stagnation (Acs and Audretsch, 1988; Henderson and Clark, 1990; Christensen, 1997; Cetorelli and Strahan, 2006). Thus, if entrepreneurial activities indeed lead to economic growth, it is crucial for us to understand the underlying dynamics that drive such activities. Moreover, recent evidence indicates that the reward to entrepreneurs who build venture backed startups is zero in almost 75% of the outcomes (Hall and Woodward, 2010).[9] This large failure rate in entrepreneurship can exacerbate the negative impact of fixed obligations such as student debt on such activities, especially given that student debt is much harder to discharge through bankruptcy in the U.S. Studies in this area also analyze employer conditions (Lin, Picot, and Yates, 1999), financing (e.g., Bernstein, Giroud, and Townsend, 2015; Tian, 2011), location (Delgado, Porter, and Stern, 2010), and human capital (e.g., Glaeser and Kerr, 2009; and Ewens and Marx, 2014). There is no study that we are aware of, however, that studies the link between student debt and high impact entrepreneurship.

Second, our study contributes to the literature on household finance (see, e.g., Campbell (2006)). This literature has thus far focused on issues such as portfolio decisions of households (e.g., Carlin and Manso, 2011, and Ivkovic, Siam, and Weisbenner, 2008) and mortgage and credit card debts (e.g., Bertaut, Haliassos, and Reiter, 2009, and Agarwal, Driscoll, and Laibson, 2013). This literature also utilizes data from the SCF to analyze household finance issues related to ownership of certain types of securities (see, e.g., Bergstresser and Cohen, 2015). See Guiso and Sodini (2012) for a detailed survey of this field of research. However, this strand of literature has tended to largely ignore student debt, and we contribute by analyzing two aspects of household finance. First, the extent of student debt held by households, and second, the risk of career paths chosen by household individuals (in particular, whether or not they engage in high impact entrepreneurship).

[9] Kerr and Nanda (2009) point out that in recent years there has been a gradual slowdown in entrepreneurial activity as measured by the relative entry counts of startups.

Third, we contribute to the extensive literature on the impact of education financing on educational enrollment, attainment and other related outcomes. Ellwood and Kane (2000) and Belley and Lochner (2007) argue that family income is significantly related to college attendance rates. Stinebrickner and Stinebrickner (2008) conclude that some college students are credit constrained, though they argue that this does not account for family income differences in college persistence. In related work, Marx and Turner (2015) find that Pell grant aid substantially reduces borrowing but has modest effect on educational attainment. Studies also find that financial aid increases student college attendance (see, e.g., Dynarski (2003)). Several other studies have found a positive relation between state subsidies and scholarships and college attendance and enrollment (see, e.g., Dynarski, 2003; Cornwell, Mustard, and Sridhar, 2006; Kane, 2003, 2007; Abraham and Clark, 2006).

Various studies have documented a significant positive value of higher education. For instance, Goldin and Katz (2008) and Avery and Turner (2012) document that the earnings premium of a college degree relative to a high-school degree has substantially increased over time. Kangasharju and Pekkala (2002) study the role of education on self-employment in Finland. Pekkarinen, Uusitalo, and Kerr (2009) study the impact of school reform and its impact on intergenerational income mobility. Others have analyzed the career effects of how higher education is financed. Rothstein and Rouse (2011) find results that are consistent with ours, namely that debt causes graduates to choose substantially higher-salary jobs and reduces the probability that students choose low-paid "public interest" jobs. They interpret their evidence as arising from credit constraints. Similarly, Minicozzi (2005) finds that higher educational debt is associated with higher initial wage rate the year after finishing school and lower wage growth over the next four years. Dynarski and Scott-Clayton (2013) provide a detailed survey of this literature as well as institutional details of financing of higher education in the United States.

The paper that is the closest to our study is a contemporaneous working paper by Ambrose, Cordell, and Ma (2015) and by Krishnan and Wang (2017). However, unlike us, the primary focus in Ambrose, Cordell, and Ma (2015) is on the relation between student debt and aggregate county level business formation. Unlike their paper, we also try to understand whether the relation between student debt and entrepreneurship is causal and provide evidence on the possible mechanisms behind this relation. Our analysis, unlike both aforementioned papers, is focused on high-impact, innovative, and venture capital backed entrepreneurship. This is an important distinction as the prevailing view is that innovative entrepreneurship is a strong driver for economic growth.

3.3 Hypothesis Development

Manso (2011) shows that risky activities such as innovation and entrepreneurship need a certain extent of tolerance for failure. In particular, innovative and high impact entrepreneurship is characterized by unexpected negative developments, need to pivot or overhaul business models, and experimentation, which may in turn adversely affect the cash flows generated by the business. Moreover, entrepreneurship carries with it a high overall likelihood of failure (e.g., Hall and Woodward, 2010). Entrepreneurs thus need the flexibility to weather income shocks due to such failures. However, having student debt on their personal balance sheets can significantly reduce such flexibility. Given the uncertainty in both the timing and level of cash flows generated by a new business, entrepreneurs may not be able to support repayments on student loans if their expectations regarding income from their businesses do not materialize. Not repaying student debt obligations can induce significant short- and long- run costs on the borrower. As a result, student loans can reduce tolerance for failure, especially in innovative entrepreneurship. Thus, our cost of business failure hypothesis predicts that student loans will be negatively related to high-impact, high technology entrepreneurship. Moreover, venture capitalists, who typically invest in more innovative industries, are more likely to invest in companies that are run by entrepreneurs with a lower extent of student loans.

Based on the above arguments, we expect a greater proportion of universities' graduating student body engages in high impact, high-technology, entrepreneurship when they implement no-loans financial aid policies. Moreover, lower student loans resulting from such policies allow entrepreneurs to invest in riskier projects and projects that produce more innovative products and enter unexplored markets. As a result, such firms are more likely to be favored by venture capitalists as they specialize in investing in innovative business models. Furthermore, we expect that ventures started by entrepreneurs graduating from no-loans universities are likely to get more venture capital dollar investments and such entrepreneurs are more likely to get backing from higher reputation venture capitalists. Prior literature (e.g., Chemmanur, Krishnan, and Nandy, 2011) finds higher reputation venture capitalists are more likely to invest in higher value startups and help further enhance their outcomes.

Next, we expect that student loans impact entrepreneurship more for universities with higher levels of tuition costs. Thus, we expect the impact of no-loans financial aid policies on university entrepreneurship and entrepreneurial success to be stronger in more expensive universities. Finally, we expect R&D activity in universities to spill over into high technology ventures started by the graduates from such universities (e.g., Jaffe, Trajtenberg, and Henderson, 1993). As a result, we expect the impact of no-loans financial aid policies on university entrepreneurship and entrepreneurial success to be stronger in universities that engage in more R&D activity.

3.4 Data, Sample Selection, and Variable Descriptions

Our data comes from several sources. We collect entrepreneurial data from Crunchbase, a database that provides information of predominantly high technology entrepreneurial ventures. This database comprises company (especially startup) profiles and information on people behind them. In particular, we obtained a pool of startups, their start years, and their founders' education, if available.[10] Universities and year from which entrepreneurs graduated are crucial for our analysis. Thus, we additionally collected education history of those entrepreneurs in our pool from LinkedIn. We then merge entrepreneurial education history obtained from LinkedIn with our original Crunchbase database.[11] We then restricted our our sample to entrepreneurs who obtained their undergraduate degrees from universities within the U.S.

We utilize data from VentureXpert, which provides information on venture capital firms and the companies and amount they have invested in. We matched this dataset with entrepreneurial

[10]Many entrepreneurs did not have their complete education histories listed. Any verified Crunchbase user can create as well as as make updates to any profile type, but all edits to profiles are reviewed and moderated by Crunchbase team.

[11]LinkedIn profiles in general have more complete education histories and they are provided by inidividuals themselves. Thus, we use education information collected from LinkedIn when avaiable.

ventures in our sample using Fuzzy String Matching Method programs and augmented this approach with additional hand cleaning. For our main analysis, we aggregate our sample entrepreneurs to the university-year (year of completion) level, then merge this data with data from the Integrated Postsecondary Education Data System (IPEDS), which is a longitudinal dataset maintained by the U.S. Department of Education. The IPEDS contains university enrollment, completions and student aid data for academic years 1986-87 through 2011-12.

We then create a matched sample by selecting appropriate control universities that are comparable with the treated universities that implemented no-loans financial aid policies based on number and growth rate of entrepreneurs. First, we select universities that are in the same Carnegie Classification 2000[12] as the treated universities. From there, we then select universities of which the average number of entrepreneurs in three years prior to the policy is within 15% of a treated university in the policy year.[13] Lastly, in this pool of universities, we select universities whose three year growth rate of entrepreneurial rate is closest to the treated university.[14] Our sample comprises 74 unique treated universities and 37 control universities spanning from 1987 to 2012.

The other main source of data is obtained from National Establishment Time-Series (NETS) database. This database contains information about more than 54.7 million establishments between January 1990 and January 2013, and provides information on firm performance such as industry, employment, and sales. We match this dataset with entrepreneurial ventures in our sample using a Fuzzy String Matching Method program, and utilize it for the analysis in firm performance. In particular, for each sample firm, we randomly select three control firms in the complete NETS database from the same industry and started in the same year as the sample firm.

In our first set of results, we test the impact of no-loans financial aid policies on financial aid. The dependent variables are *Total Aid* and *Fraction of Students Taking Loans*. *Total Aid* is the log of the sum of student loan, federal, state, and institutional grant provided to students as financial

[12] Carnegie Classification is a framework for classifying universities to identify groups of relatively comparable institutions.

[13] Those who have started ventures within five years of graduation. We explain more on this in the discussion of variables.

[14] Entrepreneurial rate is the fraction of entrepreneurs who started a venture within five years of graduation out of total number of undergraduate degrees granted. It is defined by *Fraction of Entrepreneurs 5 Years After Graduation*, described in the discussion of variables.

aid. *Fraction of Students Taking Loans* is the fraction of undergraduates at a university receiving student loans.

Our measures of entrepreneurship are *Fraction of Entrepreneurs 3 Years After Graduation* and *Fraction of Entrepreneurs 5 Years After Graduation*. *Fraction of Entrepreneurs 3 Years After Graduation* is the number of entrepreneurs who started a venture within three years of graduation divided by the total number of undergraduate degrees granted in a given university-year. Similarly, *Fraction of Entrepreneurs 5 Years After Graduation* is the total number of entrepreneurs who started a venture within five years of graduation divided by the total number of undergraduate degrees granted. In particular, we selected three- and five-year measures because they are within a relatively close range after graduation, and we expect the impact of having a student loan from college would be the greatest during this period.

We also construct a series of measures for venture capital backed entrepreneurship. *Fraction of VC-Backed Entrepreneurs 3 Years After Graduation* is the fraction of entrepreneurs who started a venture within three years of graduation and has got venture capital financing (at anytime) out of total number of undergraduate degrees granted in a given university-year. *Total Venture Capital Invested (for Ventures Starting within 3 Years after Graduation)* is the log of one plus the aggregated amount (in thousand) of venture capitalist dollars raised for ventures that started within three years of graduation of entrepreneurs. *Fraction of High Reputation VC-backed Ventures Starting within 3 Years after Graduation* is the fraction of entrepreneurs who started a venture within three years of graduation and has got financed by at least one high-reputation venture capitalist (at anytime) out of total number of undergraduate degrees granted in a given university-year. High-reputation venture capitalist is defined by one if a venture capitalist's market share of accumulated fund raised is greater than the 50th percentile of all venture capitalists in VentureXpert database. *Fraction of High Reputation VC-backed Ventures Starting within 3 Years after Graduation in VC-backed Ventures* is the fraction of entrepreneurs who started a venture within three years of graduation and has got financed by at least one high-reputation venture capitalist (at anytime) out of number of entrepreneurs started within 3 years of graduation and get VC financed in a given university-year. Other "5 Years" variable are defined similarly only if a entrepreneur started a venture within five years of graduation.

Our main explanatory variable is *Policy*, which is dummy varible that is defined by one if a university has implemented no-loans financial aid policy in a given year. We also create pre-trend variables *PrePolicy1*, *PrePolicy2*, and *PrePolicy3*, which are defined by one if it is one year, two years, and three years respectively before the first year of the adoption of no-loans financial aid policy by a university.

We also control for other university characteristics in analysis. *Tuition and Fees* is the log of in-state tuition and fees for full-time undergraduates (in real 2012 dollars). *Total Revenue* is the log of total amount of university revenue (in real 2012 dollars). It includes revenues from fees and charges, appropriations, auxiliary enterprises, and contributions and other nonexchange transactions. *Educ Share* is education-related share of expenses. It includes spending on instruction, student services, research, and public service. *Bachelors*, *Masters*, and *Doctoral Degrees* are the log of number of Bachelors, Masters, and Doctoral degrees granted respectively.

In interaction tests, we construct *High Tuition*, which is defined by one if tuition is higher than the 75th percentile of our sample. *High R&D*, which is a dummy variable defined by one if research-related share of expenses is greater than 75 percentile of our sample. Similarly, *High Doctoral Degrees* is defined by one if number of doctoral degrees granted is greater than the 75th percentile of our sample. *MA or CA* is a dummy variable defined by one if a university is located in Massachusetts or California.

In our individual level tests, we define *D(VC-Backed Entrepreneurship 3 Years After Graduation)* as a dummy variable, which is equal to one if an entrepreneur started a venture within three years of graduation and subsequently got venture capital financing. *Number of VCs investing in Entrepreneur* is the total number of venture capitalists that financed an entrepreneur's venture(s). [15] *D(High Reputation VC-backed Ventures)* is a dummy variable indicating whether an entrepreneur's venture has ever got financed by a high-reputation venture capitalist.

Finally, we uses NETS data to analyze entrepreneurial firm performance. We measure firm performance by sales and employment. Specifically, *ln(Sales After 5 Years of Founding)* is the log

[15] An entrepreneur could have multiple startups in our sample.

of one plus an entrepreneurial firm's sales after five years of its start. *ln(Employment After 5 Years of Founding)* is the log of one plus an entrepreneurial firm's number of employees after five years of its start. In certain regressions, we also control for the sales and employment of control firms. These control firms are randomly selected from the complete NETS database conditional on they are in the same industry and started in the same year with the sample firm. Each sample firm is then matched with three control firms. *ln(Sales of Control Firms in 5 Yrs)* is the log of one plus the average sales of three control firms after five years of their start. Similarly, *ln(Employment of Control Firms in 5 Yrs)* is for average number of employees.

3.5 Empirical Methodology and Results

3.5.1 No-Loans Financial Aid Policies

Over the course of the last decade, various schools established no-loans financial aid policies. These policies were motivated by concerns of college affordability, particularly for lower income group students. As Rothstein and Rouse (2011) point out, schools did not implement these policies with any explicit intent to impact post-graduate careers. Instead, the motivation was purely to lower financial barriers to higher education. The range of schools, in terms of academic prestige and costs, varies widely among the schools that implemented such policies. We obtain our sample of no-loans schools and the years of implementation through hand collection of data through Google searches.

We use a reduced form approach in our analysis, given that we do not have data on individual level student loans. Instead, we document how the presence of a no-loans financial aid policy impacted graduates' loan taking propensity and subsequent choice to become an entrepreneur (and successfully get VC backing). We directly address certain concerns with our approach. First, students may choose to go to universities that implement no-loans financial aid policies. To avoid any contamination through such effects, our regression models restrict the sample to cohorts that entered college prior to the implementation of no-loans financial aid policy at a school. Thus students could not choose their institution based on its choice of financial aid policy. Instead, the benefit from such a policy in the time after the policy is implemented, providing a plausibly exogenous variation in their student loans.

Second, there may be a concern that only certain types of institutions can afford to implement such policies. Indeed, our evidence in Panel D of Table 1 indicates that the median in-state tuition and fee is higher for no-loans financial aid offering schools (at $20,296) compared to schools not offering such policies ($15,957). We believe our results are not driven by any such selection issues, however. First, we utilize university fixed effects in all our regression models to account for time-invariant university characteristics. Typical university characteristics are generally expected to move slowly through time, thus this control should wipe out a majority of university-specific unobservable effects. Second, we also control for prior trends before the implementation of no-loans financial aid policies to test our parallel trends assumptions in our regression models. As we see in our results below, we do not have significant effects in universities that implement no-loans financial aid policies compared to previous years. Third, we create our control group of universities to ensure that there are no particular biases in the sample. As described above, our matched control group of universities are matched on Carnegie classification and prior entrepreneurship levels and trends of graduates, thus mitigating any effects of unobservable variables correlated with the propensity to implement no-loans financial aid policy. Finally, we note that such policies are implemented by wide variety of schools ranging from Princeton University to the College of Holy Cross, and so are not driven by university rankings.

3.5.2 Description of the Data and Summary Statistics

Table 1 reports descriptive statistics of our sample in university-year level. Panel A summarizes universities' financial aid statistics. The median total financial aid including both grants and loans is about $13.8 million. On average, 42% undergraduates take loans to finance their college education.

Panel B shows that, on average, a university produces 0.36 entrepreneurs per year who start their ventures within three years of graduation, and 0.56 entrepreneurs who start their ventures within five years of graduation, as listed in Crunchbase. Furthermore, 0.10 entrepreneurs who have started ventures within three years of graduation got venture capitalist financing. In particular, 0.09 are backed by a high-reputation venture capitalist. That indicates most of those who got VC financing are backed by high-reputation VCs. Similarly, 0.16 entrepreneurs who have started up within five years of graduation got venture capitalist financed, and 0.14 are backed by high-reputation VCs. The average amount VCs invested in entrepreneurs who start a venture within three years of graduation in a university is about \$2.7 million. That amount is \$4.3 million for those who start a venture within five years of graduation.

Panel C summarizes university characteristics. The average amount of in-state tuition and fees is \$18,680. At the median, universities grant 1,408 Bachelors degrees, 533 Masters degrees and 104 Doctoral degrees. Panel D compares universities that have implemented no-loans financial aid policies with control universities that have not implemented such policies. Tuition and fees of treated universities that have institute no-loans financial aid policies are slightly higher than the control universities, and they also have a lower level of total financial aid. Additionally, treated universities grant less Bachelors and Masters degrees compared to control universities. The two groups have similar levels of Doctoral degrees granted.

3.5.3 Impact of No-Loans Financial Aid Policy on Total Financial Aid and Loan

We start by examining the impact of no-loans financial aid policy on financial aid and the propensity to take student loans. To ensure the exogeneity of no-loans financial aid policy, we restrict our sample to students who enrolled in college prior to the year it implemented no-loans financial aid policy.[16]

For our exclusion restriction to hold, we expect that no-loans financial aid policy impacts student loan negatively, but does not impact overall financial aid. We estimate the following OLS model,

$$y_{it} = \alpha + \beta_1 Policy_{it} + \sum_{j=1}^{3} \beta_2^j PrePolicyj_{it} + \gamma X_{it} + \lambda_i + \kappa_{st} + \epsilon_{it} \tag{3.1}$$

y_{it} is *Total Aid* or *Fraction of Students Taking Loans*. X_{it} are control variables, including university-year characteristics such as tuition and fees, revenue etc. We also include three year

[16]For instance, if a university implemented no-loans financial aid policy in 1998, we only include students who enrolled before 1998.

pre-trends (Pre-policy variables). λ_i are university fixed effects and κ_{st} are state-year fixed effects. We include pre-trend dummy variables to ensure that our results are not driven by any trend effects prior to the university's implementation of no-loans financial aid policy.

The results for OLS estimations of the model above are reported in Table 2. Column (1) shows that no-loans financial aid policy does not change total financial aid amount. It indicates that the policy does not affect the total availability of financial aid to students, and that the reduction in loan amount was not offset by a similar reduction in overall financial aid amount. Column (2) shows that no-loans financial aid policy is associated with a decrease of 3.3 percentage points in the percentage of students taking loans. At the average number of Bachelors degree granted in the sample, it corresponds to 85 less students having loans. Consistent with our expectation, no-loans financial aid policy decreases the fraction of student who take loans, but does not affect the total financial aid availability to students. We also note that the pre-policy trend variables are not statistically significant, further validating our identification strategy. In particular, there is no difference in financial aid trends prior to policy implementation between treatment and control groups. Other control variables have intuitive coefficient estimates as well. Total financial aid and fraction of students taking student loans are higher for schools with higher tuition and fees and that grant more Bachelors degrees.

The results above support our identification strategy of using no-loans financial aid policies as a natural experiment for providing variation in student loans.

3.5.4 Impact of No-Loans Financial Aid Policy on Entrepreneurship

In this section, we examine the impact of student debt on entrepreneurial activity of university graduates. We use a similar OLS model as before, with the dependent variable changed to *Fraction of Entrepreneurs 3 Years After Graduation* or *Fraction of Entrepreneurs 5 Years After Graduation.*

The results of this analysis are reported in Table 3. We find that universities that have implemented no-loans financial aid policies graduate more students that subsequently start a venture. This effect is also economically significant. The average number of entrepreneurs who started up within five year of graduation is 0.56 in a given university. Universities that have implemented no-loans financial aid policies produce 1.43 more entrepreneurs (using Column (2)). That is almost three times of the average number of entrepreneurs. Additionally, high tuition and fees are negatively related to entrepreneurship. As before, the statistically insignificant coefficient estimates on the *PrePolicy* variables indicate that there is no prior trend differences prior to the implementation of no-loans policies between treatment and control universities.

3.5.5 Impact of Student Debt on VC-Backed Entrepreneurship

We then examine the impact of student debt on venture capitalist backed entrepreneurship. We use a similar specification as before, with the dependent variable *Fraction of VC-Backed Entrepreneurs 3 Years After Graduation* or *Fraction of VC-Backed Entrepreneurs 5 Years After Graduation*. The results, reported in Table 4, are consistent with student loans dampening the emergence of entrepreneurs that subsequently get venture capital backing. Universities with no-loans financial aid policies are more likely to produce venture capitalist backed entrepreneurs by an addition of 0.6 (using Column (2)). Given the average in our sample is 0.16, these results are both statistically and economically significant.

In Table 5, we conduct a similar analysis with *Total Venture Capital Invested* as the dependent variable. We find that graduates from universities with no-loans financial aid policies are likely to raise more venture dollars. This effect is economically large and (from the results in Column (1) of Table 5) associated with an increase over 250% in venture capital raised. This corresponds to an increase of $6.9 million invested by venture capitalists (using the mean VC amount raised over 3 years as our base case).

Finally, we use VC reputation as our dependent variable. Results reported in Table 6. Both Panel A and Panel B show that graduates from universities with no-loans financial aid policies have a higher chance to be backed by high reputation venture capitalists. Panel A reports results for high reputation venture backed entrepreneurs as a fraction of all university graduates in a year as the dependent variable and Panel B reports the results for high reputation venture backed entrepreneurs as a fraction of all venture backed entrepreneurs in a year as the dependent variable. In both cases, we find a significant positive relation between no-loans financial aid policies and the reputation of VCs backing ventures started by graduates.

These findings consistently show that student loans negatively impact high impact entrepreneurship and subsequent quantity and quality of venture capital backing of such ventures. The literature has shown that venture capital financing, especially high reputation VCs, is indicative of quality and subsequent success. Chemmanur, Krishnan, and Nandy (2011) found that VC-backed firms are more efficient prior to receiving financing compared to non-VC-backed firms, and also experience greater growth subsequently through both screening and monitoring. Sorensen (2007) showed that companies funded by more experienced VCs are more likely to go public from both their experience and market sorting. Thus, our findings of student loan negatively impacting VC-backed entrepreneurs indicate that student loans dampen the development of high quality entrepreneurship.

3.5.6 Impact of Student Debt on High Impact Entrepreneurship - Cross Sectional Heterogeneity

In this section, we try to get a better understanding of the cross-sectional heterogeneity in the negative relation between student debt and entrepreneurship that we find above. This can help us provide additional evidence regarding the mechanism underlying the negative relation between student loans and high impact entrepreneurship. We interact *High Tuition* with *Policy* in all specifications in Table 7 and 8. Universities that are engaged in a greater extent of R&D activities are likely to have knowledge spill overs (e.g., Jaffe, Trajtenberg, and Henderson, 1993), and thus more likely to produce entrepreneurs. We interact *High R&D* with *Policy.* Similarly, we also interact *High Doctoral Degrees* (and *MA or CA*) with *Policy.*

The results of these interaction tests are reported in Tables 7 and 8 with fraction of entrepreneurs and fraction of VC backed entrepreneurs as the dependent variables, respectively. In Table 7, the coefficient estimate on the interaction term between *High Tuition* and *Policy* is statistically significantly and positive, consistent with the impact of student loans being more important in more expensive schools. Further, we find that the impact of no-loans financial aid policy is greater for universities actively engaged in R&D activities, grant more doctoral degrees or are located in entrepreneurial hubs (California and Massachusetts).

Table 8 reports similar, though statistically weaker, results for fraction of venture capital backed entrepreneurship. In particular, we find that the positive impact of no-loans financial aid policy on the creation of ventures that get subsequent venture backing is stronger for universities that are engaged in R&D activities.

3.5.7 Impact of Student Debt on VC-Backed Entrepreneurship - Individual Level Analysis

We also examine the impact of student debt on VC-backed entrepreneurship through no-loans financial aid policy on individual level. Specifically, we run the same specification as before with individual level data. In addition, we now control for industry fixed effects in our analysis. In Column (1) of Table 9, we find that individuals graduated from universities with no-loans financial aid policies are more likely to get subsequent venture capital backing. Further, they are more likely to get backed more venture capitalists as shown in Column (2). Lastly, these graduates from no-loans financial aid policy schools are more likely to be backed by a high-reputation venture capitalist. Our findings are consistent with previous findings on university level.

These results provide supporting evidence for our hypotheses. They also rule out the possibility that our venture capital results at the university level are driven by the fact that venture backed entrepreneurship increases with no-loans financial aid policies simply as a result of increase in overall entrepreneurship.

3.5.8 Impact of Student Debt on Entrepreneurial Firm Performance

In this section, we test the impact of student debt on individual entrepreneurial firm performance. We estimate the an OLS model similar to earlier where the dependent variables are *ln(Sales After 5 Years of Founding)* or *ln(Employment After 5 Years of Founding).* These variables are available for only those firms that survive for at least 5 years after founding. In these regressions, we control for university, year, and 6 digit SIC code fixed effects.[17] We note that due to hand-matching between the NETS and our Crunchbase-IPEDS-VentureXpert dataset, we end up with fewer observations

[17] We did not include state-year fixed effects as in previous specifications because we lose power in estimation with too many fixed effects for a relatively small number of observations.

because we cannot find matching observations in some cases.

Table 10 reports the results of these tests. Column (3) and (4) show the results including control firm variables *ln(Sales of Control Firms in 5 Yrs)* and *ln(Employment of Control Firms in 5 Yrs)* respectively, while Column (1) and (2) do not include them. Overall, we find that conditional on surviving, entrepreneurial firms' sales and employment after five years of founding are higher if its founder graduated from a university where no-loans financial aid policies were in place. Specifically, sales is 89% higher for after fiver years of founding for firms that were founded by entrepreneurs graduated from no-loans financial aid policy schools. And employment is 76% higher. This result provides further evidence that student debt not only hinders entrepreneurial activity, but negatively affects economic growth by impacting high performance entrepreneurship that can create more employment.

3.6 Conclusion

Student debt can impose a significant burder on entrepreneurship. We use universities' implementations of no-loans financial aid policies as a natural experiment to understand the causal impact of student debt on particularly VC-backed entrepreneurship. We first show universities that replace loans with grants in their financial aid packages do not affect overall financial aid available to students, but decrease percentage of students who have student loans significantly. This validates our identification. We find that graduates from universities that implemented no-loans financial aid policies are more likely to start entrepreneurial ventures, and their ventures are more likely to raise venture capital financing, and greater extent of VC dollars. Additionally, ventures started by graduates from no-loan policy financial aid policy schools are backed by high reputation venture capitalists, which is indicative of higher likelihood of subsequent success. Our results are stronger for high-tuition universities, universities with a greater extent of R&D activities and that grant a greater number of doctoral degrees. Using firm-year level data, we find that ventures started by graduates from no-loan policy schools have a greater level of sales and employment over five years after founding.

We contribute to the literature by highlighting the impact of student loans on an important aspect of economic value creation, namely, the creation of high impact, high technology, and venture-backed startups. Prior literature (Krishnan and Wang, 2017; Ambrose, Cordell, and Ma, 2015) has analyzed entrepreneurship in a broad sense, and due to data limitations and limitations related to identification, does not delve deeply into the *type* of entrepreneurs impacted by student loans or their outcomes. We overcome this gap in the literature by creating a new dataset and utilizing a relatively new identification strategy. Moreover, our results have implications for policymakers and practitioners. First, our results indicate that university financial aid policies can have impact on the economy. Second, our results indicate that excessive dependence on student loans may end up stifling innovative ventures, which can be very harmful for the economy in the long run. Finally, since no-loans policies are geared more toward lower income groups, such policies may help in building long-term wealth and promoting risk-taking in this group, which may have implication for long-term income inequality.

Table 3.1: Summary Statistics

Panel A. Financial Aid Variables

	Mean	Std.Dev.	Median	Obs
Total Aid	20,272,775.85	21,930,662.26	13,766,850.00	1280
Fraction of Students Taking Loans	0.42	0.15	0.41	1411

Panel B. Entrepreneurship after Graduation

	Mean	Std.Dev.	Median	Obs
Entrepreneurs 3 Years after Graduation	0.36	0.92	0.00	2885
Entrepreneurs 5 Years after Graduation	0.56	1.22	0.00	2885
VC-Backed Entrepreneurs 3 Years After Graduation	0.10	0.35	0.00	2885
VC-Backed Entrepreneurs 5 Years After Graduation	0.16	0.47	0.00	2885
Total Venture Capital Invested (for Ventures Starting within 3 Years after Graduation)	2,760.87	26,533.33	0.00	2885
Total Venture Capital Invested (for Ventures Starting within 5 Years after Graduation)	4,319.10	31,992.86	0.00	2885
High Reputation VC-backed Ventures Starting within 3 Years after Graduation	0.09	0.32	0.00	2885
High Reputation VC-backed Ventures Starting within 5 Years after Graduation	0.14	0.44	0.00	2885

Panel C. University Variables

	Mean	Std.Dev.	Median	Obs
Tuition and Fees	18,680	13,322	17,743	2808
Bachelors Degrees	2,575	3,157	1,408	2875
Masters Degrees	1,026	1,379	533	2797
Doctoral Degrees	187	226	104	2711

Panel D. Comparison of Variables for Schools with and without No-Loans Financial Aid Policies

	No Loan Policy = 0			No Loan Policy = 1		
	Mean	Median	Obs	Mean	Median	Obs
Tuition and Fees	17,480	15,957	911	19,256	20,296	1897
Bachelors Degrees	3,311	1,763	956	2,209	1,288	1919
Masters Degrees	1,295	741	956	886	448	1841
Doctoral Degrees	184	105	915	189	104	1796
Total Aid	26,288,240	16,238,640	426	17,272,088	12,421,249	854

Table 3.2: The Impact of No-loans Financial Aid Policy on Total Financial Aid and Fraction of Students Taking Loans

	(1) Total Aid	(2) Fraction of Students Taking Loans
PrePolicy3	0.032	-0.014
	(0.032378)	(0.010979)
PrePolicy2	0.028	-0.013
	(0.037217)	(0.012177)
PrePolicy1	-0.004	-0.015
	(0.040885)	(0.014534)
Policy	0.062	-0.033**
	(0.044834)	(0.015769)
Tuition and Fees	0.630***	0.157***
	(0.120440)	(0.045548)
Total Revenue	-0.000	0.014
	(0.019246)	(0.015104)
Educ Share	0.055	-0.123
	(0.313281)	(0.078292)
Bachelors Degrees	0.398***	0.094***
	(0.121040)	(0.035318)
Masters Degrees	0.068	0.009
	(0.042508)	(0.012767)
Doctoral Degrees	0.058**	0.013
	(0.029484)	(0.009846)
University FE	Yes	Yes
State-Year FE	Yes	Yes
R^2	0.982	0.885
Observations	1045	1130

Table 3.3: The Impact of No-loans Financial Aid Policy on Entrepreneurship after Graduation

	(1) Fraction of Entrepreneurs 3 Years After Graduation	(2) Fraction of Entrepreneurs 5 Years After Graduation
PrePolicy3	0.000061	0.000137
	(0.000119)	(0.000181)
PrePolicy2	-0.000023	0.000223
	(0.000147)	(0.000230)
PrePolicy1	-0.000120	0.000093
	(0.000232)	(0.000247)
Policy	0.000365**	0.000554***
	(0.000148)	(0.000176)
Tuition and Fees	-0.000528***	-0.000766***
	(0.000134)	(0.000210)
Total Revenue	-0.000069	-0.000047
	(0.000064)	(0.000088)
Educ Share	0.000087	0.000130
	(0.000417)	(0.000625)
Bachelors Degrees	-0.000079**	-0.000121***
	(0.000033)	(0.000047)
Masters Degrees	0.000008	0.000059
	(0.000041)	(0.000061)
Doctoral Degrees	-0.000023	-0.000037
	(0.000034)	(0.000048)
University FE	Yes	Yes
State-Year FE	Yes	Yes
R^2	0.492	0.501
Observations	2536	2536

Table 3.4: The Impact of No-loans Financial Aid Policy on VC-Backed Entrepreneurship

	(1) Fraction of VC-Backed Entrepreneurs 3 Years After Graduation	(2) Fraction of VC-Backed Entrepreneurs 5 Years After Graduation
PrePolicy3	0.000052	0.000194
	(0.000099)	(0.000134)
PrePolicy2	-0.000055	-0.000051
	(0.000069)	(0.000091)
PrePolicy1	-0.000156	-0.000116
	(0.000148)	(0.000152)
Policy	0.000178*	0.000233**
	(0.000092)	(0.000101)
Tuition and Fees	-0.000184***	-0.000255***
	(0.000071)	(0.000097)
Total Revenue	-0.000028	0.000002
	(0.000030)	(0.000031)
Educ Share	0.000024	-0.000028
	(0.000225)	(0.000329)
Bachelors Degrees	-0.000021	-0.000026
	(0.000015)	(0.000018)
Masters Degrees	-0.000025	-0.000024
	(0.000025)	(0.000030)
Doctoral Degrees	0.000000	0.000019
	(0.000018)	(0.000025)
University FE	Yes	Yes
State-Year FE	Yes	Yes
R^2	0.418	0.395
Observations	2536	2536

Table 3.5: The Impact of No-loans Financial Aid Policy on Total Amount of Venture Capital Invested

	(1) Total Venture Capital Invested (for Ventures Starting within 3 Years after Graduation)	(2) Total Venture Capital Invested (for Ventures Starting within 5 Years after Graduation)
PrePolicy3	-0.274	0.844
	(0.542442)	(0.690030)
PrePolicy2	-0.470	-0.570
	(0.527376)	(0.623816)
PrePolicy1	-0.476	-0.122
	(0.759161)	(0.816813)
Policy	0.917*	1.159**
	(0.517561)	(0.554366)
Tuition and Fees	-0.198	0.102
	(0.522725)	(0.564563)
Total Revenue	0.020	0.194
	(0.179034)	(0.208442)
Educ Share	-0.605	-0.882
	(1.811485)	(2.019398)
Bachelors Degrees	-0.100	-0.036
	(0.129434)	(0.149868)
Masters Degrees	-0.238	-0.223
	(0.150697)	(0.186857)
Doctoral Degrees	-0.010	0.173
	(0.127690)	(0.165414)
University FE	Yes	Yes
State-Year FE	Yes	Yes
R^2	0.402	0.471
Observations	2536	2536

Table 3.6: The Impact of No-loans Financial Aid Policy on Reputation of Venture Capitalists Invested in Startups

Panel A

	(1) Fraction of High Reputation VC-backed Ventures Starting within 3 Years after Graduation	(2) Fraction of High Reputation VC-backed Ventures Starting within 5 Years after Graduation
PrePolicy3	0.000055	0.000148
	(0.000098)	(0.000123)
PrePolicy2	-0.000055	-0.000061
	(0.000070)	(0.000087)
PrePolicy1	-0.000125	-0.000089
	(0.000148)	(0.000148)
Policy	0.000149*	0.000210**
	(0.000088)	(0.000100)
Tuition and Fees	-0.000175**	-0.000242**
	(0.000069)	(0.000095)
Total Revenue	-0.000014	0.000010
	(0.000025)	(0.000027)
Educ Share	0.000085	0.000005
	(0.000205)	(0.000320)
Bachelor Degrees	-0.000024	-0.000026
	(0.000015)	(0.000018)
Master Degrees	-0.000023	-0.000019
	(0.000024)	(0.000029)
Doctor Degrees	0.000001	0.000016
	(0.000018)	(0.000024)
University FE	Yes	Yes
State-Year FE	Yes	Yes
R^2	0.413	0.380
Observations	2536	2536

Panel B

	(1) Fraction of High Reputation VC-backed Ventures Starting within 3 Years after Graduation in VC-backed Ventures	(2) Fraction of High Reputation VC-backed Ventures Starting within 5 Years after Graduation in VC-backed Ventures
PrePolicy3	-0.005109	0.101812
	(0.060022)	(0.070826)
PrePolicy2	-0.025831	-0.047056
	(0.061624)	(0.070503)
PrePolicy1	0.021518	0.031817
	(0.085283)	(0.088242)
Policy	0.119036**	0.151530**
	(0.056783)	(0.063350)
Tuition and Fees	-0.028248	-0.000565
	(0.053615)	(0.059985)
Total Revenue	0.004566	0.025716
	(0.020848)	(0.024549)
Educ Share	-0.047130	-0.069853
	(0.187866)	(0.216986)
Bachelors Degrees	-0.019418	-0.006664
	(0.014280)	(0.016605)
Masters Degrees	-0.013533	-0.019699
	(0.015229)	(0.019138)
Doctoral Degrees	-0.005028	0.007244
	(0.013484)	(0.017768)
University FE	Yes	Yes
State-Year FE	Yes	Yes
R^2	0.411	0.466
Observations	2536	2536

Table 3.7: The Impact of No-loans Financial Aid Policy on Entrepreneurship - Interaction Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Fraction of Entrepreneurs 3 Years After Graduation	Fraction of Entrepreneurs 5 Years After Graduation	Fraction of Entrepreneurs 3 Years After Graduation	Fraction of Entrepreneurs 5 Years After Graduation	Fraction of Entrepreneurs 3 Years After Graduation	Fraction of Entrepreneurs 5 Years After Graduation
Policy*High R&D	0.000602***	0.000611***				
	(0.000157)	(0.000180)				
Policy*High Doctoral Degrees			0.000423*	0.000605**		
			(0.000221)	(0.000269)		
Policy*MA or CA					0.000770**	0.000836*
					(0.000389)	(0.000441)
Policy*High Tuition	0.000737**	0.000829*	0.000883**	0.000979**	0.000670**	0.000756*
	(0.000327)	(0.000431)	(0.000344)	(0.000436)	(0.000340)	(0.000458)
Policy	-0.000144	-0.000075	-0.000202	-0.000238	-0.000108	-0.000054
	(0.000111)	(0.000151)	(0.000142)	(0.000160)	(0.000101)	(0.000134)
High R&D	0.000018	0.000078				
	(0.000049)	(0.000067)				
Tuition and Fees	-0.000391***	-0.000588***	-0.000435***	-0.000648***	-0.000460***	-0.000668***
	(0.000119)	(0.000201)	(0.000120)	(0.000201)	(0.000123)	(0.000204)
Total Revenue	-0.000056	-0.000020	-0.000065	-0.000029	-0.000065	-0.000029
	(0.000060)	(0.000086)	(0.000061)	(0.000086)	(0.000061)	(0.000087)
Educ Share	0.000424	0.000621	0.000144	0.000233	0.000305	0.000399
	(0.000396)	(0.000620)	(0.000396)	(0.000601)	(0.000381)	(0.000593)
Bachelors Degrees	-0.000063*	-0.000110**	-0.000069**	-0.000117**	-0.000075**	-0.000124**
	(0.000033)	(0.000048)	(0.000033)	(0.000049)	(0.000033)	(0.000049)
Masters Degrees	0.000033	0.000080	0.000026	0.000069	0.000028	0.000070
	(0.000041)	(0.000061)	(0.000041)	(0.000061)	(0.000041)	(0.000060)
Doctoral Degrees	-0.000001	-0.000015	-0.000005	-0.000014	-0.000009	-0.000023
	(0.000032)	(0.000047)	(0.000033)	(0.000048)	(0.000033)	(0.000048)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.513	0.512	0.508	0.512	0.510	0.511
Observations	2536	2536	2536	2536	2536	2536

Table 3.8: The Impact of No-loans Financial Aid Policy on VC-Backed Entrepreneurship - Interaction Tests

	(1) Fraction of VC-Backed Entrepreneurs 3 Years After Graduation	(2) Fraction of VC-Backed Entrepreneurs 5 Years After Graduation	(3) Fraction of VC-Backed Entrepreneurs 3 Years After Graduation	(4) Fraction of VC-Backed Entrepreneurs 5 Years After Graduation	(5) Fraction of VC-Backed Entrepreneurs 3 Years After Graduation	(6) Fraction of VC-Backed Entrepreneurs 5 Years After Graduation
Policy*High R&D	0.000245**	0.000245**				
	(0.000100)	(0.000105)				
Policy*High Doctoral Degrees			0.000068	0.000100		
			(0.000144)	(0.000156)		
Policy*MA or CA					0.000424	0.000513*
					(0.000286)	(0.000297)
Policy*High Tuition	0.000280	0.000255	0.000339	0.000322	0.000211	0.000169
	(0.000193)	(0.000220)	(0.000216)	(0.000241)	(0.000165)	(0.000193)
Policy	-0.000001	0.000039	0.000036	0.000055	-0.000006	0.000014
	(0.000051)	(0.000062)	(0.000107)	(0.000108)	(0.000049)	(0.000060)
High R&D	-0.000024	0.000021				
	(0.000028)	(0.000035)				
Tuition and Fees	-0.000144**	-0.000209**	-0.000153**	-0.000225**	-0.000174**	-0.000250**
	(0.000066)	(0.000099)	(0.000066)	(0.000100)	(0.000071)	(0.000103)
Total Revenue	-0.000026	0.000003	-0.000030	0.000000	-0.000031	-0.000001
	(0.000028)	(0.000030)	(0.000029)	(0.000030)	(0.000029)	(0.000031)
Educ Share	0.000096	0.000148	0.000036	0.000004	0.000134	0.000122
	(0.000230)	(0.000336)	(0.000223)	(0.000326)	(0.000223)	(0.000324)
Bachelors Degrees	-0.000013	-0.000019	-0.000016	-0.000022	-0.000018	-0.000025
	(0.000013)	(0.000018)	(0.000014)	(0.000018)	(0.000014)	(0.000018)
Masters Degrees	-0.000016	-0.000016	-0.000017	-0.000020	-0.000015	-0.000018
	(0.000024)	(0.000030)	(0.000024)	(0.000030)	(0.000024)	(0.000030)
Doctoral Degrees	0.000010	0.000028	0.000005	0.000025	0.000006	0.000026
	(0.000017)	(0.000024)	(0.000018)	(0.000025)	(0.000018)	(0.000025)
University FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.425	0.396	0.421	0.394	0.426	0.397
Observations	2536	2536	2536	2536	2536	2536

Table 3.9: The Impact of No-loans Financial Aid Policy on VC-Backed Entrepreneurship - Individual Level Analysis

	(1) D(VC-Backed Entrepreneurship 3 Years After Graduation)	(2) Number of VCs investing in Entrepreneur	(3) D(High Reputation VC-backed Ventures)
PrePolicy3	-0.020	-0.021	-0.017
	(0.034089)	(0.035865)	(0.033029)
PrePolicy2	0.004	0.005	0.004
	(0.040181)	(0.042049)	(0.042215)
PrePolicy1	-0.012	-0.032	0.001
	(0.045252)	(0.049095)	(0.040254)
Policy	0.069*	0.084**	0.061*
	(0.035630)	(0.037502)	(0.035347)
Tuition and Fees	-0.033	-0.066	-0.032
	(0.055418)	(0.072355)	(0.054498)
Total Revenue	-0.041**	-0.037*	-0.032
	(0.020510)	(0.022063)	(0.019381)
Educ Share	-0.166	-0.196	-0.152
	(0.149728)	(0.196423)	(0.142170)
Bachelors Degrees	-0.030	-0.024	-0.040
	(0.067365)	(0.079880)	(0.064317)
Masters Degrees	-0.096**	-0.115***	-0.085**
	(0.037535)	(0.041741)	(0.037064)
Doctoral Degrees	0.042	0.032	0.062*
	(0.038753)	(0.039444)	(0.032125)
Constant	1.793**	2.121**	1.511**
	(0.765867)	(0.911466)	(0.747547)
University FE	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.210	0.214	0.212
Observations	3841	3841	3841

Table 3.10: The Impact of No-loans Financial Aid Policy on Entrepreneurial Firm Performance

	(1) ln(Sales After 5 Years of Founding)	(2) ln(Employment After 5 Years of Founding)	(3) ln(Sales After 5 Years of Founding)	(4) ln(Employment After 5 Years of Founding)
PrePolicy3	0.371	0.345	0.352	0.363
	(0.431)	(0.315)	(0.419)	(0.310)
PrePolicy2	-0.189	-0.073	-0.199	-0.080
	(0.394)	(0.269)	(0.414)	(0.273)
PrePolicy1	-0.305	-0.163	-0.296	-0.157
	(0.428)	(0.335)	(0.429)	(0.338)
Policy	0.638**	0.568**	0.614*	0.574**
	(0.320)	(0.231)	(0.320)	(0.229)
ln(Sales of Control Firms in 5 Yrs)			0.031	
			(0.020)	
ln(Employment of Control Firms in 5 Yrs)				0.074
				(0.081)
Tuition and Fees	-0.310	-0.114	-0.328	-0.126
	(0.693)	(0.597)	(0.677)	(0.592)
Total Revenue	0.281	0.252	0.259	0.242
	(0.269)	(0.207)	(0.273)	(0.207)
Educ Share	3.753*	2.512	3.821**	2.500
	(1.951)	(1.527)	(1.935)	(1.533)
Bachelors Degrees	-0.743	-0.745	-0.830	-0.742
	(1.159)	(0.830)	(1.151)	(0.828)
Masters Degrees	0.363	0.105	0.365	0.082
	(0.721)	(0.582)	(0.716)	(0.585)
Doctoral Degrees	-0.354	-0.247	-0.216	-0.217
	(0.734)	(0.508)	(0.751)	(0.509)
University FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SIC6	Yes	Yes	Yes	Yes
R^2	0.808	0.741	0.776	0.740
Observations	724	724	722	722

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