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Microeconometric Essays on Entrepreneurship

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By

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Abstract

This dissertation empirically analyzes decisions taken to support the growth of small, young, entrepreneurial firms. It is a collection of three Microeconometric essays. These papers broadly fit within the field of Behavioral Empirical Microeconomics as they analyze the beliefs and biases of entrepreneurs.

The first *paper*: *Local Supply Shocks of Bank Credit Deter Young Firms from Loan Applications*, co-authored with Frank M. Fossen, estimates changes in rates of young firms who are deterred from applying for commercial bank loans following a change in the credit supply due to their belief that they will be denied credit. By estimating short-run firm responses to an identified supply shock, we reveal unmet demand and inefficiencies in small business credit markets that have previously been masked in loan application and approval data due to the adverse selection problem in banking and a lack of information about individual entrepreneurs beliefs relative to their creditworthiness. The methodology for this paper is instrumental variable (IV) regression. We utilize start-up firm panel data from The Kauffman Firm Survey and lending data from U.S. Community Reinvestment Act mandated reporting.

The second paper: *Public Entrepreneurship Training for Startup Firms: Evidence from the Kauffman Firm Survey* studies the selection decision of small young entrepreneurial firms into start-up firm specific entrepreneurship training. The Kauffman Firm Survey offers a unique opportunity to observe entrepreneurs who selected no training, private, and public training. I estimate outcomes relevant to the development of start-ups: survival, growth rates of profit, growth rates of employment, commercial bank loan

applications, loan approvals, loan deterrence, and forecasting ability. I use probit propensity score matching methodology to analyze selection and differences in performance outcomes between training program types including U.S. Small Business Administration (SBA) training.

The third paper: *The Art Market as Keynes' Beauty Contest with a $10,000 Prize*, co-authored with Federico L. Guerrero estimates income differences between myopic and strategic artists. We discuss visual fine arts as assets and find an income premium at a threshold level of secondary market strategic awareness without full information. This study demonstrates incentives for content convergence in arts and cultural production.

Dedicated to my greatest love and joy, my daughter Iris Happe Griffiths.

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Introduction

Small, young, entrepreneurial enterprises hold the potential for growth in an evolving economy. They are the focus of this dissertation thesis. In his classic work supporting entrepreneurship, *Capitalism, Socialism, and Democracy* (1942), Joseph Schumpeter describes the special role of these firms in a metaphor of the economy as a forest. Young firms bring innovations which expand the system with new growth and ideas. Like trees, young firms still have the flexibility to bend and adapt to local changes, but lack the strength and stability of older firms whose sheltering canopy and experience they rely on. I extend this metaphor and study three factors that potentially support the growth of young firms into stable employers: access to credit, entrepreneurship training, and strategic awareness.

The first *paper*: *Local Supply Shocks of Bank Credit Deter Young Firms from Loan Applications*, co-authored with Frank M. Fossen, estimates young firm's bank loan application behavior in response to large-scale credit supply shocks. Forests are subject to local climate events and disasters such as wildfires and droughts that stress all life in the area. Similarly, the economic ecosystem can be shocked by business cycle and widespread catastrophic events such as the Financial Crisis of 2008, which led to a 55% decrease in U.S. small business lending from 2007 to 2010 (FFIEC, 2022). Without the fertilizer needed for growth, young firms were left vulnerable to the subsequent Great Recession.

Our paper reveals previously hidden unmet demand for commercial small business loans during the Great Recession in the form of entrepreneurs who were deterred from applying due to local credit conditions. This demand is not immediately observable in loan application rates which also increased during this period. We adapt shift-share methodology developed by Bartik (1987), Bernanke and Lown (1991), and Greenstone et al. (2020) to separately identify credit supply shocks from local credit demand. We then estimate small young firm responses to these shocks using start-up cohort panel data from the Ewing Marion Kauffman Foundation (Robb and DesRoches, 2012). After controlling for credit-worthiness, we estimate that $20 billion in bank financing was deterred from young firms in 2009.

The second paper: *Public Entrepreneurship Training for Startup Firms: Evidence from the Kauffman Firm Survey* analyzes selection into and outcomes of firm specific start-up training programs. Business incubators, and mentoring programs such as SCORE (Service Corps of Retired Executives) and Chambers of Commerce are designed to form a sheltering canopy for new businesses. While the U.S. Small Business Administration (SBA) has a mandate to make these resources available to all entrepreneurs, private consultants, accountants, and others offer fee-for-service training courses. Using start-up panel data from the Kauffman Firm Survey (Robb and DesRoches, 2012) gives me a unique opportunity to observe firms that select into public, private, and no training programs. Previous program evaluations of SBA training have begun with firms who select into the training (Benus et al. 2009; Michaelides and Benus 2012; Fairlie et al. 2015). I use probit propensity score matching methods to compare survival, growth, and financing outcomes for similar firms that selected into a training compared to those that selected no training. Despite lofty goals, I find little evidence of measurable performance outcomes from public or private training programs compared to receiving no training. Trained firms apply for bank loans at higher rates than untrained firms, but are no more likely to be approved.

The third paper: *The Art Market as Keynes' Beauty Contest with a $10,000 Prize*, co-authored with Federico L. Guerrero, studies self-employed visual fine artists as entrepreneurs. This special class of entrepreneurs creates value beyond innovation and employment by creating assets that may appreciate in value as they are resold. As creators, artists can work solely from inspiration or behave with strategic awareness to create a work with broader appeal to the secondary market. In the metaphor of the forest, this can be seen as the adaptations of seeds that make them appealing to being carried by birds and animals.

In *The General Theory of Employment, Interest and Money*, Keynes (1936) describes a game he calls *The Beauty Contest* as a metaphor for the behavior of asset traders. In the game, strategic traders choose the picture they believe to have the broadest appeal to the group rather than selecting a picture from personal preference. This game was mathematically formalized by Nagel (1995) as *The Guessing Game* and extended out to greater levels of strategic awareness. We apply this game to artists as entrepreneurs creating assets for resale. For our analysis we use data from an original U.S. wide survey designed for this study (Flanigan, 2019). We analyze selection of strategy using a logit model and compare the income distributions of strategic and myopic artists by characteristic group, finding that strategy is especially useful for young artists seeking to establish themselves as professionals. Our study has implications beyond artist entrepreneurs, showing that in asset markets a premium can be realized from a threshold level of strategic awareness without full information. It also demonstrates incentives for content convergence and the homogenization of arts and cultural products in a search for universal recognizability and mass appeal.

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Local Supply Shocks of Bank Credit Deter Young Firms from Loan Applications*

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Abstract:

When creditworthy entrepreneurs need financing but do not apply because they believe they will be denied a bank loan, this unmet demand creates inefficiencies in lending markets. We study loan deterrence of young small firms using the Kauffman Firm Survey, a cohort study of startups founded in 2004 and followed through the Financial Crisis of 2008-09 until 2012. We analyze the effects of county-level credit supply shocks on young businesses' access to commercial bank loans. We find that a large segment of young firms are deterred from applying for loans following a local credit supply shock while controlling for the credit risk score of the business and demographics of the ownership team. We also document that loan application rates by young firms do not respond to local credit supply changes, plausibly explaining why the deterrence effect has been largely overlooked in prior literature.

Keywords: Loan deterrence, credit supply shock, entrepreneurship, startup, ownership team

JEL Codes: L26, G01, G21, G32, G40

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1. Introduction

Entrepreneurial credit demand, particularly in a recession, is usually expected to be greater than bank loan supply. There is no shortage of ideas, and in trying times desperate young businesses will do what they can to survive. However, similarly creditworthy entrepreneurial businesses in the United States are in fierce competition for available loans at the local level and must be aware of current credit market conditions and their options. When creditworthy startups drop out of the credit market because they believe they will not receive loans in the current economic conditions, this creates inefficiency in credit markets that may spread to other sectors. The entrepreneurial process of creative destruction, described by Schumpeter (1942), relies on innovative young firms replacing slower firms. If young firms become deterred from credit markets, loans are made to older firms that are more focused on survival than growth. This inefficiency can slow employment growth at young firms and inhibit the process of bringing innovations to the consumer marketplace. In this study, we ask how local credit supply shocks affect entrepreneurial businesses who have just survived through the startup phase.

During the Great Recession, entrepreneurial businesses faced supply shocks from lenders who cut small business credit volume by 55% from a high of $148 billion in 2007 to a low of $67 billion in 2010 (Table 1). Banks cut credit availability at the same time young businesses needed it most: when consumers had less income to spend due to the foreclosure crisis and job losses in the recession. Small business loans may be a lifeline for firms and jobs during a recession. In our study, 27% of surveyed firms closed from 2007-2010. Brown and Earle (2017) find a direct connection between credit supply and job creation at young firms in weak local credit markets. During the Covid-19 pandemic, the

SBA's Paycheck Protection Program aimed to protect small businesses from simultaneous recessionary and credit market shocks (Howell et al. 2022). No such support program for small businesses existed during the 2008 Financial Crisis.

In this paper, we investigate how a decrease in local commercial bank credit supply affects financing of young entrepreneurial firms. In particular, we investigate the extent to which young firms are deterred from loan applications because of fear of being denied. We also estimate effects on loan applications by young firms and subsequent loan approvals.

Our first contribution to the literature is that we study loan deterrence by *young entrepreneurial firms*. We analyze firm behavior using the Kauffman Firm Survey (KFS), an annual panel survey that follows a cohort of small firms that started up in 2004 over eight years. Thereby we respond to increasing interest among academics and policymakers in young entrepreneurial firms as drivers of employment and economic growth (Haltiwanger et al. 2013). Most of the literature on financing effects of credit supply shocks focuses on large businesses due to data availability, for example by analyzing syndicated loans, which are usually large (Ivashina and Scharfstein 2010, Chodorow-Reich 2014, Acharya et al. 2018). Some papers include *small* firms (Jiménez et al. 2012, 2014, Degryse et al. 2019, De Jonghe et al. 2020, Dwenger et al. 2020, Greenstone et al. 2020), but little is known about the financing behavior of *young* firms. While young firms are usually small, they differ from older small firms by being more innovative and having larger growth potential. In contrast to older small firms, young firms also lack a track record of business success and a credit history, which makes it harder for them to obtain financing; this is a component of their "Liability of Newness" (Stinchcombe 1965, Gimenez-Fernandez et al.

2020). Studied firms were often self-financed from owner equity and lacked access to outside equity from venture capital and government agencies (Table 2).

Our second contribution is that we focus on *loan deterrence*, i.e., the research question to what extent young firms are deterred from applying for needed credit when banks cut lending. When facing local bank-led credit supply shocks, firms may keep applying for loans even when rejection rates increase, or they may be deterred from applying for loans. Loan deterrence is a very relevant phenomenon: in each year 2008 – 2011, more firms were deterred than applied for small business loans (Table 2). We use data that reveals unmet demand from deterred loan applications. We define loan deterrence using the KFS question: *"Was there a time you needed credit in the previous year but did not apply because you thought you would be denied?"* (DesRoches et al. 2010). This is a component of unmet entrepreneurial business credit demand that cannot be observed by solely analyzing loan application and approval rates, which we also investigate. Thereby, our analysis extends prior studies based on loan or loan application data (Khwaja and Mian 2008, Jiménez et al. 2012, 2014, Iyer et al. 2014, Ioannidou et al. 2015, Amiti and Weinstein 2018, Degryse et al. 2019, Bottero et al. 2020, De Jonghe et al. 2020). Our paper also complements survey evidence regarding firms' difficulties in accessing the credit markets and discouraged loan applications (Campello et al. 2010, Popov and Udell 2012, Beck et al. 2018).

Our third contribution is that we identify the causal effect of local *credit supply shocks* on loan deterrence by young firms. Entrepreneurs change their minds quickly about local lending climates. In 2008, 10% of those denied business loans following application believed they had been denied due to "restrictions on lending." The remaining 90% had an internal attribution. By 2009 this belief had flipped, with 92% of applicants believing their application was denied due to current credit market conditions rather than personal or business conditions (Table 2). In contrast to the Covid-19 crisis in 2020, there was no increase in SBA loan guarantees during the Financial Crisis (Table 2). If applicants believe they are creditworthy, but denied loans because loans are scarce, they may be deterred from taking the time and effort to apply. For example, if entrepreneurs observe that banks are going bankrupt and locally business loans are becoming scarce, as in the Financial Crisis, they may be deterred. We study entrepreneurial loan demand that is deterred following an observed supply shock in the market for small business credit. This requires us to separate supply and demand effects from changes in credit volume. We achieve this by constructing a shift-share instrument that exploits exposure of businesses to supply shocks at the level of national banks through local bank market shares, similar to Greenstone et al. (2020). To assess local supply shocks, we aggregate over four million publicly available small business lending reports to Federal Reserve identified bank holding companies. We also control for the credit risk scores of the businesses.

There is a discrimination component to loan deterrence in addition to the supply response (Fairlie et al. 2022). Structural racism, historical redlining, micro-aggressions, and inequality in geographic distribution of banks can all discourage Black and other minority entrepreneurs from applying for needed small business loans. Loan deterrence in the KFS has been studied in this discrimination context (Braggion et al. 2017, Fairlie et al. 2022). Black entrepreneurs are more likely to be deterred from applying for a small business loan. Age and immigration status also play a role, but entrepreneur demographics do not fully explain deterred demand. Bloom et al. (1983) were early in recognizing the loan deterrence problem as a self-selection problem in mortgage lending. This research was extended to small businesses lending by Cavalluzzo et al. (2002) using the National Survey of Small Business Finances, a point in time study. These studies, along with Braggion et al. (2017) and Fairlie et al. (2022), use a demographic lens to investigate deterrence. In contrast, we study loan deterrence by using panel data that allows us to track changes in deterrence behavior in response to changes in credit supply. We control for potential discrimination factors by including demographic characteristics of the firms' ownership team. We expect discrimination-based deterrence to remain at a constant level over the short term, in contrast to expectations about local lending climates.

Our results indicate that a large segment of young firms are deterred from applying for loans following a local credit supply shock. We also document that loan application rates by young firms do not respond to local credit supply changes. This may explain why the deterrence effect has been largely overlooked in prior literature.

The paper is organized as follows: Section 2 discusses the KFS private firm data and constructing loan data; Section 3 presents descriptive analysis; Section 4 develops our conceptual and empirical models and instrument; Section 5 presents econometric results; Section 6 discusses significance and scale of deterrence; Section 7 concludes.

2. Data

2.1 Kauffman Firm Survey

Our firm-level panel data comes from the Kauffman Firm Survey (KFS), full panel (Kauffman Foundation, 2020). The KFS is a longitudinal panel that followed 4,928 entrepreneurial businesses for eight years, from 2004 – 2011 (Farhat and Robb, 2014). All firms in the panel started up and began operations in 2004. Firms were sampled from the Dun & Bradstreet (D&B) database. DesRoches et al. (2010) describe the KFS sampling, inclusion, and response rates. We use the full private access version of KFS data with additional variables including D&B commercial credit scores and nine-digit zip codes. Access was granted by the Ewing Marion Kauffman Foundation through the NORC Data Enclave. Throughout the survey, initial results were released, and additional questions were added. In the 2009 wave, during the Financial Crisis, several behavioral finance questions were added, including the loan deterrence question that we use as our primary outcome (Table 2). Each wave of the KFS asks entrepreneurs about their experiences in the previous year. In 2008, there were 2,599 surviving KFS firms (Table A1 in the Appendix). A unique feature of the KFS is that it attempts to interview all owners of a firm. 3,732 owners were surveyed in 2009 asking about their situation in 2008 (Table A1).

2.2 Loan Data

This study combines seven data sets to create a comprehensive estimate of the credit supply available to small businesses in counties. First, (1) Annual Federal Financial Institutions Examination Council (FFIEC) Community Reinvestment Act (CRA) Disclosure Flat Files are merged with (2) FFIEC CRA Transmittal Sheets to match mandated small business lending origination reports to banks (FFIEC, 2022). Banks' reports are by county for the years 2004 – 2011. Then, the FFIEC data is recursively merged with (3) the Federal Reserve Historical Relationship Database to aggregate lending from commercial banks to bank holding companies and account for mergers and acquisitions (Federal Reserve, 2018). (4) The Federal Deposit Insurance Corporation Institution

Directory is used to determine the number of bank branches for CRA lenders in each county (FDIC, 2022). All these data sets are publicly available. We match the firm level microdata from the KFS to counties using (5) HUD-USPS Zip Code Crosswalk Files (HUD, 2022). We use (6) Bureau of Economic Analysis county level economic indicator file CAGDP9 to test the plausibility of the instrument (BEA, 2022). Finally, we use (7) the Bureau of Labor Statistics (2022) *CPI for All Urban Consumers* to convert reported amounts to real 2011 U.S. dollars.

CRA reports are made to the FFIEC, which makes them publicly available. Analysis by Greenstone et al. (2020) finds that approximately 86% of small business loans are reported. Unreported loans are made by banks that do not reach the asset threshold for reporting. We are interested in measuring year-to-year changes in small business lending by bank holding companies at the national and county levels. To measure annual changes in lending, we needed to aggregate multiple lending reports by each bank, in each county, over the year, then aggregate local bank's lending reports to their bank holding company. To construct the bank data set, we consolidated 5,967,228 CRA lending reports and matched them to bank holding companies. We summed loan amounts at bank locations over each year. The CRA reports list the lender's regulator ID number and regulator (Office of Controller of the Currency, Federal Reserve, or Federal Deposit Insurance Company). We used the regulator IDs to match CRA reports to their FFIEC Transmittal Sheets. These sheets list the location county (FIPS code) and a Federal Reserve ID number (RSSD) for the lender. We matched the CRA reports to the Federal Reserve Historical Relationship Dataset using the reporter's RSSD number from their report Transmittal Sheet.

RSSD numbers are assigned for individual locations and functions, so it is common for one commercial bank to have many RSSD numbers. The RSSD of each CRA reporting entity is matched to an Offspring RSSD number in the Relationship dataset. Each Offspring RSSD has a Parent RSSD in the Relationship data. The Parent RSSD is the holding company id number. Some entities are also the holding company. Some holding companies also have a holding company. We recursively assigned the holding company RSSD to CRA reports until there were no more holding companies above the holding companies listed as lenders. This took up to 17 matching iterations. In 2004, 22,661 offspring RSSDs were consolidated into 772 holding companies. For mergers and acquisitions, we match the CRA report to the final holding company in the year and merge lending into the Parent bank for the entire year. For example, loans made by Wachovia bank in 2008 are assigned to acquiring bank Wells Fargo throughout that year.[2]

3. Descriptive Analysis

3.1 Lending Data

This study examines the relationship between local changes in the credit supply by banks to small businesses and deterred demand for small business loans, using a panel cohort study of firms founded in 2004. We use reporting on lending by banks mandated by the 1977 Community Reinvestment Act (CRA) to observe lending to small businesses. The CRA was enacted to promote equity and accountability in bank lending to firms and provides comprehensive data on local credit markets (Bates and Robb, 2014). Funding for

[2] This differs from Greenstone et al. (2020), who assign loans to the acquiring firm for their entire study period.

small business loans reported by CRA lenders decreased by 55% during the Great Recession from 2007 to 2010. National changes in lending to small businesses are shown in Figure 1.

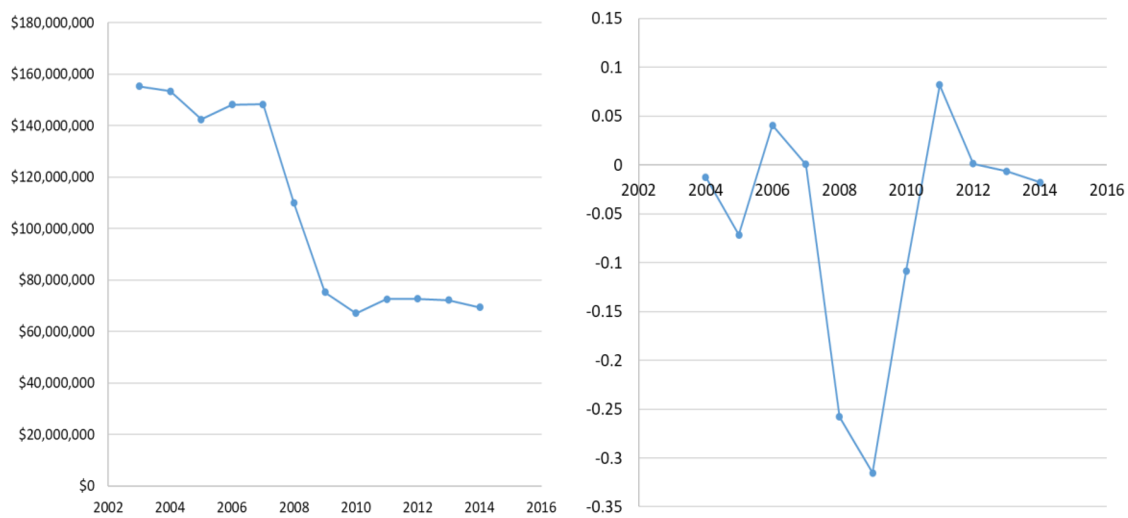
The initial shock to the bank holding company may be national or international and difficult to observe. Banks set annual levels of lending at the holding company level and allocate funds to local banks. The change in credit supply in a county depends on the composition of banks in the county. When Bank of New York Mellon cut small business lending by 90% during the Financial Crisis, this impacted credit supply in counties with New York Mellon branches. Our study interacts holding company level changes in lending with county level bank market shares to estimate local changes in credit supply. We do this by constructing a shift-share style instrument similar to the one used in Greenstone et al. (2020).

Table 1 is a summary of CRA reports aggregated by year. Banks report the number and amounts of small business loans made at a single location over a 2–16 week period. The CRA definition of a small business loan is a loan made to a firm with less than $1m in revenue in the previous year (FFIEC, 2022). This definition uses a lower threshold for small business than definitions used by the IRS, SBA, or recent Paycheck Protection Program loans. Many KFS firms are sole proprietorships, with approximately 96% of surveyed owners representing firms that meet the CRA definition of a small business. We convert all loan amounts into real 2011 dollars, which is the last year referenced by the KFS. As mentioned in the introduction, banks reduced small business credit volume during the Great Recession by 55% from a high of $148 billion in 2007 to a low of $67 billion in 2010 (Figure 1).

Figure 1

Commercial Bank Lending to Small Firms with Less Than $1 Million in Annual Revenue, 2004-2014

Lending to Small Firms **Percent Change in Lending to Small Firms**



Note: Left panel: Lending in thousands of 2011 USD. *Source:* Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting.

3.2 Bank Holding Company Data

Table 3 shows some expansion of holding companies before the Great Recession and consolidation subsequently, without much variation in the number of lenders. It also shows a lot of variation in the amount of funds individual holding companies supply for small business loans.

Table 4 shows variation in changes in lending levels during the Great Recession for some large bank holding companies. Rather than responding uniformly to the recession, there is wide variation in the changes in lending by individual banks. Table 4 Column 1 is our replication of Greenstone et al. (2020) finding very similar changes in lending using the same data source. The Rank column shows the 10 banks who filed the most CRA reports for small business loans in 2007. It is important to note that banks can report multiple loans on one report, making the rank a rough estimate of scale.

Table 5 shows that the number of bank branches in each county remains stable over time. Branching and mergers require regulatory charter approval leading to slow growth of branching (Adams and Gramlich, 2014). This creates a structural barrier to changing market shares over time. Our IV approach uses the fact that the banks and market shares encountered by firms during the base startup year remain mostly stable over the study period. Therefore, firms do not see expanding local options over time. Erel and Liebersohn (2022) find that the median number of branches per county is 9.5 in 2020; we find a median of 9 in 2004.

3.3 Outcomes for Young Firms

Our study investigates three outcome variables at the level of the young firms. Loan deterrence in response to a credit supply shock is our main focus. We also model applications and approvals as dependent variables. Loan deterrence during the recession could imply a decrease in applications or a segmenting of the market during a time of high demand. The approval outcome complements the picture of the conditions firm owners observe. This indicates how the supply shock reduces the number and proportion of applications approved. Table 2 shows summary statistics for loan deterrence and other credit demand questions in the KFS. The loan deterrence question was first asked in 2009 referring to the previous year. The widespread change in firm owner's beliefs about why they were rejected for loans gives an example of their awareness of current market conditions. We ask if the SBA stepped in and increased loan guarantees as the Federal government did during the Covid pandemic shock (Howell et al., 2022). This does not appear to be the case.

4. Conceptual and Empirical Model

4.1 Conceptual Model of Loan Deterrence

Loan deterrence is a specific type of unmet demand in the market for small business loans. Table 2 shows that loan deterrence reported by KFS startups increased by 1.73 percentage points from 2008 to 2009. In the same period, surveyed firm loan approval rates decreased by 3.99 percentage points. In each year 2008 – 2011, more KFS firms were deterred than applied for small business loans. Denied and deterred loan applications are both separate components of unmet credit demand, i.e., credit demand minus credit supply ($CD - CS$). We suggest decomposing loan deterrence D further into components due to current market conditions, firm characteristics (credit score, credit ratio and profitability), discrimination (owner characteristics and experience), and unknowns. We do not consider debt aversion to be part of deterred demand, because in this case, the owners have decided the risks of credit outweigh the benefits and do not have unmet demand (Ikeda and Kang, 2015). Similarly, a decrease in demand due to rising interest rates is not deterred demand based on a likelihood of rejection belief. We summarize this formally:

$$CD - CS = unmet\ credit\ demand + loan\ deterrence \quad (1)$$

$$loan\ deterrence = market + firm + \ discrimination + unkowns \quad (2)$$

This study estimates the current market conditions component of loan deterrence. We are most interested in the change in loan deterrence given a change in local credit supply. Short-run deterrence is the firm owner’s response to observing the change in market conditions since the previous period, and their assessments of credit worthiness and bank stringency. Loan deterrence is a behavioral response based on the owner’s belief in likelihood of application rejection. There may be rational and overreaction components in the firm's short-run response function when observing local trends in lending.

Opportunity cost is foundational to the deterrence decision. Applying for loans has time and accounting costs. The firm owners decide if it is worth their time and effort to apply given their expectation of approval. It is costlier to apply relative to expected returns for borrowers who perceive they are less likely to be approved, leading owners to be deterred based on their rejection belief. Firm owners update their beliefs about bank's decision making given the current credit environment. In recessionary year 2009, 92% of denied loan applicants in the KFS reported the belief that their application was denied due to "restrictions on lending." Only 10% believed this in the previous year (Table 2). We expect the market component to explain much of the variation in deterrence rates from year to year. In this study we identify the causal effect of local credit supply on loan deterrence by young firms.

The firm component of deterrence reflects the ownership team's belief that the firm will be denied a loan based on firm criteria for loan approval such as: credit score, debt to equity ratio, profitability, and industry. If owners were not deterred, some rejection expectations would be correct and result in denied applications; Cassar (2014) studies KFS owners' forecasting accuracy for their firms. So the firm component of loan deterrence describes both, applications that would be denied and deterrence based on incorrect beliefs about firm creditworthiness. In our estimations we control for the time-varying firm factors through covariates and for the time invariant firm factors through differencing.

The discrimination component is based in observations of historical discrimination (Fairlie et al. 2022). Minorities who are aware of historical discrimination are more likely to expect discrimination and be deterred. Disparate treatments such as race-based redlining, and requirements for women to have a male co-signer, were diminished by the Equal Credit Opportunity Act of 1974. However, banker bias and disparate impact criteria for loan approval are slower to change (Blanchard et al. 2008). When firm loan approval criteria systemically vary by race, this leads to disparate impact discrimination (Blanchard et al. 2008). Long-standing structural racism and classism prevent wealth accumulation in families, contributing to disparate impact in lending criteria, and leading minority founders to start businesses with lower levels of equity (Fairlie and Robb 2007). Identity-based deterrence can also occur when structural inequalities lead to lack of experience with the banking system. Fairlie et al. (2022) find that black firm owners are less likely to be deterred if they have previously been approved for a bank loan. There may also be an interaction between the firm component and the discrimination component of loan deterrence, as Fairlie et al. (2022) find that beliefs about credit worthiness based on debt to equity vary by race.

Groups who have been subject to historical discrimination still frequently experience overt hostility and subtle questioning of their qualifications (West, 2019). Lived experiences of microaggressions in entrepreneurship and banking lead to discrimination-based deterrence. Since experiences of microaggressions increase the likelihood of job quitting (Batool and Kashif, 2023), they may also precede entry into entrepreneurship.

Change comes slowly. We expect discrimination to represent a constant baseline level of deterrence during the survey period. The discrimination component varies with the demographic composition of firm owners, with Black entrepreneurs reporting the highest levels of deterrence (Fairlie et al., 2022). Demographics in the KFS change with firm survival, and when the within firm ownership team changes (Table A1). We estimate discrimination-based deterrence through race, immigration status, gender, and age, which are federally protected classes.

It is likely that there are unknown factors influencing deterrence beyond discrimination, credit worthiness, and credit supply shocks. Braggion et al. (2017) find that firms in more unequal counties are more likely to be deterred. Likewise, a strong entrepreneurial ecosystem could help mitigate deterrence by providing more opportunities for mentoring and networking. In our model, we are able to control for county effects that are fixed over time using first differencing.

Other unknowns may operate through opportunity cost. The decision not to apply based on the expectation of being denied is in relation to the time and effort it takes to apply. Disabled owners often enter entrepreneurship because they are time constrained (Norstedt, 2021). These owners will have a shifted reference point for their time to apply for loans vs their expected probability of rejection. Individual variation in abilities can make some aspects of the application process more difficult, including getting organized, traveling to a bank, and interacting with bankers. Disability can vary greatly over time with health status and access to assistive technologies. The KFS does not include disability variables.

Individual variation in ability to apply for a loan can also include entrepreneurship experience. In this case, serial entrepreneurs and those from within industry could be at an advantage. Cassar (2014) finds wide variation in KFS owners' abilities to forecast their businesses growth trajectory. Forecasting is an important skill in the business planning needed to apply for a loan, and in forming expectations of creditworthiness. Experience and forecasting are mutable factors that can change over time.

4.2 Hypothesis

Our hypothesis centers on the current market conditions component of bank loan deterrence. We hypothesize a negative relationship between credit supply (CS) and loan deterrence *D*: if credit supply by banks in a county decreases, the percentage of firms reporting loan deterrence behavior in the county increases:

$$H_o: \frac{\partial D}{\partial CS} < 0 \quad (3)$$

The hypothesis is about credit supply, not the credit volume which is determined by both demand for loans and supply of loans. Our empirical strategy is targeted at identifying the causal effect of credit supply. In contrast, concerning credit volume, reverse causality is plausible: As more firms are deterred from applying for loans, loan applications decrease, leading to a decrease in credit volume. This occurs when loan acceptance rates and average loan amounts are held constant by bank policy. It seems likely that *CD* > *CS*, with *CS* being set by banks. In this case, deterrence depends on the owner's application rejection belief and affects who gets loans rather than the volume of loans.

4.3 Structural Model

Initially, we can only observe changes in credit volume, which are the net of changes in supply and demand. To calculate changes in county level credit volume, we summed CRA reported small business loan amounts by county for each year from 2006 –

2011. The credit volume measure in each county is the sum of CRA reported small business lending by each bank holding company where: *c=county, b=bank*, and *t=year*:

$$CV_{c,t} = \sum_{b}^{N_t} CV_{c,b,t} \quad (4)$$

This leads to a structural empirical model for loan deterrence. $D_{f,t}$ is a dummy variable indicating that *firm f* is deterred from applying for a bank loan in year *t*. In extensions, we also use loan applications and loan approvals as alternative dependent variables instead of loan deterrence.

$$D_{f,t} = \propto + \beta logCV_{c,t} + \lambda CR_{f,t-1} + \delta X_{f,t} + \gamma M_{f.t} + \eta F_f + \mu_f + \varepsilon_{f,c,t} \quad (5)$$

where

$$CR_{f,t-1} = firm\ credit\ risk_{\ t-1} \in \mathbb{Z}\{1:5\}$$

$$X_{f,t} = firm\ financials: [\ln(revenue)\ , profit \in \{0,1\}, \ln(equity)]$$

$$M_{f,t} = \ firm\ owners: [\overline{age}, \%female, \%immigrant, \%non\text{-}white, n\ owners]$$

$$F_f = firm\ type\ dummies: [high\ tech, medium\ tech, low\ tech, sole\ prop, llc, s\ corp, c\ corp]$$

$$\mu_f = unobserved\ time\text{-}invariant\ firm\ effects$$

Credit risk, $CR_{f,t-1}$, is the risk class of the firm's D&B commercial credit score in the previous year. Credit risk is a five-point ascending scale of default risk. Firm component $X_{f,t}$ is a vector of firm financial performance characteristics that vary by year: natural log of revenue, natural log of equity, and a positive profit indicator. F_f is a vector of firm characteristics that do not change over time: technology level and organizational structure.

Discrimination component $M_{f,t}$ is a vector of firm ownership team characteristics in the current year. These can change over time if the ownership team changes. We exploit the KFS feature of interviewing up to 10 firm owners of each firm (instead of one representative owner as is done in most other data sources) to construct firm demographic variables as a composite of the ownership team: average age, percent female, percent immigrant, and percent non-white. This specification allows for a 100% non-white ownership team to exhibit different deterrence behavior from a 10% non-white ownership team, for example. $M_{f,t}$ also contains the number of firm owners. KFS firms had a median of 1 owner in all years. We do not include time variables as this would remove a large part of the variation in credit supply. Table 6 shows yearly summary statistics for KFS control variables contained in *CR, X, F* and *M;* Table A1 in the Appendix shows counts for these characteristics and represented counties.

4.4 Empirical Model

While the firm and ownership team characteristics control for variables associated with credit worthiness and discrimination, there can still be unobserved firm-specific effects in the structural model (5). Therefore, we take first differences (FD) of Eq. (5) to focus on within firm changes between years, eliminating time-invariant firm fixed effects μ_f.[3] This leads to:

[3] To take first differences we drop firms that are not observed in two consecutive years for that year pair.

$$D_{f,t} - D_{f,t-1} = \varphi + \beta\left(logCV_{c,t} - logCV_{c,t-1}\right) + \lambda\left(CR_{f,t-1} - CR_{f,t-2}\right) + \delta\left(X_{f,t} - X_{f,t-1}\right) + \gamma\left(M_{f.t} - M_{f.t-1}\right) + \Delta\varepsilon_{f,c,t} \quad (6)$$

This model reduces omitted variable bias by removing unobserved heterogeneity due to time-invariant factors at the firm and county level (because firms in the data do not move across counties). First differencing also implies that coefficients of time-invariant variables such as the firm types F_f cannot be estimated, but these are not the focus of this paper.[4] The outcome in (6) is the change in loan deterrence from *t-1* to *t.* We are especially interested in the change in loan deterrence as a response to an observed change in credit supply, as indicated by the coefficient β when the change in credit volume is properly instrumented. In extensions, we analogously use the year-over-year changes in loan applications and loan approvals as the dependent variables instead of the year-over-year change in loan deterrence.

Operationalizing our model with CRA reports, we find that annual percent changes in lending at the bank holding company level are too large during the Financial Crisis to be approximated well with log differences (Table 4). Therefore, going forward, we use the year-over-year change in credit volume instead:

$$\frac{\Delta CV_{c,t}}{CV_{c,t-1}} = \frac{credit\ volume_{c,t} - credit\ volume_{c,t-1}}{credit\ volume_{c,t-1}} \quad (6a)$$

Thus, in lieu of Eq. (6) we estimate:

[4] We also considered including year dummy variables, but these would remove much of the variation in credit supply.

$$D_{f,t} - D_{f,t-1} = \varphi_2 + \rho_2 \frac{\Delta CV_{c,t}}{CV_{c,t-1}} + \lambda_2 (CR_{f,t-1} - CR_{f,t-2}) + \delta_2 (X_{f,t} - X_{f,t-1}) + \gamma_2 (M_{f.t} - M_{f.t-1}) + \varepsilon_{2,f,c,t} \quad (6b)$$

We are interested in the causal effect of a change in local credit supply on loan deterrence, whereas the local credit volume is also influenced by credit demand. Therefore, we introduce an instrumental variable (IV) for the change in county credit supply, allowing us to isolate the effect of changes in credit supply from changes in demand within the credit volume. Eq. 6a is the second stage in the IV estimation, while the first stage is given by

$$\frac{\Delta CV_{c,t}}{CV_{c,t-1}} = \varphi_1 + \rho_1 Z_{c,t} + \lambda_1 (CR_{f,t-1} - CR_{f,t-2}) + \delta_1 (X_{f,t} - X_{f,t-1}) + \gamma_1 (M_{f.t} - M_{f.t-1}) + \mu_{1,f,c,t} \quad (7)$$

The next subsection explains the instrument $Z_{c,t}$.

4.5 Instrumental Variable

We model a change in loan deterrence given a change in local credit supply, where local credit volume is likely endogenous. An observed change in credit volume within a county could be driven by a change in credit supply or demand. Without parceling out the changes in supply and demand, we are observing a change in the credit volume equilibrium from year to year. For example, the observed decreases in the volume of credit to small businesses during the Financial Crisis could include a decrease in credit demand as consumer demand and firm expansions slow during the recession. Or the decrease in credit volume could contain an increase in credit demand as firms try to make up for lost revenue and cover fixed costs or payroll in a recession.

To isolate the effects of a credit supply shock, we move to instrumental variable IV estimation. We use a shift-share, Bartik type, instrument to estimate county level changes in credit supply around the Financial Crisis (Bartik 1987, Bernanke and Lown 1991, Greenstone et al. 2020). In the Bartik (1987) instrument, counties are exposed to national level shifts through their local level shares. Here the shift is the national change in small business lending levels by individual bank holding companies in each year, decided at the national bank level; the share is the bank's market share in the county in the base year. The county-level credit supply shock is the change in lending by national banks weighted by the presence of bank branches in the county. Our instrument is a modification of the approach by Greenstone et al. (2020).

We construct an instrument $Z_{c,t}$: the estimated relative change in county credit supply from year *t-1* to *t.* First, we estimate $V_{c,b.t}$ (8), the year-over-year change in credit volume, for each lender in each county in each year, from CRA lending reports:[5]

$$\Delta V_{c,b.t} = \frac{credit\ volume_{c,b,t} - credit\ volume_{c,b,t-1}}{credit\ volume_{c,b,t-1}} \quad (8)$$

In the following regression equation (9), we estimate coefficients $\phi_{c,t}$ and $\xi_{b,t}$ to parcel out the county effects (ΔCD) and bank holding company effects (ΔCS) from the change in credit volume. $C_{c,t}$ is a dummy variable for each county; the coefficient $\phi_{c,t}$ captures variation in credit demand at the county level.[6] $B_{b,t}$ is a dummy variable for each bank holding company. The coefficient $\xi_{b,t}$ shows variation in credit supply by banks. It is the shift in our shift-share instrument. We include weights for the loaned amount in t-1 to control for the scale of banks. We individually estimate (9) for each year 2006-2011.

[5] To avoid errors due to nonexistent banks, we set the lending volume of banks that stop lending at a minimal level of $1,000 per year. Going forward, we also exclude outlier reports that increased lending by greater than 4000% to reduce the skewness of our instrument distribution.
[6] We choose an omitted base county for eq. (9) that has an approximately mean change in CV.

$$\Delta V_{c,b.t} = \phi C_{c,t} + \xi B_{b,t} + \epsilon_{c,b,t} \quad (9)$$

The market share is the fraction of bank branches in the county controlled by the bank holding company in the base year (2004). Each KFS firm was founded in the base year. This market share reflects the importance of relationship banking to the smallest businesses by giving banks that are the most visible locally the most weight. In this model, entrepreneurs become aware of lender reputations through participation in the local startup ecosystem during their first year, then anchor to this information as a reference point. Many commercial banks do not engage in small business lending under the CRA definition. We exclude branches of banks that did not file CRA reports in 2004 from the market share calculations.

$$ms_{c,b} = \frac{n\ branches_{c,b}}{n\ branches_{c}}, \quad t = 2004 \quad (10)$$

For each county in each year, we interact each bank's estimated national shift in credit supply $(\xi_{b,t})$ with their base year market share in the county $(ms_{c,b})$. To construct the instrument for change in credit supply at the county level, we sum the market share weighted shifts in lending within each county.

$$Z_{c,t} = \sum_{c,t} (\hat{\xi}_{b,t} * ms_{c,b}) \quad (11)$$

Instrument $Z_{c,t} = \frac{\Delta CS_{c,t}}{CS_{c,t-1}}$ is the component of change in credit volume in a county attributed to national level supply decisions by banks, purged of local demand conditions in a county that affects all banks in the county. The instrument will be relevant if bank holding companies use branching to spread risk over locations, making decisions about the level of small business lending in the company portfolio at the national company level.

Several recent studies have discussed testing the validity of shift-share instruments. Borusyak et al. (2020) recommend that exogeneity of either the shift or the share should be established, and Jaeger et al. (2018) discuss meeting validity for shift-share instruments with exogeneous shifts. Our instrument meets this requirement. The decrease in credit volume during the global Financial Crisis was initially driven by bank's proprietary trading losses (Dwenger et al. 2020). Our shift is at the national level of banks' lending decision, which does not depend on local conditions. Our instrument includes the important step of estimating separate bank and county shocks, separating changes in credit demand from shifts in credit supply.

Our instrument follows the instrument suggested by Greenstone et al. (2020). Goldsmith-Pinkham et al. (2020) discuss this instrument in detail.[7] Table 7 presents a test similar to Empirical Example 1 from Goldsmith-Pinkham et al. (2020). This test is used for instruments that rely on the exogeneity of shares. We present a series of regressions of local county characteristics on the market shares of select banks. The banks tested here have the largest share variances among the large lenders identified in Table 4. Looking at the R^2 statistics, we find that local economic and population growth only explain a small fraction of each bank's variation in market share from county to county. Goldsmith-Pinkham et al. (2020) are concerned with correlation in the changes, not the levels. Looking at our results, we find some correlations but no constancy of directionality from bank to bank. This gives us confidence in the independence of our instrument shares.

[7] A difference between our instrument and that used in Greenstone et al. (2020) is that we use exact relative changes in lending to instrument for a year-over-year supply change, where they use standardized logs of lending to instrument for the deviation of the percent change in lending.

5. Empirical Results

5.1 Loan Deterrence

The results from the main IV models for loan deterrence, estimated in first differences, are reported in Table 8 (second stage). These tables report results from the full panel in the years the KFS loan deterrence question references, 2008 – 2011. The dependent variable is the one-year difference in loan deterrence behavior at the firm level. The focal independent variable is the relative change in credit volume in each county and year, instrumented such that the coefficient shows the causal effect of local credit supply on loan deterrence. We refer to this variable as $\frac{\Delta CS_{c,t}}{CS_{c,t-1}}$ in the tables. For each combination of control variables, the *F* statistic of significance of the excluded instrument in the first-stage regression is larger than 450 (reported at the bottom of the table and Table A2), indicating that the instrument is not weak. Model (I) controls for changes in the firm's credit rating as well as firm financial variables, which vary between years for most firms. Models (II) through (IV) present more parsimonious specifications, which allow including additional observations with missing values in some of the control variables, while models (V) and (VI) add demographic characteristics of the ownership teams as additional controls. Model (VI) includes the full set of control variables and is therefore our preferred specification. We estimate standard errors clustered at the county-year level, which follows variation in our IV estimation (Abadie, et al., 2022). A robustness check clustering at the county level did not make a meaningful difference in our estimates.

In all these models, the coefficient of the change in credit supply is negative and significant at the 0.1%-level. The point estimate in the preferred Model (VI) indicates that increasing credit supply by 10% will decrease the likelihood of a firm being deterred from applying for a loan by 1.2 percentage points. Given the mean deterrence rate of 18% in 2008, this corresponds to an estimated increase of the deterrence rate by 3.9 percentage points in 2009. When the average bank decreased lending by almost 30% during the Financial Crisis (Table 4), the estimated model predicts economically large effects of credit supply shocks on loan deterrence; we elaborate more on this further below in Section 6.2.

To gauge the bias in OLS estimations, we show OLS results for estimating the second stage equation (6) in Table A3. We expect these estimates to be biased because the change in credit volume is endogenous; in particular, it may be partially driven by loan deterrence. While the estimated coefficient of loan deterrence is still negative and significant in all models, the point estimates are only about a quarter of the point estimates obtained from the consistent IV estimations. The finding that the OLS estimates are closer to zero may also indicate that there is attenuation bias in the OLS estimates due to measurement error in the change of credit volume; the IV approach addresses this source of bias as well and leads to consistent estimates.

We present robustness checks in Tables A4 and A5 in the Appendix. The estimations in Table A4 exclude firms with annual revenue greater than $1 million US Dollars. This amount is the upper limit to meet the definition of small business lending for CRA reporting which we use to measure credit volume. The results are very similar, which shows that larger firms and outliers do not have overdue influence. The estimates in Table A5 include a lag in the credit supply change to capture potential dynamic responses to changes in the lending environment over a longer period. Both the contemporaneous and the lagged credit supply changes are modeled as endogenous, and the lag of our main IV is used as an additional IV. Estimates in this specification are similar to the main (Table 8) results. The estimated coefficient of the change in credit supply from two years previous is not significant, indicating that the lag can be dropped from the model, as we did in our main model.

5.2 Loan Applications and Loan Approvals

Next, we extend our analysis by using the year-over-year change in a firm's decision to apply for a loan instead of the year-over-year change in loan deterrence as the dependent variable in the otherwise unchanged model, keeping the same instrument for change in credit supply and the same controls in the first differenced estimation equation. Results for estimated changes in small business loan applications are reported in Table 9 for the full panel. OLS results are shown in Table A6 for comparison, and Tables A7 and A8 in the Appendix present results from robustness checks for firms with less than $1m in annual revenue and a lag in the change in credit supply. The change in credit supply does not cause a significant change in application rates in any of our estimations. Thus, the main effect of a credit supply shock seems to be on loan deterrence, not credit applications, which have predominantly been studied in the extant literature due to data availability.

Next, we use the year-over-year change in loan approval as the dependent variable in the otherwise unchanged model. In a given year, the binary variable loan approval equals one if at least one loan to the firm was approved, and zero otherwise. Loan approvals are conditional on application; firms that did not apply for new commercial bank loans are excluded from the estimation. This leads to a smaller estimation sample and lower first stage F statistics in comparison to previous estimations. The instrument still has sufficient relevance with $F > 45$ in all models. The results for estimated changes in small business loan approvals are reported in Table 10; Appendix Table A9 shows OLS results for comparison, Table A10 a robustness check excluding large firms, and Table A11 a robustness check with credit supply lag. While the point estimates for the coefficient of the change in credit supply are all positive and also statistically significant at the 5% level in three columns of Table 10, the estimate is insignificant in the preferred model in Column VI as well as in the robustness checks in Tables A10 and A11. Thus, an increase in credit supply does not have a robust effect on loan approvals. Table 1 shows that in 2011 banks lend to more businesses when they increase their credit supply rather than making larger loans. Banks made fewer loans in the years when credit supply decreased and increased the average loan size in some of these years. These results are consistent with our findings on loan deterrence: when local banks cut credit supply, the local entrepreneurs' expectations are that applications are more likely to be rejected.

6. Discussion

6.1 Components of Loan Deterrence

The results from estimating IV regressions in first differences reported in Table 8 confirm our hypothesis. A 10% decrease in county credit supply increases loan deterrence by about 1.2 percentage points (Table 8) or about 7% of the baseline deterrence rate. This is an economically significant effect given that in 2008, during the Financial Crisis, credit volume decreased by 26%, followed by 32% in 2009 (Table 1). Our estimation results on loan deterrence are highly significant in all specifications. The point estimate of the deterrence effect becomes even larger in absolute terms when we control for credit worthiness and owner demographics. The finding that a credit supply shock deters loan applications by young firms who report credit need, keeping firm credit risk constant, shows that efficiency of lending is distorted by credit supply shocks.

Surprisingly, a firm's credit risk score does not predict deterrence (Table 8). We would expect that deterrence would increase given a worse credit score. For example, Fairlie et al. (2022) find that credit scores explain one third of the difference between the deterrence rates between Black and White entrepreneurs. Instead, we find no significant relationship. In our sample of startup firms, the expected positive effect of a worse credit score may be offset by a moral hazard effect, which might occur when riskier firms have a greater need for loans to survive and therefore apply despite a higher likelihood of rejection. It is also possible that based on credit score, entrepreneurs instead form intensive margin expectations, rather than loan rejection expectations, such as expectations of higher interest rates or collateral requirements to secure the loan. Black owners who have recent experiences of discrimination may have a heightened awareness of their credit score and other factors that signal credit worthiness (West 2019), while White owners may exhibit overconfidence. Black owners often have less available collateral to mitigate risk (Fairlie and Robb 2007) which could lead to the difference in rejection expectations.

Results for other firm-level criteria of loan approval, i.e. equity and profitability, are in line with expectations. While all firms in this panel have survived for at least 5 years, achieving profitability significantly reduces deterrence. This suggests that firm owners form reasonable rejection expectations around a more accessible performance criterion than the credit score. Becoming profitable decreases the probability of loan deterrence by 4.3 percentage points (Table 8). We do not find a relationship between equity and deterrence.

The demographics of the ownership teams do not play a large role in our results. We do not find significant differences in deterrence from changing the demographic composition of ownership teams by age, gender, immigration status, or race. Blanchflower (2003) and Blanchard (2008) find that in recent decades women have not faced as much discrimination in lending as they did before the Women's Business Ownership Act of 1988. While agreement may be more difficult in a group, we did not find that adding on to the number of owners increased deterrence.

We would expect an increase in deterrence from an increase in non-white ownership, but do not find evidence for this. While Fairlie et al. (2022) find a large gap between Black and White owners' deterrence, we may be diluting this difference by grouping all non-white respondents. The KFS does not have large enough sub-groups of Asian, Indigenous, and other non-white respondents for separate analysis. The insignificant result could also be due to using the first differenced estimator because relatively few firms exhibit a change in racial composition of the ownership team from year to year, whereas most firms exhibit a constant rate of White or Non-White ownership. The focus of this paper is to estimate the causal effect of credit supply shocks on loan deterrence, and to this aim, first differencing is necessary to eliminate unobserved firm fixed effects; an analysis with a primary focus on the demographics of firm owners might need to resort to different econometric methods.

6.2 Application: Financial Crisis, 2008-2009

To better understand the economic significance of our results, we apply our estimated coefficient for loan deterrence to the CRA reported national changes in lending during the peak of the Financial Crisis, 2008-2009. First, we estimate the expected percentage of deterred firms in the next year (t+1) and compare it to reported deterrence in the KFS for this period. Then we calculate an estimated amount of loanable funds deterred from KFS firms using the average CRA small business loan amount for the period. We use the estimated coefficients from our final specification (Model VI in Table 8). We use the 95% confidence interval to present a range of estimates for each year. The results of our application are presented in Table 11.

To calculate yearly estimated deterrence rates, we use the point estimate of the regression coefficient on the year-over-year change in credit supply $\frac{credit\ supply_{c,t} - credit\ supply_{c,t-1}}{credit\ supply_{c,t-1}}$, which is -.1223. If the credit supply decreased by 1% over the year *t*, we would expect loan deterrence to increase by .1223 percentage points in the next year *t+1*. From 2008 to 2009, US small business lending decreased by 31.52% as calculated from CRA reports shown in Table 1: $\%\Delta Credit\ Volume = \frac{110{,}024{,}828 - 75{,}347{,}636}{75{,}347{,}636} * 100 = -31.52\%$. This was the largest one-year shock in our data. Multiplying the percent change in credit volume by the coefficient gives us an expected 3.89 percentage point increase in loan deterrence due to the credit supply shock from 2008 to 2009 (Table 11).

In 2008 17.58% of KFS firms reported being deterred (Table 2); this was the first year firms were asked about their deterrence. Our point estimate for deterrence in 2009 if only credit supply had changed is 17.58% + 3.89 = 21.47% (Table 11). This would be a 22.11% increase in deterrence over the previous year. Including upper and lower bound estimates from the regression confidence interval, puts the KFS 2009 reported deterrence rate of 19.31% slightly below our estimated interval (Table 11). It is important to note that while the KFS is reporting deterrence from all components, we are estimating deterrence solely from the change in credit supply. Loan deterrence may have increased less in 2009 than what the change in credit supply alone predicts because the recession increased the value of loans for small and young businesses when their focus changed from growth to survival.

In Table 12 we extend our application from yearly deterrence rates to counts of deterred firms and funds. To estimate the amount of loanable funds deterred from KFS firms following a change in credit supply, we first multiply the estimated percent deterred by the number of surviving firms (Table A1). Then we multiply the estimated number of deterred KFS firms by the average CRA reported small business loan amount for the year (Table 1).[8] For 2009 this yields .2147 * 2389 firms * $47,081 = $24 million deterred funds for KFS firms (Table 12).

If the estimated percentage of KFS firms deterred in 2008 is taken as a rough approximation of the percentage of small businesses loans deterred, we can extrapolate from the 1,600,392 CRA reported small business loans in 2009 (Table 1) to assume there were $\frac{1{,}600{,}392}{1-.2147} = 2{,}037{,}844$ potential loans, so there were 2,037,844 * .2147 = 437,452 estimated deterred CRA loans in the US in 2009 (Table 12). Our estimate of 437,452 * $47,081 = $20.6 billion deterred funds for US firms in 2009 illustrates the magnitude of distortion in small business lending from firm deterrence behavior. The caveat of these extrapolations is that the KFS does not claim to be representative of US small businesses

[8] All loan amounts are reported in 2011 US dollars.

(Farhat and Robb, 2014). It is a highly specific cohort. Sampling from the D&B database makes it reasonable to assume these firms are formal enough to be in the market for business credit. Each firm first reported for at least one form of US business taxes in 2004. When they initially report on loan deterrence the firms have survived the most critical startup period and are in their fifth year. While KFS firms could be entering a growth phase, Haltiwanger et al. (2013) point out that many small young firms are not interested in scaling up. At the conclusion of the KFS in 2012, eight years after startup, 28% of the firms remain sole proprietorships and 50% are considered low technology operations (Table A1). 14% are considered high-tech and therefore are likely to also be capital intensive.

The scale of loan deterrence may be hidden from banks, as Table 9 shows that a credit supply shock does not lead to a decrease in loan applications. Firm owners who have an awareness of the current credit market conditions and some ability to survive without new loans are deterred. This leaves firms with less awareness, more confidence, or greater desperation left to apply, along with owners who correctly forecast that they will be approved. Deterrence reduces competition for loans by keeping firms with demand out of the market. When creditworthy firms are deterred, this may decrease the quality of the applicant pool following the credit supply shock. Thus, deterred loans due to a credit supply shock in the dimension of the Financial Crisis may lead to missing or misallocated funds of $19-22 billion in the United States.

6.3 New Markets

In the period since the end of the KFS in 2012, firms have had more opportunities to pursue financing with non-local banks by using fintech platforms that were not available when the KFS began in 2004. Fintech offers a centralized, non-local, approach to lending. It represents a shift from relationship banking to automation. Fintech lenders that meet the asset threshold are subject to CRA reporting of small business loan volume to counties (FFIEC). However, these banks do not have branches. The emergence of fintech leads to open questions about its impact on deterrence.

In recent history, expanses in finance, and the resulting increases in competition between lenders, have led to increased entry into entrepreneurship. This is observed by Chatterji et al. (2012) investigating 1978 credit card deregulation and Kerr and Nanda (2009) studying a wave of interstate bank branching deregulation in the 1970's through 1990's. These authors find that expanding credit markets has especially increased participation by minority entrepreneurs who are more often deterred. Correspondingly, online lending may increase access to banking for people with disabilities, and groups who have experienced discrimination in their local communities, leading to a reduction in loan deterrence. However, there is concern that automating loan criteria again puts Black entrepreneurs, who typically start businesses with lower levels of capital and assets, at a disadvantage (Fairlie et al. 2022). Without banker relationships to understand the business, the owners, and how a business fits in with the local community, young firms will need to show more traditional financial assets to qualify for a loan. Therefore, automated lending may also increase deterrence for those who perceive they are more likely to be denied a loan based on quantitative criteria.

During the Covid-19 pandemic, the smallest scale businesses and minority owned businesses widely turned to fintech lenders to access the new Paycheck Protection Program (PPP) loans (Erel and Liebersohn 2022, Fairlie and Fossen 2022). A greater share of Black owned firms received PPP loans from fintech lenders than traditional banks. However, these loans represent a special case by removing default risk (Howell et al., 2022). There may also have been variance in risk tolerance for in-person interaction during the pandemic. While PPP loans are viewed as a supply response to a demand shock, these studies find previously deterred small businesses entering the credit market when these government supported loans are supplied. In particular, PPP borrowers used fintech lenders more often in areas with fewer bank branches (Erel and Liebersohn, 2022). Therefore, after our period of analysis that ended in 2012, fintech banks entering a county may have smoothed out local supply shocks to a certain degree and decreased the associated deterrence effects. This is an important area for future research.

7. Conclusion

We find strong evidence that credit supply shocks lead to large numbers of young firms being deterred from applying for small business loans. The deterrence response persists, despite controlling for firms' credit ratings, firm financial characteristics, and demographic characteristics of the ownership team. The finding that credit supply shocks lead to loan deterrence by young firms implies inefficiencies in small business credit markets because creditworthy young firms drop out of credit markets due to their expectations of rejection in the current lending climate. In contrast to deterrence, we do not find evidence that supply shocks lead to a decrease in loan applications. Therefore, prior literature that analyzed loan or loan application data overlooked the large share of unmet demand through loan deterrence during credit supply shocks. It is in the interest of economic efficiency, banks, entrepreneurs and consumers to fund the most innovative creditworthy businesses. As these startups enter their growth phase and seek capital, they will create jobs and bring innovative products to the broader marketplace.

This insight has important implications for bank managers. To mitigate supply-shock based deterrence, owner's likelihood of rejection beliefs need to change. Banks can help prevent deterrence by providing more information and transparency to their potential startup customers. When implementing credit supply reductions, banks can reach out to their potential diverse customers, including minority entrepreneurs, and invite them to apply for business loans. Banks can also provide young firms with vital information about their lending criteria, such as acceptable credit scores, debt to equity ratios, and asset levels to help these firms form acceptance expectations.

For academic research, the findings from this paper imply that the economic consequences of credit supply shocks are larger than extant studies that rely on loan application and loan approval data suggest, because loan deterrence effects have been mostly overlooked in the prior literature. Entrepreneurs not applying for loans do not appear in credit registers, but are an important part of unmet credit demand. We show that this unmet credit demand fluctuates with credit supply conditions. Inefficiencies in credit markets for young firms may therefore be larger than previously known and warrant more research. Loan deterrence may be especially relevant to explain racial inequalities in small business financing and performance.

For policymakers, this implies additional previously overlooked costs of credit supply shocks for entrepreneurial businesses. Preventing credit crises through appropriate banking regulation and mitigating credit supply shocks through government-backed loans, e.g., through the U.S. Small Business Administration, are therefore important policy objectives to support the functioning of the entrepreneurial economy. It remains to be seen whether and how innovations in financial markets such as fintech are able to reduce the dependence of young firms on local bank branches and thereby make them less vulnerable to credit supply shocks.

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Tables

Table 1

CRA Disclosed Loan Originations to Firms with less than $1m in Annual Revenue (amounts in 2011 USD)

Year	Amount loaned (thousands)	% Change in loaned amount	Small business percent of CRA lending	Number of small business loans	Average small business loan amount
2003	155,365,204		46.4	2,974,963	52,224
2004	153,413,614	- 1.26%	44.7	3,016,039	50,866
2005	142,449,414	- 7.15%	45.5	3,769,093	37,794
2006	148,224,363	+ 4.05%	44.2	4,634,059	31,986
2007	148,283,011	+ 0.04%	41.9	5,167,318	28,696
2008	110,024,828	- 25.80%	37.3	3,272,026	33,626
2009	75,347,636	- 31.52%	37.4	1,600,392	47,081
2010	67,162,212	- 10.86%	36.9	1,489,952	45,077
2011	72,665,454	+ 8.19%	37.8	2,228,573	32,606
2012	72,742,133	+ 0.11%	37.0	2,232,045	32,590
2013	72,261,206	- 0.66%	36.5	2,364,710	30,558
2014	69,489,338	- 1.8%	35.2	2,539,316	27,365

Source: Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting and author's calculations.

Table 2

Credit Demand by Young Entrepreneurial Firms in the Kauffman Firm Survey, 2008-2011

	2008		2009		2010		2011	
	%	Firms	%	Firms	%	Firms	%	Firms
Loan Deterrence: "needed credit in the previous year but did not apply because you thought you would be denied?"	17.58	457	19.31	463	18.10	384	16.42	328
Applied for new bank loans	13.15	341	12.78	306	11.23	238	10.78	215
New bank loan approved (conditional on applied)	85.04	290	81.05	248	80.25	191	81.40	175
New bank loan denied belief: "restrictions on lending" (conditional on denied)	10.09	11	91.59	98	90.36	75	74.60	47
New secured SBA loan guarantee	2.54	66	2.88	69	2.83	60	2.86	57
Equity from Owners	29.99	787	24.85	603	23.32	500	22.38	453
Equity from Family	2.52	46	2.10	36	1.79	27	2.28	33
Equity from Others	1.32	24	1.46	25	1.53	23	1.18	17
Actively seeking equity but did not obtain funding	n/a	n/a	5.23	125	4.67	88	4.26	85
N Firms Total	2,599		2,398		2,122		1,998	

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The table shows sample means. Equity from family includes owner's spouses, parents, and children. Equity from others includes venture capital, government agencies, and other companies. Number of respondents varies by question, percent is based on the number of yes or no responses to each question.

Table 3

Volume of Small Business Lending by Year and Bank Holding Company, 2004-2011

Year	Number of Bank Holding Companies with Small Business Lending	Distribution of Small Business Lending by Bank Holding Company In thousands of 2011 USD (to firms with <$1m in annual revenue)			
		Low	Median	Mean	High
2004	772	635	58,046	2,765,195	325,000,000
2005	841	766	291,133	1,131,547	68,100,000
2006	956	178	203,200	768,320	13,423,423
2007	922	44	210,846	840,371	85,462,963
2008	886	664	209,442	719,555	79,514,563
2009	866	229	149,207	483,019	59,904,762
2010	809	104	136,212	497,308	72,692,308
2011	783	126	162,708	565,827	64,900,000

Source: Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting, and Board of Governors of the Federal Reserve System Bulk Data Download.

Table 4

Changes in Lending for Selected Large Bank Holding Companies, 2007 – 2009

Bank Holding Company	**Percent Change in Small Business Lending: to Firms with less than $1m USD Annual Revenue**	**Rank: CRA reports filed in 2007**
Discover Bank	-100	
10th Percentile	-96.9	
Bank of New York Mellon	-90.2	
JP Morgan Chase	-88.9	2
Citibank	-84.1	7
Capital One Financial	-73.1	8
Home Savings Bank	-65.3	
25th Percentile	-64.7	
SunTrust Banks	-43.4	6
Regions Financial	-39.4	5
Median Bank	-35.8	
Trustco Bank	-35.3	
HSBC	-33.7	9
Wells Fargo	-33.2	1
Bankfinancial, NA	-30.9	
Average Bank	-28.1	
Oceanfirst Bank, NA	-25.7	
Country Bank for Savings	-22.5	
Dime Bank	-13.2	
Brookline Bank	-9.9	
75th Percentile	-9.9	
PNC Financial	-5.5	4
U.S. Bancorp	-3.8	3
90th Percentile	+22.9	
Northwest Bank	+26.6	10

Source: Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting, and Board of Governors of the Federal Reserve System Bulk Data Download. *Notes:* Bank Holding Companies may operate under more than one commercial bank brand name. The distribution of percent changes in lending from 2007-2009 is reported for banks with small business lending in 2007. Rank is based on number of CRA reports filed in 2007.

Table 5

Number of Bank Branches by US County for all Bank Holding Companies, 2004-2010

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Min	1[1]	1	1	1	1	1	1
Median	9	9	9	9	9	10	10
Mean	21	22	23	24	24	25	25
Max	1242[2]	1296	1342	1389	1427	1456	1489
SD	50	52	55	57	60	61	63
N Counties	3182	3183	3184	3186	3188	3188	3191

Source: Federal Deposit Insurance Corporation (FDIC) Location Directory. *Notes:* [1]Minimum branches are located in Prince of Wales-Hyder Unorganized Borough, Alaska. [2]Maximum branches are located in New York County, New York.

Table 6

Summary Statistics: Firm Level Control Variables for 2004 Startups in the Kauffman Firm Survey

	2008		2009		2010		2011	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Financial Characteristics								
Credit Risk$_{t-1}$	2.87 (.0202)	3	2.80 (.0212)	3	2.79 (.0248)	3	2.88 (.0261)	3
Equity $_t$	$21,799 ($105,354)	0	$20,622 ($104,257)	0	$17,055 ($96,691)	0	$17,250 ($95,831)	0
Positive Profit $_t$	.5879 (.0097)	1	.5959 (.0100)	1	.6338 (.0105)	1	.6682 (.0105)	1
Revenue $_t$	$676,790 ($82,881)	$60,000	$1,021,346 ($253,429)	$75,000	$1,593,961 ($477,851)	$80,000	$1,906,380 ($476,057)	$86,000
Demographic Characteristics of Firm Ownership Teams								
Number of Owners	3,732		3,421		2,955		2,800	
Age, avg.	49.38 (.2008)	49	50.35 (.2088)	48	46.13 (.2226)	46	47.00 (.2240)	47
Female %	26.79 (.7748)	0	26.01 (.8340)	0	26.16 (.8562)	0	26.10 (.8813)	0
Immigrant %	9.87 (.55)	0	10.20 (.58)	0	10.14 (.62)	0	9.94 (.63)	0
N Owners	1.43 (.0174)	1	1.42 (.0189)	1	1.39 (.0184)	1	1.39 (.0191)	1
Non-White %	14.61 (.6625)	0	14.66 (.6928)	0	15.34 (.7550)	0	14.76 (.7646)	0
Firm Types								
Number of Firms	2,599		2,398		2,122		1,998	
Low Tech	.5637 (.0097)	1	.5556 (.0105)	1	.5521 (.0112)	1	.5414 (.0116)	1
Med Tech	.2866 (.0089)	0	.2975 (.0097)	0	.2996 (.0103)	0	.3077 (.0108)	0
High Tech	.1497 (.0070)	0	.1470 (.0075)	0	.1483 (.0080)	0	.1509 (.0084)	0
Sole prop	.3378 (.0097)	0	.3378 (.0097)	0	.3399 (.0111)	0	.3269 (.0114)	0
LLC	.3741 (.0099)	0	.3664 (.0106)	0	.3678 (.0113)	0	.3791 (.0118)	0
S-Corp	.2632 (.0030)	0	.2711 (.0098)	0	.2699 (.0104)	0	.2735 (.0108)	0
C-Corp	.0250 (.0032)	0	.0253 (.0035)	0	.0224 (.0035)	0	.0205 (.0034)	0

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* Standard errors are shown in parentheses. Monetary amounts are in real US$ in prices of 2011. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table 7

Relationship Between 2004 Bank Shares and County Characteristics

	Wells Fargo	U.S. Bank	Regions Bank	SunTrust Bank	Capital One	Z 2008
Levels (2004):						
GDP	.00015	-.000101*	-.0002*	-.000101***	-.00016	-.000115
	(.00013)	(.00005)	(.00008)	(.00003)	(.00009)	(.000064)
Population	.00125***	-.00159***	-.00251***	.00003	-.00146**	-.00147***
	(.00033)	(.00027)	(.00038)	(.00023)	(.00052)	(.00033)
Percent Changes:						
GDP	-.00107	.02506	.01915	.07240	.22244*	.05169*
2002-2003	(.02101)	(.04256)	(.07381)	(.04442)	(.10241)	(.02207)
GDP	-.05963**	.15357**	.11322	-.14659**	-.14936	.08720***
2003-2004	(.02234)	(.05891)	(.08989)	(.04852)	(.11553)	(.02486)
Population	-.00218	-.00121	-.00572	-.00285	-.00199	-.00258
2002-2003	(.00204)	(.00226)	(.00405)	(.00380)	(.00567)	(.00177)
Population	.00433*	-.00761**	-.00647	.00843*	-.00716	-.00173
2003-2004	(.00198)	(.00247)	(.00450)	(.00347)	(.00620)	(.00184)
R^2	.0166	.0872	.0801	.0449	.1236	.0318
N	2,998	1,001	623	640	229	75,724
Variance (shares)	.0082	.0049	.0139	.0036	.0069	.0062

Sources: BEA, Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting, Federal Deposit Insurance Corporation (FDIC) Location Directory. *Notes:* Each column represents one regression with market shares as the dependent variable; the last column uses our shift-share instrument as the dependent variable. Standard errors are in parentheses and clustered at the county level. There are 3,137 clusters when using all banks. Significance is noted as: * = .05, ** = .01, *** = .001. GDP level is in billions of real 2012 dollars. Population level is in thousands of persons.

Table 8

Estimated Changes in Firm Level Loan Deterrence in Small Young Firms During the Great Recession

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	-.1177*** (.0327)	-.1113*** (.0303)	-.1131*** (.0313)	-.1016*** (.0292)	-.1053*** (.0308)	-.1223*** (.0346)
Δ *Credit Risk* $_{f,\,t\text{-}1}$	.0030 (.0066)		.0029 (.0063)			.0032 (.0066)
Δ *Ln Equity* $_{f,\,t}$	.0014 (.0014)	.0021 (.0013)				.0014 (.0015)
Δ *Positive Profit* $_{f,\,t}$	-.0435*** (.0109)	-.0360*** (.0095)				-.0432*** (.0109)
Δ *Average Age* $_{f,\,t}$					-.0017 (.0017)	-.0026 (.0019)
Δ *% Female* $_{f,\,t}$					.0003 (.0004)	.0001 (.0006)
Δ *% Immigrant* $_{f,\,t}$					-.2049 (.2072)	-.0705 (.2337)
Δ *N Owners* $_{f,\,t}$					-.0158 (.0147)	-.0071 (.0148)
Δ *% Non-White* $_{f,\,t}$					-.0002 (.0008)	-.0003 (.0011)
Constant	-.0091 (.0060)	-.0109* (.0054)	-.0102 (.0057)	-.0115* (.0052)	-.0139* (.0058)	-.0121 (.0067)
N	4517	5651	4824	6072	6052	4506
F ($Z_{c,\,t}$) *- first stage*	501	572	512	587	605	488

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,950 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table 9

Estimated Changes in Firm Level Loan Applications by Small Young Firms During the Great Recession

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	-.0119 (.0364)	-.0149 (.0329)	.0182 (.0354)	.0044 (.0324)	.0047 (.0340)	-.0078 (.0384)
Δ ***Credit Risk*** $_{f,\ t-1}$	-.0089 (.0075)		-.0144 (.0074)			-.0092 (.0075)
Δ ***Ln Equity*** $_{f,\ t}$	.0020 (.0015)	.0019 (.0013)				.0021 (.0015)
Δ ***Positive Profit*** $_{f,\ t}$	-.0016 (.0122)	-.0070 (.0104)				-.0019 (.0122)
Δ ***Average Age*** $_{f,\ t}$					.0008 (.0017)	.0016 (.0020)
Δ ***% Female*** $_{f,\ t}$					.0003 (.0005)	.0002 (.0006)
Δ ***% Immigrant*** $_{f,\ t}$					-.0196 (.2056)	.0177 (.2755)
Δ ***N Owners*** $_{f,\ t}$					-.0285 (.0205)	-.0375 (.0257)
Δ ***% Non-White*** $_{f,\ t}$					-.0006 (.0009)	.0003 (.0011)
Constant	-.0082 (.0063)	-.0123* (.0056)	-.0067 (.0061)	-.0113 (.0054)	-.0114 (.0061)	-.0073 (.0071)
N	4507	5637	4811	6054	6034	4496
F (Z $_{c,\ t}$***) - first stage***	500	570	510	586	604	486

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,950 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table 10

Estimated Changes in Loan Approvals for Small Young Firms During the Great Recession

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	.2099 (.1375)	.2344* (.1180)	.2576 (.1412)	.2604* (.1238)	.2657* (.1246)	.2159 (.1396)
Δ ***Credit Risk*** $_{f,\ t\text{-}1}$	.0098 (.0174)		.0053 (.0176)			.0088 (.0176)
Δ ***Ln Equity*** $_{f,\ t}$	.0078 (.0044)	.0058 (.0038)				.0085 (.0050)
Δ ***Positive Profit*** $_{f,\ t}$	.0125 (.0360)	.0415 (.0348)				.0129 (.0366)
Δ ***Average Age*** $_{f,\ t}$					-.0013 (.0044)	-.0014 (.0049)
Δ ***% Female*** $_{f,\ t}$					.0023 (.0015)	-.0020 (.0022)
Δ ***% Immigrant*** $_{f,\ t}$					.0537 (.6418)	2.9609 (2.0644)
Δ ***N Owners*** $_{f,\ t}$					-.0460 (.0338)	.0018 (.0486)
Δ ***% Non-White*** $_{f,\ t}$					.0013 (.0010)	.0009 (.0014)
Constant	-.0324 (.0219)	-.0293 (.0196)	-.0307 (.0210)	-.0216 (.0194)	-.0246 (.0209)	-.0342 (.0251)
N	271	317	283	335	334	270
F (Z $_{c,\ t}$***) - first stage***	51	66	61	77	72	46

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 245 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table 11

Estimated Changes in Firm Level Loan Deterrence Rates for Small Young Firms Following a Credit Supply Shock, Given National Percent Changes in Credit Volume, 2008-2009

	Reported	Loan Deterrence Estimates		
	KFS or CRA	Lower Bound	Point Estimate	Upper Bound
Δ ***Credit Supply Coefficient***		-0.0887	-.1223	-0.1579
2008 Loan Deterrence	17.58%			
2008-2009 %Δ Credit Volume	-31.52%			
2009 Est. Δ Deterrence		+ 2.80 points	+ 3.89 points	+ 4.98 points
2009 Est. Deterrence		20.38%	21.47%	22.56%
2009 Est. %Δ Deterrence		+ 15.90%	+ 22.11%	+ 28.31%
2009 Loan Deterrence	19.31%			

Sources: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave; Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting; and authors' calculations.

Table 12

Estimated Deterred Small Business Lending Following a Credit Supply Shock, 2008-2009

	Reported	**Estimated Loan Deterrence**		
			Point Estimate	**Lower Bound**
2009 Est. Loan Deterrence		20.38%	21.47%	22.56%
2009 Average Loan Amt.	$47,081			
2009 Small Business Loans Made	1,600,392			
2009 Est. KFS Firms Deterred		489	515	541
2009 Est. KFS Lending Deterred		$23,004,354	$24,235,635	$25,466,916
2009 Est. US Firms Deterred		409,540	437,452	466,150
2009 Est. US Lending Deterred		$19,281,564,970	$20,595,681,837	$21,946,810,841

Sources: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave; Federal Financial Institutions Examination Council (FFIEC) 1977 Community Reinvestment Act (CRA) mandated reporting; and authors' calculations.
Notes: The dependent variable is change in loan deterrence. All loan amounts are reported in 2011 US dollars. [1]When credit volume increases again, the lowest estimated change in deterrence results in the highest estimated remaining percentage of firms deterred. [2]Number of 2012 KFS firms estimated from the 2010-2011 survival rate.

Appendix

Table A1

Counts of Firm and Owner Types for 2004 Startups in the Kauffman Firm Survey

Survey Year	**2009**	**2010**	**2011**	**2012**
Firms	2,599	2,398	2,122	1,998
Owners	3,732	3,421	2,955	2,800
States (+DC)	51	51	51	51
Counties	901	844	778	755
Positive Profit	1,528	1,429	1,345	1,335
Female	505	461	411	379
Male	2,092	1,936	1,711	1,617
Immigrant	203	197	176	161
Person of Color	462	427	390	365
Low Tech	1,465	1,240	1,091	994
Medium Tech	745	664	592	565
High Tech	389	328	293	277
Sole Proprietorship	810	694	622	557
LLC	897	754	673	646
S-Corp	631	558	494	466
C-Corp	60	52	41	35

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The loan deterrence question was asked in early 2009-2012 referring to the years 2008-2011. Individual firm technology level and organizational type do not change over time; the changes in counts for these variables reflect firm survival. Firm ownership, and the demographic composition of individual firm owners, can change over time.

Table A2

First Stage

Estimated Changes in Firm Level Loan Deterrence in Small Young Firms During the Great Recession

	I	II	III	IV	V	VI
Z	.9177*** (.0410)	.9213*** (.0385)	.9150*** (.0404)	.9196*** (.0380)	.8779*** (.0357)	.8759*** (.0397)
Δ ***Credit Risk*** $_{f,\,t\text{-}1}$	.0111* (.0053)		.0099 (.0054)			.0117* (.0051)
Δ ***Ln Equity*** $_{f,\,t}$	-.0005 (.0012)	.0009 (.0012)				-.0005 (.0012)
Δ ***Positive Profit*** $_{f,\,t}$	-.0053 (.0079)	.0019 (.0074)				-.0019 (.0076)
Δ ***Average Age*** $_{f,\,t}$					-.0249*** (.0021)	-.0238*** (.0023)
Δ ***% Female*** $_{f,\,t}$					-.0004 (.0004)	-.0005 (.0005)
Δ ***% Immigrant*** $_{f,\,t}$					.0868 (.0724)	.2012* (.0869)
Δ ***N Owners*** $_{f,\,t}$					-.0090 (.0110)	-.0261* (.0121)
Δ ***% Non-White*** $_{f,\,t}$					-.0003 (.0006)	-.0005 (.0008)
Constant	.0736*** (.0136)	.0747*** (.0129)	.0735*** (.0134)	.0752*** (.0127)	.0490*** (.0114)	.0470*** (.0128)
N	4517	5651	4824	6072	6052	4506
F ***(Z*** $_{c,\,t}$ ***) - first stage***	501	572	512	587	605	488

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,950 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table A3

Estimated Changes in Firm Level Loan Deterrence in Small Young Firms During the Great Recession OLS Results

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Volume_{c,t}}{Credit\ Volume_{c,t-1}}$	-.0300* (.0135)	-.0314* (.0152)	-.0322* (.0129)	-.0324* (.0144)	-.0311* (.0149)	-.0301* (.0140)
Δ Credit Risk $_{f,\,t-1}$	.0009 (.0065)		.0010 (.0062)			.0009 (.0065)
Δ Ln Equity $_{f,\,t}$	.0014 (.0014)	.0019 (.0013)				.0014 (.0014)
Δ Positive Profit $_{f,\,t}$	-.0435*** (.0109)	-.0364*** (.0094)				-.0435*** (.0109)
Δ Average Age $_{f,\,t}$					.0004 (.0045)	-.0001 (.0017)
Δ % Female $_{f,\,t}$					.0003 (.0004)	.0001 (.0006)
Δ % Immigrant $_{f,\,t}$					-.2119 (.2066)	-.0905 (.2367)
Δ N Owners $_{f,\,t}$					-.0155 (.0149)	-.0048 (.0147)
Δ % Non-White $_{f,\,t}$					-.0001 (.0008)	-.0002 (.0012)
Constant	.0003 (.0051)	-.0025 (.0048)	-.0016 (.0049)	-.0043 (.0046)	-.0047 (.0049)	-.0002 (.0053)
N	4517	5651	4824	6072	6052	4506
R^2	.0047	.0037	.0009	.0008	.0017	.0048

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The dependent variable is the annual firm level change in loan deterrence. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,950 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table A4

Estimated Changes in Firm Level Loan Deterrence in Small Young Firms During the Great Recession Excluding Firms with Greater Than $1m USD Annual Revenue

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	-.1131** (.0376)	-.1053** (.0355)	-.1125** (.0362)	-.1004** (.0343)	-.1019** (.0360)	-.1167** (.0397)
Δ ***Credit Risk*** $_{f,\,t-1}$	.0071 (.0075)		.0084 (.0073)			.0073 (.0075)
Δ ***Ln Equity*** $_{f,\,t}$	.0005 (.0016)	.0020 (.0015)				.0006 (.0017)
Δ ***Positive Profit*** $_{f,\,t}$	-.0374** (.0120)	-.0322** (.0104)				-.0374** (.0121)
Δ ***Average Age*** $_{f,\,t}$					-.0021 (.0021)	-.0033 (.0023)
Δ ***% Female*** $_{f,\,t}$					.0002 (.0005)	.0002 (.0007)
Δ ***% Immigrant*** $_{f,\,t}$					-.0329 (.2595)	.3298 (.2616)
Δ ***N Owners*** $_{f,\,t}$					-.0258 (.0224)	-.0388 (.0258)
Δ ***% Non-White*** $_{f,\,t}$					-.0000 (.0009)	-.0002 (.0014)
Constant	-.00856 (.0067)	-.0100 (.0060)	-.0096 (.0064)	-.0108 (.0058)	-.0133* (.0066)	-.0122 (.0076)
N	3592	4572	3763	4825	4812	3583
F $(Z_{c,\,t})$ ***- first stage***	414	487	421	497	508	400

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,733 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team. The definition of small business lending for CRA reporting is lending to firms with less than $1m in annual revenue.

Table A5

Estimated Changes in Firm Level Loan Deterrence in Small Young Firms During the Great Recession Including Time Lag for Change in Credit Supply

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	-.1000*** (.0284)	-.0906*** (.0268)	-.0985*** (.0269)	-.0886*** (.0254)	-.1022** (.0345)	-.1252** (.0401)
$\frac{\Delta Credit\ Supply_{c,t-1}}{Credit\ Supply_{c,t-2}}$	-.0269 (.0334)	-.0313 (.0294)	-.0215 (.0319)	-.0190 (.0286)	-.0032 (.0389)	.0062 (.0481)
Δ ***Credit Risk*** $_{f,\ t-1}$	.0027 (.0066)		.0025 (.0063)			.0029 (.0066)
Δ ***Ln Equity*** $_{f,\ t}$	.0014 (.0015)	.0020 (.0013)				.0014 (.0015)
Δ ***Positive Profit*** $_{f,\ t}$	-.0434*** (.0109)	-.0362*** (.0095)				-.0434*** (.0110)
Δ ***Average Age*** $_{f,\ t}$					-.0016 (.0023)	-.0029 (.0027)
Δ ***% Female*** $_{f,\ t}$					.0003 (.0004)	.0002 (.0006)
Δ ***% Immigrant*** $_{f,\ t}$					-.2852 (.2052)	-.1644 (.2261)
Δ ***N Owners*** $_{f,\ t}$					-.0164 (.0149)	-.0083 (.0152)
Δ ***% Non-White*** $_{f,\ t}$					-.0001 (.0008)	-.0001 (.0011)
Constant	-.0118 (.0077)	-.0140* (.0067)	-.0123 (.0073)	-.0134* (.0065)	-.0141* (.0066)	-.0116 (.0078)
N	4487	5611	4789	6027	6007	4476
F (Z $_{c,\ t}$***) - first stage***	398.60	435.68	407.79	447.61	364.79	297.25
F (Z $_{c,\ t-1}$***) - first stage***	249.95	267.27	256.83	273.83	216.00	182.66

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,921 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team. The definition of small business lending for CRA reporting is lending to firms with less than $1m in annual revenue.

Table A6

Estimated Changes in Firm Level Loan Applications by Small Young Firms During the Great Recession OLS Results

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Volume_{c,t}}{Credit\ Volume_{c,t-1}}$	-.0132 (.0154)	-.0067 (.0137)	-.0080 (.0143)	-.0018 (.0130)	-.0002 (.0133)	-.0091 (.0154)
Δ ***Credit Risk*** $_{f,\ t\text{-}1}$	-.0089 (.0074)		-.0138 (.0073)			-.0092 (.0074)
Δ ***Ln Equity*** $_{f,\ t}$	.0020 (.0015)	.0019 (.0013)				.0021 (.0015)
Δ ***Positive Profit*** $_{f,\ t}$	-.0016 (.0122)	-.0070 (.0104)				-.0019 (.0122)
Δ ***Average Age*** $_{f,\ t}$					.0007 (.0014)	.0015 (.0017)
Δ ***% Female*** $_{f,\ t}$					.0003 (.0005)	.0002 (.0006)
Δ ***% Immigrant*** $_{f,\ t}$					-.0192 (.2056)	.0180 (.2755)
Δ ***N Owners*** $_{f,\ t}$					-.0285 (.0205)	-.0375 (.0257)
Δ ***% Non-White*** $_{f,\ t}$					-.0006 (.0009)	.0003 (.0011)
Constant	-.0084 (.0056)	-.0114* (.0049)	-.0095 (.0053)	-.0119* (.0047)	-.0120* (.0049)	-.0075 (.0058)
N	4507	5637	4811	6054	6034	4496
R^2	.0010	.0005	.0010	.0000	.0009	.0023

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The dependent variable is the annual firm level change in new loan applications. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,950 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table A7

Estimated Changes in Firm Level Loan Applications by Small Young Firms During the Great Recession Excluding Firms with Greater Than $1m USD Annual Revenue

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	-.0194 (.0374)	-.0065 (.0337)	-.0049 (.0369)	-.0038 (.0336)	-.0025 (.0350)	-.0177 (.0395)
Δ ***Credit Risk*** $_{f,\ t-1}$	-.0069 (.0081)		-.0114 (.0081)			-.0068 (.0081)
Δ ***Ln Equity*** $_{f,\ t}$	.0013 (.0016)	.0013 (.0013)				.0013 (.0016)
Δ ***Positive Profit*** $_{f,\ t}$	-.0134 (.0122)	-.0150 (.0103)				-.0131 (.0122)
Δ ***Average Age*** $_{f,\ t}$					.0004 (.0018)	.0014 (.0021)
Δ ***% Female*** $_{f,\ t}$					.0001 (.0005)	-.0001 (.0005)
Δ ***% Immigrant*** $_{f,\ t}$					.2424 (.2278)	.4121 (.3044)
Δ ***N Owners*** $_{f,\ t}$					-.0073 (.0264)	-.0005 (.0311)
Δ ***% Non-White*** $_{f,\ t}$					-.0015 (.0009)	-.0001 (.0010)
Constant	-.0081 (.0064)	-.0111* (.0056)	-.0075 (.0062)	-.0112* (.0055)	-.0110 (.0062)	-.0062 (.0073)
N	3584	4561	3754	4812	4799	3575
F ($Z_{c,\ t}$) ***- first stage***	413	486	419	496	507	399

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,733 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team. The definition of small business lending for CRA reporting is lending to firms with less than $1m in annual revenue.

Table A8

Estimated Changes in Firm Level Loan Applications by Small Young Firms During the Great Recession Including Time Lag for Change in Credit Supply

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	-.0243 (.0326)	-.0168 (.0288)	.0019 (.0314)	-.0036 (.0282)	.0003 (.0375)	-.0142 (.0450)
$\frac{\Delta Credit\ Supply_{c,t-1}}{Credit\ Supply_{c,t-2}}$	.0201 (.0362)	.0028 (.0307)	.0250 (.0344)	.0114 (.0299)	.0047 (.0405)	.0088 (.0502)
Δ ***Credit Risk*** $_{f,\ t-1}$	-.0093 (.0075)		-.0148* (.0074)			-.0096 (.0075)
Δ ***Ln Equity*** $_{f,\ t}$	.0020 (.0015)	.0019 (.0013)				.0020 (.0015)
Δ ***Positive Profit*** $_{f,\ t}$	-.0028 (.0122)	-.0071 (.0104)				-.0029 (.0122)
Δ ***Average Age*** $_{f,\ t}$					.0004 (.0023)	.0011 (.0027)
Δ ***% Female*** $_{f,\ t}$					.0003 (.0005)	.0002 (.0006)
Δ ***% Immigrant*** $_{f,\ t}$					-.0858 (.2087)	-.0738 (.2704)
Δ ***N Owners*** $_{f,\ t}$					-.0296 (.0207)	-.0389 (.0258)
Δ ***% Non-White*** $_{f,\ t}$					-.0005 (.0009)	.0005 (.0012)
Constant	-.0061 (.0082)	-.0119 (.0072)	-.0045 (.0079)	-.0103 (.0071)	-.0115 (.0071)	-.0070 (.0082)
N	4477	5597	4776	6009	5989	4466
F ($Z_{c,\ t}$) ***- first stage***	397.25	434.45	406.51	446.30	363.64	296.01
F ($Z_{c,\ t-1}$) ***- first stage***	249.31	266.59	256.39	273.31	215.36	181.87

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 1,921 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team. The definition of small business lending for CRA reporting is lending to firms with less than $1m in annual revenue.

Table A9

Estimated Changes in Firm Level Loan Approvals for Small Young Firms During the Great Recession

OLS Results

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Volume_{c,t}}{Credit\ Volume_{c,t-1}}$	.0714 (.0384)	.0851* (.0370)	.0629 (.0392)	.0749* (.0378)	.0707 (.0374)	.0664 (.0387)
Δ ***Credit Risk*** $_{f,\ t-1}$	.0175 (.0170)		.0170 (.0164)			.0167 (.0175)
Δ ***Ln Equity*** $_{f,\ t}$	.0070 (.0040)	.0054 (.0033)				.0079 (.0046)
Δ ***Positive Profit*** $_{f,\ t}$	.0103 (.0360)	.0376 (.0343)				.0100 (.0368)
Δ ***Average Age*** $_{f,\ t}$					-.0044 (.0043)	-.0035 (.0046)
Δ ***% Female*** $_{f,\ t}$					.0018 (.0013)	-.0022 (.0021)
Δ ***% Immigrant*** $_{f,\ t}$					.0934 (.8051)	2.3953 (2.0437)
Δ ***N Owners*** $_{f,\ t}$					-.0435 (.0358)	-.0050 (.0481)
Δ ***% Non-White*** $_{f,\ t}$					.0007 (.0009)	.0003 (.0015)
Constant	-.0432* (.0201)	-.0413* (.0179)	-.0454* (.0196)	-.0360* (.0177)	-.0427* (.0190)	-.0481* (.0223)
N	271	317	283	335	334	270
R^2	.0153	.0153	.0079	.0062	.0136	.0188

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The dependent variable is the annual firm level change in new loan approvals. Firms that did not apply for a loan are excluded. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 270 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team.

Table A10

Estimated Changes in Firm Level Loan Approvals for Small Young Firms During the Great Recession Excluding Firms with Greater Than $1m USD Annual Revenue

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	.0197 (.2525)	.1197 (.2067)	.1495 (.2711)	.1192 (.2264)	.1465 (.2415)	.0579 (.2599)
Δ ***Credit Risk*** $_{f,\,t\text{-}1}$	.0309 (.0470)		.0279 (.0458)			.0307 (.0478)
Δ ***Ln Equity*** $_{f,\,t}$	.0146 (.0099)	.0105 (.0075)				.0159 (.0108)
Δ ***Positive Profit*** $_{f,\,t}$	.0698 (.0579)	.1115 (.0577)				.0727 (.0607)
Δ ***Average Age*** $_{f,\,t}$					.0081 (.0096)	.0035 (.0104)
Δ ***% Female*** $_{f,\,t}$					.0028 (.0025)	-.0042 (.0044)
Δ ***% Immigrant*** $_{f,\,t}$					2.6233 (1.7165)	3.7387 (2.6241)
Δ ***N Owners*** $_{f,\,t}$					-.0260 (.0435)	-.0134 (.0578)
Δ ***% Non-White*** $_{f,\,t}$					.0013 (.0010)	.0021 (.0014)
Constant	-.0496 (.0399)	-.0462 (.0354)	-.0431 (.0391)	-.0410 (.0345)	-.0317 (.0418)	-.0461 (.0494)
N	118	141	124	150	149	117
F **(*Z*** $_{c,\,t}$**) - *first stage***	31	56	30	51	48	29

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 116 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team. The definition of small business lending for CRA reporting is lending to firms with less than $1m in annual revenue. Firms that did not apply for a new bank loan are excluded.

Table A11

Estimated Changes in Firm Level Loan Approvals for Small Young Firms During the Great Recession Including Time Lag for Change in Credit Supply

	I	II	III	IV	V	VI
$\frac{\Delta Credit\ Supply_{c,t}}{Credit\ Supply_{c,t-1}}$	.1495 (.1183)	.1365 (.0992)	.1977 (.1216)	.1679 (.1032)	.0744 (.1271)	.0474 (.1656)
$\frac{\Delta Credit\ Supply_{c,t-1}}{Credit\ Supply_{c,t-2}}$	.1490 (.2069)	.2167 (.1707)	.1451 (.1935)	.2054 (.1603)	.3830 (.2496)	.3841 (.3688)
Δ ***Credit Risk*** $_{f,\ t-1}$	.0072 (.0173)		.0024 (.0174)			.0008 (.0194)
Δ ***Ln Equity*** $_{f,\ t}$	.0082 (.0042)	.0065 (.0036)				.0111 (.0055)
Δ ***Positive Profit*** $_{f,\ t}$	.0059 (.0348)	.0318 (.0331)				-.0062 (.0392)
Δ ***Average Age*** $_{f,\ t}$					-.0107 (.0078)	-.0118 (.0107)
Δ ***% Female*** $_{f,\ t}$					.0012 (.0016)	-.0034 (.0028)
Δ ***% Immigrant*** $_{f,\ t}$					.1845 (.7107)	4.3524 (2.4842)
Δ ***N Owners*** $_{f,\ t}$					-.0311 (.0286)	-.0307 (.0492)
Δ ***% Non-White*** $_{f,\ t}$					.0003 (.0015)	.0001 (.0020)
Constant	-.0092 (.0436)	.0001 (.0348)	-.0077 (.0410)	.0064 (.0337)	.0202 (.0381)	.0129 (.0540)
N	270	315	282	333	332	269
F ($Z_{c,\ t}$) ***- first stage***	30.94	40.56	36.43	48.38	38.73	22.40
F ($Z_{c,\ t-1}$) ***- first stage***	25.01	33.22	24.63	33.32	26.87	16.00

Source: Kauffman Firm Survey, 2009 – 2012, NORC Data Enclave. *Notes:* The first stage results for IV regressions on loan deterrence, applications, and approvals for the full and revenue restricted models are practically the same, with slight differences varying with response counts. The first stage dependent variable is the percent change in credit volume. Covariates are modeled in first differences. Standard errors are in parentheses and clustered at the county in year level. There are 244 clusters in Model VI. Significance is shown as * = .05, ** = .01, *** = .001. Credit Risk is a 1 – 5 scale increasing in riskiness based on the firm's D&B Commercial Credit Score. Age is the average age of firm owners. Female, immigrant, and non-white are percentages of the firm's ownership team. The definition of small business lending for CRA reporting is lending to firms with less than $1m in annual revenue. Firms that did not apply for a new bank loan are excluded.

Public Entrepreneurship Training for Startup Firms: Evidence from the Kauffman Firm Survey*

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Abstract:

This study utilizes the Kauffman Firm Survey (KFS), the largest U.S. cohort panel survey of startup firms, to investigate the effects of entrepreneurship training during a startup firm's first five years on subsequent firm performance. The KFS allows me to observe firms that select into seven types of training programs or no training. I use propensity score matching methods to estimate an average treatment effect on the treated for different training treatments compared to no training: U.S. Small Business Administration (SBA), public, private, and any training. Firm performance outcomes include: survival, employment growth, profit growth, forecasting, and bank financing activities, in the firm's fifth through eighth year of operation. I find that training supports bank loan application. Firms that received SBA training, or any training type, submitted more applications for new bank loans than untrained firms. While firms that received SBA training are also less likely to be approved for loans. I find that private, but not public, training programs are associated with better entrepreneur forecasting ability. I also find evidence of adverse selection into training, especially public training. Finally, I find that female, non-white, and educated entrepreneurs are more likely to select into public trainings sponsored by the SBA, while proximity to an SBA Small Business Development Center does not predict utilization of SBA training.

Keywords: Entrepreneurship training, startup, young firm, SBA, SBDC, small business loans

JEL Codes: L26, H41, I25, L33, M13, R53

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1. Introduction

The U.S. Small Business Administration (SBA) offers subsidized counseling, training, and referrals to entrepreneurs at over 900 Small Business Development Centers (SBDCs) around the country. Public training is offered for activities such as business planning, hiring, marketing, government contracting, and legal issues, often by counselors with personal entrepreneurship experience (Michaelides & Benus, 2012). These programs are offered with the goals of increasing employment opportunities in small businesses, providing equitable access to entrepreneurship, and supporting development through innovation. While SBA trainings are highly rated by their participants (Fairlie et al., 2015) surprisingly little is known about the effectiveness of these programs in terms of their ability to support young firms' growth and access to financing.

Most SBA information on training utilization, satisfaction, and outcomes is based on reports by program participants. Empirical validation, and recent expansion, of SBA training programs is based on one randomized control trial with mixed results: Project GATE (Growing America Through Entrepreneurship) (Benus et al., 2009; Michaelides & Benus, 2012; Fairlie et al., 2015; Michaelides, 2021). Project GATE was an important step in understanding the effects of SBA training that relied on creating a control group from program applicants. This leads to my first research question: *What are the characteristics of startup firms that seek SBA training, private training, and no training?*

While little is known about the effectiveness of SBA training programs, comparisons to entrepreneurs who do not seek SBA training and to competing private entrepreneurship training programs are even rarer. Private trainings offered by accounting firms, incorporation firms, consultants, and sales coaches may be perceived as higher quality, exclusive, cutting edge, or individually tailored to the firm. However, these programs could also lead to principal agent problems when the training firms have an incentive to upsell entrepreneurs on affiliated business services or ongoing coaching. While the SBA aims to provide equitable training access to entrepreneurs from all backgrounds, 35% of the GATE control group sought private training after being excluded from GATE (Michaelides & Benus, 2012). This indicates that for some entrepreneurs with the resources to pay for private training, SBA training is their first choice. This leads to my second research question: *Do public and private entrepreneurship training programs deliver equivalent growth and financing outcomes for young firms?*

I am able to examine these questions with a quasi-experimental design using the Kauffman Firm Survey (KFS). This is the largest and longest running cohort panel survey of young entrepreneurial U.S. firms, following 4,928 firms from their startup in 2004 through 2011 (DesRoches et al., 2010). The KFS asked firms in 2009 if they have ever utilized several types of public and private training programs. This allows me to identify firms that accessed public, private, or no training during their startup phase and compare their demographics and outcomes during their growth phase. Considering the heterogeneous goals of startup firms, I evaluate a range of survival, growth, employment, and financing outcomes.

I contribute to the literature interested in identifying factors of young firm growth by evaluating the role of training after selection into entrepreneurship while controlling for selection into training in a matched sample. Finally, I contribute to the study of young firm resilience during the 2008 Financial Crisis and Great Recession, which occur in the middle of the KFS panel period.

This study also makes an independent contribution to the SBA's 2026 Enterprise Learning Agenda from outside the Administration. I contribute specifically to the first of the "cross-cutting key research and evaluation questions" that address both SBA research priorities of "equity
and customer-centric design and delivery" (SBA, 2022).

> *"1. What is the demographic and geographic makeup of the SBA's program participants, how does this compare with the eligible population, and which underserved small businesses can the SBA better serve through its programs?" (SBA Enterprise Learning Agenda 2022-2026, p.8)*

The paper is organized as follows: section 2 provides background, section 3 derives hypotheses, section 4 describes the KFS and the variables derived from it including training treatments, section 5 explains the propensity score matching methods, section 6 provides the results, section 7 discussion, and section 8 concludes the analysis. Appendix A provides a supplemental instrumental variable analysis.

2. Background

The SBA was formed by the Small Business Act of 1953 for the purpose of furthering U.S. competitiveness and economic growth through supporting the formation of innovative small businesses (Gilbertson, 1960). Prioritizing young small businesses as the sources of growth is based in the theory of Schumpeter (1942) who developed the ideas of creative destruction and the entrepreneurial ecosystem. In Schumpeter's metaphor of the economy as a forest, growing young firms contribute to employment growth and technological innovation under the sheltering canopy of older firms and institutions who lack the flexibility to innovate. Recent empirical research has confirmed that it is young businesses that drive innovation and growth (Haltiwanger et al., 2013). While young businesses start small many remain small. This has created a renewed interest in identifying young businesses with growth potential and the services that help them grow. While somewhat more prevalent in the service sector, fast growing young businesses can emerge out of any industry (Henrekson & Johansson, 2010). There is a public interest in identifying and supporting young firms with growth potential. This is primarily done through counseling and training.

Project GATE, German programs, and self-employment assistance programs in several U.S. states have proven public training effective at helping the unemployed enter entrepreneurship and write business plans (Kosanovich et al., 2002; Michaelides & Benus, 2012; Fairlie et al. 2015; Oberschachtsiek & Scioch, 2015). However, these programs have not demonstrated that training has longer term growth benefits for firms founded by participants. There is a need for empirical evidence of training program benefits beyond the startup entry decision. While they may have an important role in closing skill gaps between previously employed and unemployed entrepreneurs, benefits of programs targeted toward the unemployed may not be generalizable to most young firms. Fairlie & Fossen (2019) find that only about 20% of U.S. startups are founded by unemployed persons, who may have more short-term motivations. There is still a need for evidence on the training outcomes of opportunity and intrinsically motivated entrepreneurs.

Focusing on human capital development for nascent entrepreneurs, what types of trainings at what stage are helpful? The human capital literature has unclear results. Having a college degree gives a small positive increase in the growth of entrepreneurial ventures (Unger et al., 2011). There are educational benefits for user entrepreneurs who develop a product from experience, but there are still large entrepreneurship skill gaps (Shah et al., 2012). While highly educated entrepreneurs may see modest gains in startup performance compared to less educated entrepreneurs, they may still face lower wages than their employed peers (Sorgner et al., 2017). Human capital accumulation, through education and industry experience, leads to greater entrepreneurship benefits when the training and entrepreneurship tasks are closely matched (Unger et al., 2011). This suggests that entrepreneurs would benefit from entrepreneurship focused education.

Entrepreneurial success may be driven by factors that cannot be taught such as awareness of opportunity, flexibility, and intrinsic motivation. A challenge to evaluating the overall effectiveness of entrepreneurship education is the wide variation in duration and content of college level entrepreneurship programs (Barnard et al., 2019). In their meta-analysis of entrepreneurship education in advanced economies, Martin et al. (2013) find small positive performance outcomes from entrepreneurship education. College level training appears especially effective in helping founders clarify their entry decisions, but many report still lacking confidence in their entrepreneurship skills (Oosterbeek et al., 2010). Students with innovative business ideas worked out in the classroom still face gaps in skills, information, and financing needed to launch their ventures (Bauman & Lucy, 2021).

While there is an important role for college level entrepreneurship education, its limitations point to a need for more firm specific training and counseling for startups, such as those reported in the KFS and studied in Project GATE. Most positive evaluations of startup firm specific training interventions have been in low and middle-income countries with questionable external validity to the U.S. (Cravo & Piza, 2019). In addition to GATE, other training programs based in: the Netherlands, UK, Canada, Finland, Germany, and Japan have failed to find lasting benefits for firm performance (Storey, 2004; Oosterbeek et al., 2010). In Project GATE, business performance equalized with the control group by the 18-month follow up (Benus et al., 2009). Using KFS panel data allows me to observe startup performance over an eight-year period and evaluate the long-term effects of receiving firm specific training.

Following firms over a long period raises firm life-cycle and business-cycle considerations. In this study, the training period corresponds to the firm startup phase while the follow-up period corresponds to the scaleup phase. During normal times, half of startups fail within the first three years, with most young firm failures occurring during the first four years then tapering off (Cressy, 2006; Headd & Kirchhoff, 2009). Therefore, I would expect failure rates to have stabilized for KFS firms who survive to the fifth year when they report training status. These firms should be entering a critical phase when young firms either exhibit rapid growth or remain small scale operations (Henrekson & Johansson, 2010). These dynamics are complicated by the Financial Crisis and U.S. Great Recession that occurred from December 2008 to June 2009 (NBER, 2023). I expect the recession to contribute to greater variation in firm survival duration than would be observed during normal times. Over business cycles in the 1980’s and 1990’s young firm growth was suppressed during recessionary years, then rebounded with high growth in the second and third years of recovery (Headd & Kirchhoff, 2009). Following KFS firms through 2011 should capture post-recessionary growth.

3. Hypotheses

This study offers seven hypotheses about training programs for startup businesses. I consider selection into training or no training, as well as effects of training on firm performance and financing activities. The qualitative hypothesis is that training benefits entrepreneurs.

The first hypotheses are about how firms select into training and public training. The selection hypotheses are based on the proximity theory from Card (1995) that greater access to training will lead to greater utilization of training.

Firms located miles closer to an SBA SBDC are expected to select SBA training more often. Distance is a proxy for travel and travel time costs to attend an SBA training. Since SBDCs are usually located in regional entrepreneurship hubs (Benus et al., 2009), distance is also expected to be inversely related to receiving any training, public or private.

Hypothesis 1: Firms located closer to SBDC's are more likely to select into training.

Higher resourced firms are expected to have more access to all types of training. This includes high-tech firms, corporations, and firms where owners work more hours in the business. Since these firms can afford to choose from a wider range of training programs, they are expected to select into public training programs at lower rates than more constrained firms. Non-white and women owned firms, who typically start up with lower rates of capitalization (Fairlie et al., 2022), are expected to select into public trainings at higher rates. Older and more educated entrepreneurs, who are more likely to recognize the value of training from experience, have higher human capital resources and are more likely to select into any training. Those with higher human capital are likely to also have higher financial resources to choose between programs. Conversely, educated owners may also be more concerned with the principal agent problem in training and business services and low-quality private courses, leading them to choose public training.

Hypothesis 2: Firms with more resources are more likely to select into training.

Hypothesis 3: Firms with more resources are less likely to select into public training.

The next hypotheses are based on the assumption that training works and that firms realize value from it through survival or growth. Considering the broad objectives of young firms, I consider a range of different business performance indicators.

Survival duration, growth rate of profitability, and growth rate of employment each indicate benchmarks for startup success in terms of firm growth for entrepreneurs with varying ambitions. These growth measures are expected to increase with training. Concerning access to financing, new bank loan applications and approvals are expected to increase with training, while deterred applications due to a rejection belief are expected to decrease. Trained firms are expected to report higher levels of forecasting accuracy for their firm's growth trajectory. Owners' abilities to form realistic expectations for their firms is an important business planning skill that can be taught. In the analysis, I use firm credit scores to control for adverse selection into credit markets. *Hypothesis 4: Entrepreneurship training supports young firm growth.*

Hypothesis 5: Entrepreneurship training supports young firm access to financing.

Hypothesis 6: Entrepreneurship training increases forecasting ability.

The following comparative private vs public training hypothesis assumes that both broad types of training work since both survive in the market for training. This hypothesis is tested by comparing firms that have only accessed public training with firms that have only accessed private training when assessing the business performance outcomes.

Hypothesis 7: Public and private training programs perform equally well.

4. Data and Variables

4.1 Kauffman Firm Survey

The data for this study is from the Kauffman Firm Survey (KFS), a cohort panel survey of 4,928 US firms founded in 2004 (Kauffman Foundation, 2012). The KFS was conducted by the Ewing Marion Kauffman Foundation to better understand the dynamics of young firms (Farhat & Robb, 2014). The survey was designed and administered in consultation with Mathematica Policy Research. Owners were interviewed by phone each year from 2005 to 2012 about their previous year's activities, covering the first eight years of firm operation (DesRoches et al., 2010). The KFS was the largest and longest running panel survey of US startups at the end of the survey.

The KFS samples firms from the Dun and Bradstreet commercial credit database. Startups were identified as firms using an IRS EIN number or filing business taxes for the first time in 2004 (DesRoches et al., 2010). This definition excludes the most informal self-employed who do not file taxes but is broad enough to include sole-proprietorships. About 31% of KFS firms are unincorporated sole-proprietorships (Table 1). DesRoches et al. 2010 details KFS sampling and survey methods. The KFS surveyed up to 10 owner-operators of each sampled firm. Multiple owner interviews allow for the observation of demographics of the ownership team instead of designating one representative owner. At the beginning of the panel there were 6,858 owner interviews. Table 1 shows descriptive statistics for KFS owners and firms.

The KFS does not claim to be representative of all US firms started in 2004 (Farhat & Robb, 2014). In addition to using the D&B sample frame of businesses that had been scored for commercial credit, the KFS used stratified sampling to target female owned and high-tech firms in order to better represent these groups in sub-population analysis. High and medium tech firms are defined by the R&D intensity in their industry (Hadlock et al., 1991). I use a confidential private version of KFS microdata managed by NORC at the University of Chicago that includes firm zip codes. In this study I use the KFS variation in firm organizational structure, ownership team demographics, technology level, credit score, and location to analyze selection into training programs. I use the firm zip code to measure distance from the startup to an SBA SBDC.

4.2 Training Treatments

The KFS asks if the firm has received training from seven types of organizations, including the SBA, that I group for analysis. Training is indicated by the KFS question:

> *There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? ITEMS: The Small Business Administration or SBA, a Federal government agency other than SBA, a state or local government, a nonprofit association for small businesses such as SCORE, a community college or university, a chamber of commerce, a for-profit organization such as an accounting firm, another source. (DesRoches et al., 2010, p.1396).*

The training question is specific to the firm level and does not provide information about the training of each surveyed owner. The training question is included in the KFS Fourth Follow-Up, surveyed in early 2009 (DesRoches et al., 2010). This splits the KFS panel into two periods, the training period from 2004-2008, and the follow-up period from 2009-2011. These periods correspond to firm ages (years) 1-5 in the training period, and 6-8 in the follow-up period. These periods also correspond to the startup and growth phases of the firm life-cycle (Headd & Kirchhoff, 2009). The question explicitly connects the training to the sampled firm by name, so responses should not include any past training for other business ventures or education such as MBA programs. Since firms could have received training at any time in the training period, there is variation in the saliency of training. The long study period makes it possible to investigate lasting effects of training.

The most unique feature of SBA training is its provision as a pure public good. As a federally funded program, SBA training is mandated to be non-excludable. This exposes the SBA to the full range of entrepreneurship from every sector. SBA training may be the only training option for under-resourced firms and communities. The SBA must both support emerging entrepreneurs and identify businesses with growth and government contracting potentials. At the simplest level of training, the SBA offers self-paced free (non-excludable), online (non-rival), loan application training. However, most SBA support is interactive with SBDC counselors.[9] The SBA meets its non-excludability mandate by offering individual intake counseling and appropriate program referrals for every inquiry. The SBA operates at a scale to provide non-rival training to all small

[9] Background information on SBA programs, procedures, and challenges was informed by my interview with trainer Katie Champagne at the Nevada SBDC.

businesses regardless of scale, organization, or prior business planning (Benus et al., 2009). The public good dimensions of SBA training make direct comparisons to other training programs more difficult. In Figure 1 I categorize training programs listed in the KFS by their public, non-excludable and non-rival, dimensions.

Non-profit associations are not under mandate to be non-excludable and often charge a membership fee which is a type of exclusivity. However, these programs function like club goods in that member firms benefit from increasing local membership size. These types of trainings are typically structured as meetings, mentorship, and referral opportunities between established, new, and would-be entrepreneurs. By relying on sharing clients, ideas, and knowledge transfers between members, these groups benefit from having a non-rival character, which makes them impure public goods. The KFS question also refers to SCORE, the Service Corps of Retired Executives in the non-profit category. Since SCORE is administered by the SBA, it is also non-excludable. However, SCORE mentors are local community volunteers with limited availability and geographic coverage (SCORE, 2023). In implementation, the need to match entrepreneurs with appropriate volunteer mentors makes the program a rival, impure, public good. I also categorize government sponsored training programs at the state or local level as impure public goods. These programs may be rival if the local program has limited resources to serve interested entrepreneurs. While they are expected to be non-excludable locally, they may be exclusive to firms within the sponsoring jurisdiction.

Training by a for-profit organization such as an accounting firm is considered private. These programs limit participation by their cost, capacity of the training firm, and perceived fit of the entrepreneur. For-profit businesses often provide a free public introductory workshop; this is typically used as a recruitment, screening, and selling tool for more comprehensive private trainings and services. Since these programs are not standardized, I expect there to be greater variation in quality amongst private trainings than SBA training. The U.S. Chamber of Commerce is organized as a 501(c)(6) trade organization with a primary purpose of political lobbying (Chamber, 2023). Its programs are excludable at ideological, cost, and entrepreneur levels. Joining the organization requires an interview before cost is disclosed. Local training programs may also be rival within the organization. I have categorized these trainings as private.

University trainings are mainly private. These require acceptance to the college or class and commitment to the course, including fees. While community and city college courses often have low fees, their limited capacity makes participation rival.

For analysis, I form five treatment and control groups from the survey: *any training, no training, SBA, public, and private.* Table 2 shows counts of KFS firms that accessed each training type and were included in each training treatment group. Respondents who reported receiving "another source of training" are included in the any training treatment but excluded from the public and private training treatments due to ambiguity. Only 11.1% of KFS firms utilized SBA training (Table 2). All respondents who received SBA training are included in the SBA treatment group regardless of other training received. Keeping firms in the SBA training group who also received private training could introduce some positive bias to the SBA results but allows me to study all firms that accessed SBA programs.

I split the training programs along the excludable and rival axis to form the public and private training groups. The public training group includes all training programs that meet at least one of the public goods criteria. The private training group includes programs that were considered primarily excludable and rival. Firms that received both public and private training were excluded from the public and private training treatment groups. While university entrepreneurship training fits the excludable and rival criteria for public training, I am concerned about ambiguity between university training and SBA training since many SBDCs are operated on college campuses (SBA, 2018). Therefore, I exclude University training from the private training treatment to reduce noise. University-based training could be the subject of a future study. Firms in each training treatment group are matched with firms in the no training control group. Finally, I match firms in the private training treatment group to control firms in the public training treatment group.

4.3 Business Performance Outcomes

There are seven performance outcomes from the KFS presented in this study. Summary statistics for the outcome variables are shown in Table 3. *Duration* indicates years of firm survival since startup $D_f = \{t \in 5, 6, 7, 8\}$. The firm *growth rate of employment* is the relative change in number of full-time equivalent employees, including active owner employees, during the follow-up period $\Delta Employment_f = \frac{employees_{2011} - employees_{2008}}{employees_{2008}}$. The firm *growth rate of profit* is the difference in natural logs of profit over the follow-up period $\Delta Profit_f = [\ln(profit_{2011}) - \ln(profit_{2008})]$.

Application is a dummy variable indicating that the firm applied for a new bank loan in the first year of the follow-up period, 2009. *Approval* is a dummy variable indicating that the firm was approved for a new bank loan in 2009. Only firms that applied for loans can be approved or not. *Deterred* is an indicator of unmet credit demand from firms that did not apply for loans. It is based on the KFS question:

> *During calendar year 2009, was there any time when [NAME BUSINESS] needed credit, but did not apply because you or others associated with [NAME BUSINESS] thought the application would be denied. (DesRoches et al. 2010, p.1514).*

Forecast is formatted as a dummy variable indicating that the firm met or exceeded the owners' growth expectations. It is based on the KFS question:

> *Now I'd like you to think about how much you expected [NAME BUSINESS] to grow since the business was started. How much do you think [NAME BUSINESS] met your expectations for growth between when the business was started and December 31, 2008? Would you say [NAME BUSINESS]'s growth . . . Exceeded, Met, Did not meet your expectations? (DesRoches et al., 2010, p.1536).*

4.4 Firm and Entrepreneur Characteristics

The KFS includes both firm and entrepreneur characteristics that I use to analyze and control for selection into training treatments. Following hypotheses 1-3, I choose characteristics that can indicate access to training and founder intentions for growth. I choose firm and owner characteristics similar to Farhat and Mijid (2016), who use characteristic matching methodology with the KFS. Other factors that may influence firm performance outcomes, such as the startup lifecycle and macroeconomic recession, are controlled for by using startup cohort panel data. Table 1 shows summary statistics for KFS firms that survive the study training period.

The vector of firm characteristics $F_{f,t=2004}$: *distance, technology, organization* is fixed in the startup year 2004. While firms may expand over the course of the panel, *distance* is based on the first office zip code. *Distance,* as defined in Section 5.1, represents geographic proximity to an SBDC, which are usually located in business hubs (Benus et al., 2009). Short distance conveys the benefits of agglomeration and knowledge sharing in an entrepreneurial ecosystem (Rosenthal & Strange, 2004). *Technology* is a categorical variable that classifies firms as *high-tech, medium-tech*, or *low-tech* based on industry. DesRoches et al. (2010) details technology categorizations in the KFS, which oversampled *high-tech* firms based on Hadlock et al. (1991) definitions. There has been considerable interest from policy makers in growth driven by the *high-tech* sector (Henrekson & Johansson, 2010). In the model, I use *medium-tech* as the base category. *Organization* refers to the corporate structure of the firm. Startup organization as a corporation or LLC can be a strong signal of founder's ambitions (Short & Glover, 2011). I categorize firm types in the KFS into a four-point ordinal scale of ascending complexity based on the regulatory burdens for each type of firm as follows: *unincorporated (sole proprietorship, general partnership, other), limited liability (LLC, LLP), S corp., C corp.*

Credit risk $CR_{f,t+4}$ is the risk class of the firm's Dun and Bradstreet commercial credit score. *Credit risk* is a five-point ascending scale of default risk. Since credit scores can change in each year, I use the credit score in 2008, the first year that firms that answer the training question can also be observed closing. Access to credit is extremely important to firm survival during shocks and can facilitate growth (Brown & Earle, 2017). The fifth-year credit score also represents the firm's financial history and reputation (Chatterji & Seamans, 2012).

The KFS surveys all founders of a firm instead of one representative owner. However, the KFS training question does not indicate which owners at a firm received training. The vector of firm owner characteristics is $M_{f,t=2004}$: *age, education, gender, race, and work hours.* For each firm, I construct a composite measure of the ownership team by interacting demographic characteristics with ownership shares and summing over the firm to score the demographic variable. Using the team composition method allows me to include the lived experience of each owner while controlling for differences between minority inclusion and minority led teams. For example, a husband-wife business would be scored as .5 female for *gender*, while a solely female owned firm would be scored as 1.

Age is the average age of firm owners weighted by ownership share. Older owners have had more years of opportunity to receive previous entrepreneurship training. Increasing age is also associated with increasing risk aversion (Morin & Suarez, 1983). *Gender* is the ownership share weighted average of the ownership team, scaled from male to female. The KFS used binary gender categories. Before the Equal Credit Opportunity Act of 1974, women faced legal and institutional barriers to business ownership and financing (Blanchard et al., 2008). While women entrepreneurs have been found to be equally competitive to men (Sent & van Staveren, 2019), many women also enter entrepreneurship with differential motivations to achieve more flexibility between labor and family time (Morris et al., 2006). *Race* is an ownership weighted average showing the percent of non-white and Hispanic ownership. Using one scale for race, rather than categorical variables, allows me to include smaller sub-groups from the KFS. Non-white entrepreneurs in the U.S. have faced a long history of discrimination and oppression, often preventing them from accessing capital and accumulating intergenerational wealth. Today, Black owned startups are founded with lower levels of equity (Farleigh & Robb, 2007).

Education is the highest level of education for any owner. I use the highest level with the idea that the educated owner can contribute their expertise to the firm. User entrepreneurs and those coming from employment in the same industry have specialized education that transfers to the business (Shah et al., 2012). Education is also be seen as a proxy for human capital and ability (Unger et al., 2012). Entrepreneurship education can complicate selection into training. Founders with business education may not feel the need for additional firm specific training. However, Bauman & Lucy (2021) find college entrepreneurship classes often do not provide all the necessary steps to bring a new venture to the market.

Hours is a sum of each owners' average weekly work hours in the business multiplied by their ownership share. I choose to sum, instead of taking a weighted average of owner work hours for two reasons. First, firms with multiple owners working full-time in the business may have more available owner work hours that could be allocated to training than firms with fewer owners and fewer work hours. Second, if a firm is jointly owned by an active owner who works full-time in the firm and a passive owner who does not work in the business, taking an average of the two would reduce the apparent engagement of the active owner. Entrepreneurs accumulate entrepreneurial human capital and become more productive as they invest more work hours in the firm (Verheul et al., 2009). Direct participation in operations is expected to give owners greater understanding of the firm's performance and current market conditions.

5. Methods

5.1 Instrumental Variable Regression

I first try to analyze the effects of training programs on startup performance using instrumental variable regression. Following *hypothesis 1*: *firms located closer to SBDC's are more likely to select into training*, I first try to control for selection into training by using firm distance from the nearest SBA Small Business Development Center (SBDC) as an instrument for SBA training. This is similar to the Card (1995) distance to college instrument for education. Oosterbeek et al. (2010) also use a distance instrument for selection into an entrepreneurship training program in the Netherlands. Distance is associated with a travel cost of time, energy, and transportation to access SBA training. It may also represent awareness of the training. SBDCs are usually located in areas with high entrepreneurial activity (Benus et al., 2009), so distance is also associated with decreasing urbanity and proximity to agglomeration effects from the entrepreneurial ecosystem (Rosenthal & Strange, 2004). If proximity to the business hub also confers performance benefits to the firm, this could confound the IV. I assume that entrepreneurs choose a location appropriate to their business. For example, a firm located in a rural area is needed in that area and would not significantly benefit from relocating.

I construct this instrument by mapping the center of each firm's 2004 5-digit zip-code to the nearest current SBDC in tenths of miles using the SBA Find Local Assistance website tool [SBA, 2023]. There are around 900 SBDCs across 3,143 US counties (Benus et al., 2009). When used in IV regression models (see Appendix A) to estimate the effects of training on firm performance outcomes, the distance instrument is too weak to produce reliable results (Table A1).[10] Selection into SBA training is not predicted by distance to an SBA SBDC as shown by the small F statistics from tests of significance of the IV in the first stage regression. I find that demographics and technology level predict selection into training more than proximity to training (Tables 11 and C1-C6). It is likely that physical distance is even less relevant today with the availability of remote training than it was in

[10] Using the different outcome variables at the second stage implies different sample sizes due to missing values in these outcome variables. Therefore, the first stage results differ and are presented in separate tables.

2004-2008. The firm characteristics: *technology, organization, credit risk, age, education, gender, race, and work hours,* described in Section 4.4, are included as control variables in the IV regression. The second stage IV results (Tables A2-A8 corresponding to different outcome variables) are also reported in Appendix A, but cannot be interpreted due to the weak instrument problem.

5.2 Propensity Score Matching

In the preferred approach to control for selection, I use treatment and control firm matching to compare outcomes between training groups. The first step estimates a propensity score for training from firm and entrepreneur characteristics using a probit regression. Second, treated firms are matched to similar control firms that did not receive training by propensity score. Finally, I test the difference of business performance outcome means between matched firms to evaluate training treatment effects. The matching methods follow Caliendo and Kopeinig (2008).

The first step allows me to estimate the influence of firm and owner types on selection into training types. I use binary probit regressions to estimate likelihood of selection into a training treatment given the characteristics defined in Section 4.4: *distance, technology, organization, credit risk, age, education, gender, race, and work hours.* I estimate a separate propensity score regression for each studied training treatment and control combination: *SBA vs no training, public vs no training, private vs no training, and public only vs private only training.* In each regression, the training treatment is the dependent variable and firms that do not fit in the treatment or control groups are excluded.

The propensity score is each firm's probability of selecting into the training treatment given the combined effects of their selection characteristics. I choose to use propensity score matching, rather than characteristic matching, because of the relatively low numbers of firms in each treatment group. Using a composite score allows me to use more selection characteristics than would be feasible if finding an exact characteristic match for each treated firm. At the same time, regression provides information about the effects of characteristics on selection, rather than simply controlling for their influence. Selection equation results are reported in Tables 11-17.

This probit model appears to meet all the conditions for identification of treatment by propensity scores (Caliendo and Kopeinig, 2008). Following my hypotheses, I choose a wide variety of characteristics that indicate access to training through financial resources or time, and attitudes towards training or type of training through owner demographics. In thoroughly representing factors influencing selection into training, this model can reasonably be assumed to meet the conditional independence assumption that known characteristics influencing selection are invariant to training and represented in the model. While it may not be possible to anticipate and control for every influence on selection, I have chosen variables to represent owner's underlying motivations from multiple perspectives. If there is some remaining bias from unknown variables, the direction of bias is unknown.

Most of the model characteristics are fixed at the start of the panel and cannot be influenced by training. Levels of the variables that could change over time, *owner work hours* and *credit risk*, are measured at the end of the training period. Both the treatment and control firms are identified from the same source, KFS firms that survive the study period for each outcome. There is enough variation in training by each characteristic to meet the common support assumption, with no group overwhelmingly choosing one training type. There is also variation in the business performance outcomes by selection characteristics.

The second step implements a matching algorithm to find an appropriate control firm for each trained firm. Firms are matched to their first nearest neighbor. In the matching algorithm, I use replacement of untreated firms to find a closely scored match for each treated firm. This method allows for the same firm to be repeatedly used as the control firm and can reduce the variation of the controls. However, I am more concerned with finding high quality matches for trained firms than representing all control firms. All treated firms are within the area of common support and matched to control firms. I also tried using second and third nearest-neighbor specifications which construct a control from a weighted average of neighbors. While this method allows for more variation as more control firms are included, I found that this method introduced too much bias when multiple close neighbors could not be used. Using first-nearest-neighbor matching with replacement eliminates the need to control the matching order and minimizes the need to implement a match distance caliper.

Additionally, I evaluate match quality using t-testing for balance as in Rosenbaum & Rubin (1985). After matching, the treatment and control firm distributions are expected to be equivalent with regards to the matching characteristics. For each characteristic, the firm distributions are split into intervals and the equivalence of characteristic means between treatment and control firms is tested within each interval. Unbalanced matches are reported in the last columns of Tables 4-10 (which present matching results for different outcomes). A low pseudo R^2 in the selection equation also indicates high quality matching as it indicates that there are not distributional differences between the treatment and control groups. Pseudo R^2 is reported in Tables 11-17 (the selection equations). Technically, I implement the matching methods with the user written *Psmatch2* package in STATA (Leuven & Sianesi, 2018).

5.3 Treatment Effects

The third step of analysis investigates differences in business performance outcomes by treatment group. Each matched pair of firms now has approximately the same likelihood of selecting into training and similar characteristics but differs in the type of training received. So, the differences in outcomes between balanced matches can be attributed to training, assuming that the relevant characteristics determining selection have been taken into account. I analyze outcome differences using a Roy-Rubin-Model (Roy, 1951; Rubin, 1974) for average treatment effects on the treated (ATT).

Each KFS firm F_i has a treatment effect from training τ_i. There are two potential outcomes for the firms:

$Y_i(T_i) = Y_i(1) = selected\ into\ training$ or $Y_i(T_i) = Y_i(0) = selected\ no\ training$.

Theoretically, the treatment effect is the difference between the outcome for firm F_i after training and what the outcome would be if F_i had no training.

$$\tau_i = Y_i(1) - Y_i(0) \quad (1)$$

The average treatment effect on the treated τ_{ATT} aggregates the individual treatment effects and differences the mean outcomes with and without training for the treated group of firms. Each firm has one observed treatment; the counterfactual is not observed. So, the ATT is a theoretical model.

$$\tau_{ATT} = E(\tau|T = 1) = E\left(\overline{Y(1)}\middle|T = 1\right) - E\left(\overline{Y(0)}\middle|T = 1\right) \quad (2)$$

Since only one treatment condition can be observed, each treated firm is matched with an untreated firm by probability of treatment $P(x)$. Then the propensity score matched ATT can be estimated using the mean of the treated distribution of firms and the mean of the balanced distribution of matched control firms. This is the empirical model.

$$\tau_{ATT}^{PSM} = E_{(P(x)|T = 1)}\left\{E[\overline{Y(1)}|T = 1, P(x)] - E[\overline{Y(0)}|T = 0, P(x)]\right\}$$

(3)

ATT is interpreted in the units of the outcome variable. The standard errors are bootstrapped to estimate error ranges that include variance from the matching process. I use a two-sided t-test to determine if the difference between the treated and control means is significant.

6. Results

6.1 Treatment Results

Tables 4 – 10 show the average treatment effects on the treated (ATT) for each outcome and training treatment. These are the third step results following the selection regression and matching algorithm. Each outcome table row shows the results for a separate training. In rows 1-4, *any training, SBA, public only, and private only* treatment groups are matched with *no training* controls. In row 5, *private training only* is matched with *public training only* as the control group. The significance of the ATT is determined by the t-test of the average difference of means between matched firms. These tables also note the unbalanced matching specifications.

Table 4 reports treatment results for the *duration* outcome. *Duration* is a scale of firm survival from firm years five through eight, 2008-2011. This is a span of 47 months. Over this period 71% of KFS firms survive. This is conditional on firms already surviving the first four startup years. I find that SBA training is associated with 2.4-month shorter average survival than no training. Similarly, private training leads to a 2.8-month longer average duration than public training, but no longer duration than no training treatment.

Tables 5 and 6 show that none of the training treatments affect the growth of employment or profits over the three years following the training period. I also test the training hypotheses for growth of employment and training in the first year immediately following the training period, 2009. These results are shown in Appendix Tables B.1 and B.2. I find firms with any training had a slower growth rate of profits from 2008-2009 than matched firms with no training by 2.9 percentage points.

Tables 7, 8, and 9 show the effects of training treatments on new bank loan applications, approvals, and applications deterred by a rejection belief. All bank loan results are for 2009, the year following the treatment window. All types of training appear to support firms in making loan applications. Firms with any training were 5.0 percentage points more likely to apply for new bank loans than firms with no training; while firms with SBA training were 7.4 percentage points more likely to apply. Firms with private training were 8.8 percentage points more likely to apply than firms with public training (Table 7). Despite leading to more applications, training did not lead to more conditional loan approvals with any of the training treatments. I find that firms with SBA training that applied for new bank loans were 16.67 percentage points less likely to be approved than firms with no training (Table 8). Firms with SBA training were also 10.6 percentage points more likely to be deterred from applying for needed loans than firms with no training (Table 9). Deterred firms do not apply for loans because they believe they will be denied.

Table 10 shows ATT results for forecasting ability on a 0-1 scale. SBA training has a significant negative effect on forecast performance. The forecasting average was .045 points lower for firms with SBA training than their matched pairs with no training. The forecasting average was .105 points higher for firms with private training than their matched pairs with no training. The average for private training is .157 higher than public training. This is the only outcome where private training shows a clear advantage over public training.

No significant results come from an unbalanced matching specification, indicating that the matching algorithm was able to find a close match for each of these treatments, and the results are not known to be biased by any matching covariates in the matching process (Tables 4-10, last column). Next, I further investigate firm selection into training.

6.2 Selection Results

Tables 11 and C1-C6 show first step results for selection by firms into training types. Each column reports a separate probit regression of the matching characteristics on training type. The estimated characteristic coefficient shows the effects of the characteristic on the firm’s probability of training. Summary statistics for the matching characteristics are reported in Table 1. There is a separate regression for each training type and control group pair following the treatment and control group definitions in Section 4.2. I present selection results for the duration outcome in Table 11 and other third step outcomes in Appendix C. While the first stage regression equation is the same in each case, the number of surveyed firms varies by years included and question. This allows me to observe a wide picture of selection into training from characteristics. To compare specifications, I report the McFadden's pseudo R^2 and loglikelihood statistics. These are both goodness of fit measures, with higher pseudo R^2 and lower loglikelihood indicating better fit models. I report probit model coefficients in Table 11 and Appendix C.

Education is the strongest and most consistent selection result. In all specifications, more education predicts increased likelihood of selecting into any training. Education predicted selection into both SBA and private training, without significant difference between types. Increasing average firm owner *age* increases the likelihood of selecting into any training for most specifications, with a preference for private training in some cases. More owner work *hours* predicted selection into private training in six models. *Hours* were also associated with selection into any training and public training in many of the specifications.

As a significant characteristic in six of the seven models, *Non-white race* consistently predicts selection into SBA training; race is a significant characteristic in six of the seven models. Race is not a predictor of any other training type. *Female gender* predicted selection into any training, and specifically public training programs, including SBA training. This result was significant in four of the seven specifications.

Organization level consistently predicts selection into private training over no training and public training. The highest levels of organization in the survey are c-corp (business corporation with unlimited shareholders), followed by s-corp (small business corporation). *High-technology* firms consistently avoid private training, but do not show a clear preference for any other training type or no training. This can also be seen as a greater preference for private training by medium-technology firms that are in the base state.

I do not find evidence that *credit risk* influences selection into training over no training, or a type of training. According to the point estimate, I found *distance from SBDC* to be negatively associated with selection into any training as stated in Hypothesis 1. However, this result was not consistently significant across specifications.

7. Discussion

7.1 Selection

7.1.1 Hypothesis Tests

Table 12 summarizes the results from the seven hypothesis tests. Put together, the first stage results lead to characteristic profiles for selection into any, private, and SBA training. A few characteristics are not significant for selection in all seven outcome regressions, but there are no contradictions. I do not find evidence that the firm's credit score is associated with training, or that more creditworthy firms select more exclusive private training, suggesting that firms at all levels of creditworthiness seek training. This is an important consideration in planning training for loan application. Lower credit score applicants may need more individualized support to communicate value than standard loan advice.

Relative to their peers, entrepreneurs who access training from any source are older, more educated, work more hours in the firm, and are more likely to include women on the ownership team. The overall training profile is consistent with selection into the GATE experiment where applicants were older, more educated, and more often female than the U.S. self-employed population (Michaelides & Benus, 2012). These results provide evidence for Hypotheses 1 and 2, which state that proximity and resources lead to training uptake. Entrepreneurs who are older and more educated have already accumulated more human capital. This experience resource appears to lead these founders to recognize the value of training and seek firm specific training for their startups. Owners who work more hours in their firms have the resource of more time to potentially engage in training. The KFS interviewed active owners, not passive investors (DesRoches et al., 2010). Working more hours is also a signal that these owners have a higher level of commitment to the startup venture.

Entrepreneurs who select SBA training are more likely to be non-white, female, and educated. Again, this profile is similar to the entrepreneurs who selected into the SBA's GATE experiment (Michaelides & Benus, 2012). Non-white and female entrepreneurs did not select into private or broader public training types at significant rates. These results support Hypothesis 2, that resource constrained firms select into public training. Black, and to a lesser extent female, entrepreneurs start their businesses with much lower levels of capital than white male entrepreneurs (Fairlie & Robb, 2007). In the GATE experiment, racial differences in human capital and business skills were minimal (Michaelides, 2021). However, racial differences in startup capitalization extend into continued gaps in bank financing (Fairlie et al., 2022). Outreach to Black entrepreneurs is part of the SBA's 2026 strategic goal of *"ensuring equitable and customer centric design and delivery of programs to support small businesses and innovative startups"* (SBA, 2022). The SBA has made targeted efforts to support Black entrepreneurs with 14 SBDC's located on campuses at historically Black colleges and universities (SBA, 2018). This selection profile shows that the SBA is effective in reaching specific populations of entrepreneurs when they are identified and supported within their communities.

Entrepreneurs who are older, more educated, or work more hours in the firm are more likely to select into private training over no training. It is important to note that these owners are also more likely to select into public training over no training. Older founders have a slight preference for private training. Incorporated firms and medium technology level firms show a preference for private training only. Selection into private training by older, incorporated, and medium-tech firms somewhat confirms Hypothesis 3, the resource hypothesis applied to private over public training. However, this is contradicted by high-tech firms that show a strong preference not to select private training.

7.1.2 Implications for the SBA

Understanding groups that select private training is an important component of the SBA's Enterprise Learning Agenda for 2026 because the GATE experiment was not able to identify non-applicants to the program (SBA, 2022). Next, the SBA could survey incorporated and medium-tech firms to better understand their training needs. Firms at higher levels of organization have public or private shareholders, payroll, and more complex tax reporting requirements. The SBA may be able to outreach to these firms by specifically offering tax and compliance trainings for small business corporations; or by offering trainings about the different organizational types and how to organize as an LLC or corporation. Medium technology firms engage in research and development, but it is not the primary focus of their business. These firms are in industries such as industrial machinery, audio and visual equipment, electrical equipment, and transportation (Hadlock et al., 1991). Medium-tech firms may have preferences for more individualized, on-site trainings. They may also benefit from opportunities to network with other manufacturing firms.

High-tech firms significantly rejected private training, but did not significantly select public training. High-tech KFS firms are from industries that devote the highest proportion of employee time to research and development including firms in energy, agricultural chemical, pharmaceutical, and aerospace industries (Hadlock et al., 1991). More study is needed to understand the training needs of high-tech firms. They may avoid external training because of a need for secrecy around innovation. Research and development often requires high startup capitalization and a longer time-frame to reach profitability. If entrepreneurs in these industries are already well resourced and associate SBA training with SBA loan application, then they may not see SBA training as relevant to their firms. The SBA could outreach to these founders about their potential for government contracting.

This study identifies younger and less educated entrepreneurs as the most likely to forego all training types. These are under-resourced groups that the SBA could specifically develop training programs for to further their equitable access goals. While many SBDCs are located on college campuses, half of self-employed U.S. workers have no college education (Michaelides & Benus, 2012). For many young people, small business ownership may be a viable alternative to college. While young founders enter entrepreneurship with less human capital, they also have more time to accumulate entrepreneurship experience and have the potential to be innovative by understanding the needs and preferences of their generation. The SBA could further support the development of young entrepreneurs by partnering with high schools to offer entrepreneurship training at the pre-college stage.

7.2 Business Performance

7.2.1 Forecasting

Forecasting is the only domain where firms accessing private training clearly had better outcomes than both firms with public training and firms with no training. However, caution is needed in interpreting this result, which may be influenced by the timing of training, rather than private training assisting firms in forming more accurate growth expectations. Either way, the result points to a greater need for forecasting education in public training. Hypothesis 7 is confirmed for private training only.

The forecasting question is highly subjective. It involves both forecasting bias (Forbes, 2005) and hindsight bias (Cassar & Craig, 2009), as owners are asked to evaluate how well their firm met expectations over the first five years without reporting a starting expectation in the first year. This outcome could provide more support for the resource hypothesis in training selection beyond the demographic controls used. Firms that feel they are not meeting their goals are likely to feel more constrained and opt into public training for help, while firms that are meeting their goals are likely to feel able to afford an investment in private training to further their goals.

This result is further complicated by the US Great Recession, which covers the entire fifth year of the forecast period. This may be a once in a generation disruptive event that no firm could reasonably anticipate in a five-year forecast. While Cassar (2014) suggests using this question as a signal of the firms' size expectation at startup, I take the result of meeting or exceeding expectations as an indicator of the KFS firms most resilient to the recession.

7.2.2 Growth

I find no evidence to confirm Hypothesis 4, that entrepreneurship training supports young firm growth. Training did not lead to higher employment or profit growth rates in the three years following the training period. This is consistent with the results of project GATE (Fairlie et al., 2015). Since the beginning of the follow-up period overlaps with the end of the Great Recession, firms could see growth flatten during this period. While this does not provide a measure of the growth potential of trained firms during normal times, to confirm Hypothesis 4, I would expect to see the profits of trained firms decrease less than the profits of untrained firms.

Adverse selection may be another component of this result. If underperforming firms seek help from both public and private trainings, while healthy firms do not seek training, the growth of trained and untrained firms could equalize even if training supports growth. This is unclear since KFS firms do not report their motivations for seeking training.

There is wide variation in the growth goals of startup founders (Unger et al., 2011). I attempt to control for growth motivation using the firm organizational structure, but employment and profit growth are similar firm scale outcomes as it is difficult to achieve large profit gains without hiring additional employees. Project GATE participants reported high levels of satisfaction with the training program despite the lack of growth results (Fairlie et al., 2015). In follow-up studies, it will be helpful to survey participating owners about their motivations for seeking training and growth goals for their firms. This would allow training outcomes to be more directly matched to entrepreneur goals. It is important for training and research to acknowledge the many non-pecuniary motivations for entrepreneurship including happiness, flexibility, creativity, self-determination, and independence.

Duration is a less ambiguous outcome here, and perhaps more appropriate during the recessionary period. Even the entrepreneur who wants the independence of remaining a sole-proprietorship with no employees wants to stay in business. In this domain, SBA training underperforms both private and no training, contradicting Hypothesis 7: public and private training programs perform equally well. In this case, private training does not perform better than no training. Again, adverse selection could play a role in the results if the firms most at risk of failure select into SBA training. In GATE, where all participants selected into SBA training, there were no persistent duration effects after six months (Fairlie et al., 2015).

7.2.3 Financing

This study fails to confirm Hypothesis 5: entrepreneurship training supports young firm access to financing. All types of training increase rates of bank loan application, but this result did not extend to loan approvals. Instead, firms with SBA training have lower rates of approval and higher rates of application deterrence. This is especially concerning since I controlled for firm credit scores as well as known factors of deterrence (race, gender, and age) in the first stage. While I expected recessionary effects including a credit shortage and adverse selection into application, this does not explain the performance of SBA training after controlling for selection.

This study questions the assumption that entrepreneurship training helps young firms after startup. Providers of training, including the SBA, need to question if their trainings are relevant and timely. I find that training is increasing small business loan applications but not approvals. Training may be too technically focused on how to fill out a loan application and formal business plan. Entrepreneurs may need additional support to choose an appropriate lender. Training may not be relevant if the advice offered is for the idealized firm and founder, but the firms receiving training lack capital or collateral. These firms may need additional support to make a good case for the business. Content of training programs may need to be tailored to the constraints and discrimination faced by founders of young firms with limited resources. The SBA was successful in expanding access to financing through the recent Paycheck Protection Program which removed both risk and barriers to entry (Fairlie & Fossen, 2022). This study points to the need for upstream innovation in both training and financing, possibly by tying the two together in pipeline programs that provide constrained entrepreneurs a path to financing.

8. Conclusion

This study does not provide much evidence for benefits to startup firms from firm specific entrepreneurship training, beyond training helping firms apply for loans. I also do not find evidence that paying for private training leads to better firm outcomes. Following the SBA's mission, the outcomes studied here are firm growth oriented. More needs to be done to evaluate training in relation to the entrepreneur's goals. Further studies of training program utilization could ask participants about their goals for growth and scale, as well as their non-pecuniary motivations for entrepreneurship such as flexibility, self-determination, skill-utilization, and performing socially meaningful work. A starting point would be documenting why firms seek training. A unique feature of this study was that it used the KFS panel, allowing for outcomes to be evaluated over eight years.

While I find evidence that training increases confidence to apply for loans, it does not lead to higher rates of loan approvals. An important question that comes out of this study is what steps can the SBA take to close the gap between loan applications and approvals? This may reveal a need for more individualized application support. As banking becomes less local and more automated, can the SBA councilor act as a proxy for relationship banking? This problem calls for creative solutions to communicate the individual value and potential of young firms, and new partnerships between training organizations and lenders.

This study was successful in describing the groups that select into private training and no training over SBA training, furthering the SBA's Enterprise Learning Agenda. Of special interest here are young and less educated entrepreneurs, as well as incorporated startups and young firms intensive in research and development. Each of these groups may have specific needs that lead them to seek private training or choose no training. The SBA can take steps to better understand the needs of these groups and develop specific outreach and training programs to serve them.

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Figure

Figure 1: Select U.S. Entrepreneurship Training Programs, Public and Private Dimensions Categorization of Training Responses in the Kauffman Firm Survey		
	Rival	**Non-Rival**
Excludable	**Private:** 1. For-profit organization such as an accounting firm 2. Community college or university 3. Chamber of Commerce	**Impure Public:** 1. Non-profit association for small businesses such as SCORE
Non-Excludable	**Impure Public:** 1. A state or local government	**Pure Public:** 1. The U.S. Small Business Administration (SBA) 2. A Federal government agency other than SBA

Tables

Table 1

Startup Firm and Entrepreneur Characteristic Summary Statistics, Kauffman Firm Survey 2008

	N	%	Min	Median	Mean	Max	SD
Age: Average of owners	2598		21	49	49.37	101	10.23
Credit risk	2395		1	3	2.84	5	0.98
Education: Highest owner	2605		1	5	4.46	6	1.34
1. Less than high school	36	1.38					
2. High school	208	7.98					
3. Some college	477	18.31					
4. Trade or Associates	370	14.20					
5. Bachelor's or some grad	823	31.59					
6. Grad or professional	691	26.53					
Gender: % female ownership	2605		0	0	26.77	100	39.50
Hours: Total all owners weekly	2580		0	50	53.49	590	45.42
Organizational Structure	2405		1	2	1.97	4	0.84
1. Unincorporated:	873	33.50					
Sole proprietorship	808	31.01					
General partnership	60	2.30					
Other	5	0.19					
2. Limited Liability:	900	34.54					
LLC	868	33.31					
LLP	32	1.23					
3. S Corporation	632	24.25					
4. C Corporation	201	7.71					
Race: % Non-White ownership	2605		0	0	12.22	100	28.34
High-tech	390	14.97					
Medium-tech	748	28.70					
Non-tech	1468	56.33					

Notes: *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from the nearest SBDC in tenths of miles, used as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* pertains to the owner with the highest level on a six-point ordinal ascending scale. *Hours* is the sum of owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. ***Source:*** Kauffman Firm Survey [public use data set], 2004-2011.

Table 2

Training Utilization and Training Treatment Groups

Kauffman Firm Survey, 2004-2008

Trainings	**Number**	**Percent**
The Small Business Administration (SBA)	288	11.10
A Federal government agency other than SBA	91	3.51
A state or local government	157	6.06
A non-profit association for small businesses such as SCORE	231	8.91
A community college or university	280	10.81
A chamber of commerce	213	8.22
A for-profit organization such as an accounting firm	554	21.37
Another source	85	3.32
Treatment Groups		
Any training	1,045	40.10
SBA Training (no exclusions)	288	11.10
Public Training Only: SBA, Federal, State and Local, Non-profit (excluding Private, University, and Other)	221	12.40
Private Training Only: For-profit and Chamber of Commerce (excluding Public, University, and Other)	347	17.88
Control Groups		
No Training	1,561	59.90
Public Training Only	221	12.40

Note: Training and support for surveyed startup accessed by any owner during the first five years of operation. Public and private treatment groupings are based on excludability and rivalry criteria.

Source: Kauffman Firm Survey [public use data set], 2004-2011.

Table 3

Business Performance Outcomes, Summary Statistics

Kauffman Firm Survey, 2008 - 2011

Outcome Variable	**N**	**%**	**Min**	**Median**	**Mean**	**Max**	**Sd**
Duration:	2606	100	5	8	7.46	8	0.96
5 years	208	7.98					
6 years	249	9.55					
7 years	290	11.13					
8 + years	1859	71.34					
Profits:							
Profit, 2009	2606		0	0	$49,235	$17,000,000	408901
Profit, 2011	2606		0	0	$256,200	$500,000,000	9813134
Profit growth rate 2008-2009	2606		-1	-1	5,623	2,900,000	75061
Profit growth rate 2008-2011	2606		-1	-1	8489	5,000,000	114112
Ln profit growth rate 2008-2009	1416		-1	-0.06	-0.31	1.39	0.48
Ln profit growth rate 2008-2011	1416		-1	-0.11	-0.39	1.32	0.51
Employees:							
Employment, 2009	2606		0	1	4.12	266	11.41
Employment, 2011	2606		0	1	4.06	473	15.80
%ΔEmployment 2008-2009	1432		-100%	0	18.78%	2700%	1.20
%ΔEmployment 2008-2011	1432		-100%	0	12.95%	11000%	3.14
New Bank Loans:							
Applications, 2009	288	11.08					
Approvals, 2009	236	81.94					
Deterrence, 2009	415	15.97					
Forecasting expectations:	2601						
Below	1390	53.44					
Meeting	820	31.53					
Above	391	15.03					

Notes: *Duration* is years of firm survival. *Profits* are in real 2011 dollars. $Ln\, profit\ growth\ rate = [\ln(profit_{2011}) - \ln(profit_{2008})]$ *Employees* are full-time equivalent, including owners. *Deterrence* is by firms that needed a bank loan but did not apply. *Forecasting* refers to meeting the firms' growth expectations over the first five years. ***Source:*** Kauffman Firm Survey [public use data set], 2004-2011.

Table 4

Training Treatment Effects on Startup Firm Survival Duration

2008 – 2011, Firm Years 5-8

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training	1324	860	-.0523	.0599	-.91	0
SBA Training[4]	1946	231	-.2035*	.1185	-2.13	0
Public Training Only	1324	186	.0430	.1315	0.38	0
Private Training Only	1351	296	.0608	.0901	0.75	0
Private v Public[5]	217	421	.2328*	.1325	2.04	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .05, ** = .01, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. 4. *Education* (more), *gender* (female), and *race* (non-white) effect selection into SBA training. 5. *Technology* (medium), and *organization* (more complex) levels effect selection into private over public training. 6. Dependent variable: *Duration* (number of years surviving in the KFS since startup, 5-8). 7. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 5

Training Treatment Effects on Growth Rate of Employment at Young Firms

2008 – 2011, Firm Years 5-8

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training	670	491	.0601	.3905	0.70	0
SBA Training	1022	135	-.1512	.3274	-1.25	0
Public Training Only	670	92	-.0648	.3155	-0.40	0
Private Training Only	682	182	.0452	.4765	0.39	0
Private v Public	105	262	.0050	.1500	0.03	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .05, ** = .01, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. 4. Dependent variable: $\Delta Employment_f = \frac{employees_{2011} - employees_{2008}}{employees_{2008}}$) 5. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 6

Training Treatment Effects on Growth Rate of Profit at Young Firms

2008 – 2011, Firm Years 5-8

Treatment	**Untreated**	**Treated**	**ATT[1]**	**SE[2]**	**T-stat ATT**	**Unbalanced[3]**
Any Training	725	498	.0295	.0411	0.72	0
SBA Training	1102	119	.0234	.0909	0.34	0
Public Training Only	725	94	.0244	.1066	0.30	0
Private Training Only	737	184	.0077	.0731	0.13	0
Private v Public	108	205	-.0538	.0826	-0.56	1

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .05, ** = .01, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. Unbalanced: *credit-risk*, treated mean 2.7094, control mean 3.0264, % bias -32.2, t -3.47, P .001. 4. Dependent variable: $\Delta Profit_f = [\ln(profit_{2011}) - \ln(profit_{2008})]$. 5. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 7

Training Treatment Effects on Bank Loan Applications by Young Firms

2009, Firm Year 6

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training[4]	1324	860	.0500*	.0246	2.14	0
SBA Training[5]	1946	231	.0736*	.0480	1.87	0
Public Training Only	1324	186	0.0000	.0452	0	1
Private Training Only	1351	296	.0507	.0409	1.40	0
Private v Public[6]	217	421	.0879*	.0450	2.00	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .10, ** = .05, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. Unbalanced: *non-white race*, treated mean 15.677, control mean 8.9247, % bias 19.6, t 2.07, P .039 5. *Age* (higher), *education* (more), *gender* (female), and *owner work hours* (more) effect selection into any training. 6. *Education* (more), *gender* (female), and *race* (non-white) effect selection into SBA training. 7. *Technology* (medium), and *organization* (more complex) levels effect selection into private over public training. 8. Dependent variable: *Apply*, applied for new bank loan in 2009. 9. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 8

Training Treatment Effects on Young Firm Bank Loan Approvals

2009, Firm Year 6

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training	204	193	.0311	.0609	0.55	0
SBA Training[4]	342	54	-.1667*	.1213	-1.94	0
Public Training Only	204	28	.1071	.1463	0.80	0
Private Training Only	208	67	.0597	.0907	0.85	0
Private v Public	33	105	.1333	.1610	1.08	1

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .10, ** = .05, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. Unbalanced: *owner work hours*, treated mean 71.1, control mean 59.2, % bias 14.8, t 2.10, P .037. 4. *Distance* (less), *education* (more), and *race* (non-white) effect selection into SBA training. 5. Dependent variable: *Approve*, approved for new bank loan in 2009, given applied. 6. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 9

Training Treatment Effects on Deterred Bank Loan Applications at Young Firms

2009, Firm Year 6

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training	1180	770	.2714	.0255	1.35	0
SBA Training[4]	1745	198	.1061*	.0618	2.25	0
Public Training Only	1180	161	.0435	.0580	0.91	0
Private Training Only	1203	273	.0330	.0513	0.83	0
Private v Public	188	386	.0415	.0491	0.80	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .05, ** = .01, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. 4. *Education* (more), *gender* (female), and *race* (non-white) effect selection into SBA training. 5. Dependent variable: *deterred*, needed bank loan but did not apply in 2009. 6. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 10

Training Treatment Effects on Startup Firm's Forecasting Accuracy

2004 – 2008, Firm Years 1-5

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training	1322	859	.0454	.0307	1.53	0
SBA Training[4]	1944	230	-.0826*	.0546	-1.70	0
Public Training Only	1322	185	-.0270	.0726	-0.50	0
Private Training Only[5]	1349	296	.1047*	.0571	2.32	0
Private v Public[6]	216	421	.1568**	.0648	2.71	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .10, ** = .05, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. 4. No matching characteristics significantly predicted selection into SBA training. 5. *Age* (more), *education* (more), *owner work hours* (more), *technology level* (medium), and *organization level* (more complex) effect selection into private training only. 6. *Technology* (medium), and *organization* (more complex) levels effect selection into private over public training. 7. Dependent variable: *Forecast*, growth below or met expectations for first five years. 8. Model: second stage, propensity score matched firms, probit selection. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 11

First Stage Results: Selection into Training Treatment,

For Outcome: Survival Duration, Firm Years 5-8, 2008-2011

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0060*	.0016	.0024	.0079*	.0047
	(.0027)	(.0037)	(.0042)	(.0037)	(.0054)
Credit Risk	-.0154	-.0322	-.0198	-.0068	.0034
	(.0286)	(.0379)	(.0446)	(.0384)	(.0530)
Distance	-.0019	-.0039	-.0005	-.0045	-.0043
	(.0019)	(.0028)	(.0028)	(.0027)	(.0039)
Edu	.1081***	.0844**	.0415	.0751*	.0708
	(.0220)	(.0301)	(.0329)	(.0295)	(.0437)
Female	.0019**	.0032***	.0040***	.0002	-.0021
Gender	(.0007)	(.0009)	(.0010)	(.0010)	(.0013)
Hours	.0017*	.0002	.0006	.0025**	.0012
	(.0007)	(.0009)	(.0010)	(.0010)	(.0012)
High-Tech	-.0448	.2006	.1304	-.2713*	-.3935*
	(.0907)	(.1175)	(.1321)	(.1244)	(.1683)
Non-Tech	-.0984	-.0083	-.1701	-.1179	-.0368
	(.0644)	(.0868)	(.0993)	(.0849)	(.1222)
Non-White	.0003	.0042***	.0008	-.0023	-.0010
Race	(.0008)	(.0010)	(.0013)	(.0012)	(.0016)
Organization	.0567	.0006	.0152	.1746***	.2319**
	(.0350)	(.0006)	(.0526)	(.0461)	(.2319)
Constant	-1.176***	-1.7738***	-1.5196***	-1.9250***	-.4722
	(.2184)	(.2961)	(.3300)	(.2944)	(.4351)
N	2184	2177	1510	1647	638
Pseudo R^2	.022	.034	.003	.036	.038
Log likelihood	-1431.1	-711.2	-550.2	-747.8	-393.6

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement; probit coefficients are reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table 12

Confirmation of Hypotheses

Hypothesis		Confirmation	Results
1	*Firms located closer to SBDC's are more likely to select into training.*	Mixed	Closer is always associated with training; the result is not significant using the largest outcome group (duration), it is occasionally significant in the first stage of other outcomes.
2	*Firms with more resources are more likely to select into training.*	Yes	Greater owner education, age, and work hours predict selection into any training.
3	*Firms with more resources are less likely to select into public training.*	Mixed	Incorporated firms select into private over public training. High-tech firms select into public over private training.
4	*Entrepreneurship training supports young firm growth.*	No	Trained firms do not have higher growth rates of employment or profits.
5	*Entrepreneurship training supports young firm access to financing.*	No	Trained firms are no more likely to be approved for new bank loans than untrained firms. SBA trained firms are less likely to be approved and more likely to be deterred.
6	*Entrepreneurship training increases forecasting ability.*	Mixed	Private training is associated with greater forecasting accuracy than public training but performs equally with no training. SBA training is associated with less accuracy than no training.
7	*Public and private training programs perform equally well.*	No	Private training predicts longer firm survival duration than public training.

Notes: Hypothesis 1, 2, and 3 see tables 11 and C1-C6. Hypothesis 4, see tables 5 and 6. Hypothesis 5, see tables 8 and 9. Hypothesis 6, see table 10. Hypothesis 7, see table 4.

Appendix A: Instrumental Variable Approach

A.1 Method

Dependent variables are defined as in Section 4.3:

$$Y_f\ \{duration, \Delta employment, \Delta profit, forecast, apply, approved, deterred\}$$

Training treatments are defined as in Section 4.2:

$$training_{f,t=\{1:5\}}\ \{any, public, public\ only, SBA\}$$

Firm characteristic variables are defined as in Section 4.4:

$$F_f\ \{credit\ risk_{t=6}, technology, organization\}$$

Entrepreneur characteristic variables are defined as in Section 4.4:

$$M_{f,t=5}\ \{\overline{age}, \max(education), \overline{race}\ , \overline{gender}, \sum hours\}$$

Instrumental variable for training is defined in Section 5.1:

$$Z_f\ = distance_{miles}$$

Selection into each training treatment is estimated as a separate regression (first stage). Each outcome is estimated as a separate regression (second stage). I estimate a separate two stages least squares regression for each combination of treatment and outcome.

The first stage (1A) and second stage (2A) equations are given by

$$training_f = \alpha_1 + \beta_1 Z_f +\ \gamma_1 F_f + \delta M_f + \varepsilon_1 \quad (1A)$$

$$Y_f\ = \alpha_2 + \beta_2 training_f + \gamma_2 F_f + \delta M_f + \varepsilon_2 \quad (2A)$$

A.2 First Stage IV Results

Table A1

Distance from SBDC Instrument for Training: First Stage Results

For Survival Duration, Years 5-8, and Growth Rate of Employment, 2008-2011

Outcome:	**Survival Duration**				**Growth Rate of Employment 2008-2011**			
Treatment:	**Any Public**	**Public Only**	**Any Training**	**SBA Training**	**Any Public**	**Public Only**	**Any Training**	**SBA Training**
First Stage:								
Distance	-.0002	-.0001	-.0007	-.0006	-.0010	-.0005	-.0026**	-.0009
	(.0006)	(.0006)	(.0007)	(.0005)	(.0008)	(.0007)	(.0010)	(.0006)
Age	.0008	.0005	.0023	.0002	.0016	.0011	.0033	.0010
	(.0008)	(.0008)	(.0010)	(.0007)	(.0012)	(.0012)	(.0015)	(.0010)
Credit Risk	-.0034	-.0036	-.0056	-.0060	-.0099	-.0107	-.0124	-.0096
	(.0086)	(.0089)	(.0108)	(.0068)	(.0112)	(.0115)	(.0138)	(.0090)
Edu	.0223***	.0080	.0399***	.0144**	.0167	-.0041	.0305	.0179*
	(.0065)	(.0064)	(.0081)	(.0052)	(.0091)	(.0090)	(.0113)	(.0073)
Female	.0010	.0009***	.0007**	.0006***	.0012	.0008	.0006	.0008**
Gender	(.0002)	(.0002)	(.0003)	(.0002)	(.0003)	(.0003)	(.0004)	(.0003)
Hours	.0004	.0001	.0006	.00005	.0004	.0002	.0005	-.0001
	(.0002)	(.0002)	(.0003)	(.0002)	(.0003)	(.0003)	(.0003)	(.0002)
High Tech	.0457	.0277	-.0187	.0354	.0383	.0170	-.0496	.0153
	(.0276)	(.0280)	(.0344)	(.0218)	(.0372)	(.0374)	(.0459)	(.0298)
Non-Tech	-.0326	-.0354	-.0381	-.0045	-.0213	-.0268	-.0155	.0008
	(.0195)	(.0200)	(.0244)	(.0154)	(.0290)	(.0300)	(.0358)	(.0233)
Non-White	.0007**	.0002	.0001	.0009***	.0009**	.0003	.0003	.0012***
Race	(.0003)	(.0003)	(.0003)	(.0002)	(.0003)	(.0004)	(.0004)	(.0003)
Organizatio	.0029	.0014	.0207	-.0015	.0091	-.0040	.0352	.0015
n	(.0105)	(.0105)	(.0132)	(.0083)	(.0149)	(.0149)	(.0184)	(.0120)
Constant	.0115	.0584	.0604	.0266	.0098	.1033	.0917	-.0060
	(.0651)	(.0652)	(.0813)	(.0515)	(.0922)	(.0924)	(.1139)	(.0742)
N	2184	1510	2184	2177	1161	762	1161	1157
F (distance)	0.15	0.04	0.98	1.76	1.59	.53	7.34	2.06

Notes: Dependent variable: *training treatment*. The first stage results vary slightly by the number of respondents in the regression. This table shows the first stage results for the *distance* instrument using the duration and growth rate of employment outcomes. *Distance* is miles from SBDC. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

A.3 Second Stage IV Results

Table A2

Change in Startup Firm Survival Duration given Distance from SBDC Instrument for Training, 2004-2011

Treatment:	**Any Public**		**Public Only**		**Any Training**		**SBA Training**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Training	.7726	3.168	-2.852	-1.462	.4074	.9902	.4770	1.045
	(1.9289)	(10.514)	(11.52)	(15.32)	(.9810)	(2.211)	(1.345)	(2.506)
Age		-.0014		-.0009		-.0012		.0010
		(.0090)		(.0075)		(.0054)		(.0022)
Credit Risk		-.0833		-.1163		-.0886		-.0875***
		(.0496)		(.0612)		(.0264)		(.0268)
Edu		-.0327		.0690		-.0017		.0230
		(.2390)		(.1267)		(.0922)		(.0418)
Female		-.0037		.0003		-.0012		-.0011
Gender		(.0108)		(.0132)		(.0017)		(.0016)
Hours		-.0002		.0009		.0003		.0009
		(.0040)		(.0023)		(.0015)		(.0006)
High Tech		-.2407		.0086		-.0774		-.1323
		(.4931)		(.4337)		(.0860)		(.1142)
Non-Tech		-.0287		-.1278		-.0944		-.1287
		(.3555)		(.5499)		(.1016)		(.0529)
Non-White		-.0018		.0004		.0004		-.0005
Race		(.0079)		(.0030)		(.0008)		(.0025)
Organizatio		-.0261		-.0289		-.0374		-.0155
n		(.0529)		(.0399)		(.0542)		(.0279)
Constant	7.306***	7.560***	7.796***	.8851***	7.295***	7.537***	7.103***	7.565***
	(.3789)	(.2721)	(1.430)	(.8851)	(.3936)	(.2042)	(.1506)	(.1729)
N	2605	2184	1782	1510	2605	2184	2594	2177
F	1.74	0.15	0.13	0.04	4.12	0.98	5.36	1.76
R^2	.9819	.9565	.9676	.9802	.9832	.9803	.9831	.9819

Notes: Dependent variable: *duration*. *Duration* is years of firm survival 5-8. *Training* is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table A3

Change in Young Firm Growth Rate of Employment given Distance from SBDC Instrument for Training, 2008-2011

Treatment:	**Any Public**		**Public Only**		**Any Training**		**SBA Training**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Training	2.293	3.7473	9.625	5.989	1.045	1.410	2.308	4.009
	(5.073)	(7.448)	(37.88)	(19.14)	(2.245)	(2.612)	(5.226)	(7.985)
Age		-.0219		-.0314		-.0204		-.0199
		(.0159)		(.0264)		(.0131)		(.0132)
Credit Risk		-.0072		.0229		-.0269		-.0062
		(.1272)		(.2559)		(.1024)		(.1272)
Edu		.0295		.1487		.0491		.0207
		(.1586)		(.1418)		(.1189)		(.1738)
Female Gender		-.0045		-.0063		-.0010		-.0034
		(.0090)		(.0156)		(.0031)		(.0069)
Hours		-.0012		-.0014		-.0005		.0006
		(.0037)		(.0060)		(.0027)		(.0028)
High Tech		-.0577		.0658		.1559		.0253
		(.4472)		(.6107)		(.3520)		(.3612)
Non-Tech		.1283		.3975		.0704		.0496
		(.3210)		(.6839)		(.2587)		(.2671)
Non-White Race		-.0049		-.0048		-.0020		-.0057
		(.0077)		(.0082)		(.0032)		(.0094)
Organization		-.1317		-.0770		-.1474		-.1009
		(.1555)		(.2214)		(.1596)		(.1382)
Constant	-.3559	.7959	-1.043	.4858	-.3225	.7034	-.1483	.8555
	(1.078)	(.8592)	(4.738)	(2.253)	(.9747)	(.8130)	(6407)	(.8575)
N	1431	1161	928	762	1431	1161	1424	1157
F	2.52	1.59	.16	.53	8.27	7.34	3.62	2.06

Notes: Dependent variable: *growth rate of firm employment,* $\Delta Employment_f = \frac{employees_{2011} - employees_{2008}}{employees_{2008}}$. *Employment* is the firms' number of full-time equivalent employees. *Training* is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses.

Significance is shown as * = .05, ** = .01, *** = .001.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table A4

Change in Young Firm Growth Rate of Profit given Distance from SBDC Instrument for Training, 2008-2011

Treatment:	**Any Public**		**Public Only**		**Any Training**		**SBA Training**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Training	1.900	41.10	2.023	-6.130	.2901	.4668	1.013	1.775
	(7.600)	(2353.8)	(8.750)	(74.87)	(.6570)	(.9363)	(2.518)	(4.602)
Age		-.0777		-.0006		-.0037		-.0042
		(4.306)		(.0341)		(.0029)		(.0050)
Credit Risk		-.0755		-.0464		-.0292		-.0327
		(2.200)		(.1016)		(.0244)		(.0262)
Edu		-.6697		.0058		-.0101		-.0143
		(38.59)		(.0691)		(.0312)		(.0512)
Female Gender		-.0465		.0065		-.0004		-.0010
		(2.663)		(.0751)		(.0009)		(.0027)
Hours		-.0306		.0044		-.0002		-.0003
		(1.766)		(.0462)		(.0010)		(.0015)
High Tech		-.2772		.0559		.0656		.0296
		(17.49)		(.5021)		(.0937)		(.0707)
Non-Tech		.4545		-.0823		.0384		.0020
		(24.96)		(1.702)		(.0535)		(.0625)
Non-White Race		-.0451		.0025		.0003		-.0016
		(2.604)		(.0231)		(.0006)		(.0052)
Organization		.3878		-.0881		-.0244		-.0128
		(23.04)		(.9905)		(.0283)		(.0270)
Constant	-.7667	1.354	-.6256	.2410	-.5072	-.2195	-.4964	-.1037
	(1.519)	(87.34)	(1.042)	(5.143)	(.2727)	(.1579)	(.2730)	(.2358)
N	1416	1223	941	819	1416	1223	1414	1221
F	.10	0	.09	.01	2.72	1.5	.62	.30

Notes: Dependent variable: *growth rate of firm profit*, $\Delta Profit_f = [\ln(profit_{2011}) - \ln(profit_{2008})]$.

Training is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table A5

Change in Startup Firm Forecasting given Distance from SBDC Instrument for Training, 2004-2009

Treatment:	Any Public		Public Only		Any Training		SBA Training	
	I	II	I	II	I	II	I	II
Training	-2.387	-3.160	-9.344	-5.546	-1.283	-1.072	-1.695	-1.208
	(1.949)	(7.713)	(22.54)	(20.62)	(.8021)	(1.458)	(.9541)	(1.409)
Age		.0013		.0029		.0010		-.0013
		(.0072)		(.0119)		(.0037)		(.0013)
Credit Risk		-.0599		-.0670		-.0561***		-.0578***
		(.0362)		(.0771)		(.0176)		(.0152)
Edu		.0605		.0327		.0328		.0066
		(.1768)		(.1743)		(.0613)		(.0238)
Female		.0039		.0054		.0014		.0014
Gender		(.0080)		(.0181)		(.0011)		(.0009)
Hours		.0027		.0024		.0022*		.0016***
		(.0029)		(.0033)		(.0010)		(.0003)
High Tech		.1144		.1280		-.0503		.0133
		(.3645)		(.5932)		(.0581)		(.0655)
Non-Tech		-.1496		-.2372		-.0865		-.0522
		(.2631)		(.7549)		(.0669)		(.0311)
Non-White		.0011		-.0001		-.0012*		-.0002
Race		(.0059)		(.0044)		(.0005)		(.0014)
Organizatio		.0097		.0007		.0220		-.0018
n		(.0447)		(.0711)		(.0376)		(.0163)
Constant	.9340*	.6988***	1.613	.9066	.9801**	.7381	.6531***	.7186***
	(.3829)	(.2150)	(2.790)	(1.060)	(.3218)	(.1315)	(.1066)	(.1002)
N	2600	2181	1778	1507	2600	2181	2590	2174
F	1.86	.19	.17	.08	4.22	1.04	5.65	1.92

Notes: The dependent variable is *forecast: below or meeting expectations. Forecast* is based on the KFS question *"How much do you think [NAME BUSINESS] met your expectations for growth between when the business was started and December 31, 2008?" Training* is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table A6

Change in Young Firm Bank Loan Applications given Distance from SBDC Instrument for Training, 2008-2011

Treatment:	**Any Public**		**Public Only**		**Any Training**		**SBA Training**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Training	-.3717	.8881	-4.310	-2.064	-.1960	.2776	-.2574	.3090
	(.8057)	(3.288)	(12.55)	(10.96)	(.4078)	(.8039)	(.5480)	(.9364)
Age		-.0018		-.0011		-.0017		-.0011
		(.0028)		(.0054)		(.0020)		(.0008)
Credit Risk		-.0215		-.0276		-.0230*		-.0225*
		(.0155)		(.0437)		(.0096)		(.0100)
Edu		-.0151		.0135		-.0064		.0007*
		(.0747)		(.0906)		(.0335)		(.0156)
Female Gender		-.0014		.0013		-.0007		-.0007
		(.0034)		(.0094)		(.0006)		(.0006)
Hours		.0017		.0021		.0018***		.0020***
		(.0012)		(.0017)		(.0005)		(.0002)
High Tech		.0285		.1218		.0743*		.0585
		(.1542)		(.3101)		(.0313)		(.0427)
Non-Tech		.0545		-.0665		.0361		.0275
		(.1112)		(.3931)		(.0369)		(.0198)
Non-White Race		-.0008		.0002		-.0002		-.0004
		(.0025)		(.0022)		(.0003)		(.0009)
Organization		.0243		.0253		.0211		.0273**
		(.0165)		(.0285)		(.0197)		(.0104)
Constant	.2553	.1127	.6934	.3119	.2609	.1061	.2109***	.1078
	(.1583)	(.0851)	(1.557)	(.6328)	(.1636)	(.0743)	(.0613)	(.0646)
N	2605	2184	1782	1510	2605	2184	2594	2177
F	1.74	.15	.13	.04	4.12	.98	5.36	1.76

Notes: Dependent variable: *apply*, the firm applied for a new bank loan. *Training* is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table A7

Change in Young Firm Bank Loan Approvals given Distance from SBDC Instrument for Training, 2008-2011

Treatment:	**Any Public**		**Public Only**		**Any Training**		**SBA Training**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Training	-.7114	-.8963	-2.797	-2.043	-.6983	-.7844	-.8112	-.9880
	(.3995)	(.5901)	(3.715)	(2.516)	(.4315)	(.5481)	(.4340)	(.6143)
Age		.0065*		.0035		.0096*		.0046
		(.0032)		(.0055)		(.0048)		(.0027)
Credit Risk		-.0370		-.0276		-.0313		-.0441
		(.0253)		(.0479)		(.0261)		(.0249)
Edu		.0360		.0292		.0500		.0359
		(.0326)		(.0569)		(.0427)		(.0313)
Female Gender		.0003		.0003		.0001		.000006
		(.0010)		(.0028)		(.0010)		(.0008)
Hours		.0011		.0033		.0007		.0005
		(.0008)		(.0035)		(.0007)		(.0005)
High Tech		.0313		.0219		-.0477		.0034
		(.0853)		(.1507)		(.0876)		.0753
Non-Tech		-.0310		-.0580		-.0402		-.0023
		(.0645)		(.1417)		(.0677)		(.0648)
Non-White Race		-.0001		-.0011		-.0013		.0003
		(.0013)		(.0021)		(.0009)		(.0014)
Organization		.0144		-.0707		.0357		.0298
		(.0356)		(.1219)		(.0397)		(.0337)
Constant	.9845***	.5285*	1.174*	.7764*	1.144***	.4892	.9225***	.5704**
	(.3995)	(.2315)	(.5026)	(.3847)	(.2104)	(.2596)	(.0650)	(.2129)
N	475	397	283	232	475	397	473	396
F	7.88	4.35	.66	.83	6.13	4.08	9.20	5.40

Notes: Dependent variable: *approved*. Bank loan approvals are conditional on application. *Training* is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education*, *Gender*, *Hours*, and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table A8

Change in Deterred Loan Applications given Distance from SBDC Instrument for Training, 2008-2011

Treatment:	**Any Public**		**Public Only**		**Any Training**		**SBA Training**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Training	2.021	-26.312	10.15	-40.03	.9695	2.402	1.255	2.137
	(1.949)	(320.51)	(35.78)	(618.49)	(.6633)	(3.528)	(.7444)	(1.856)
Age		.0148		.0026		-.0063		-.0009
		(.1970)		(.0640)		(.0078)		(.0017)
Credit Risk		-.0023		.0006		.0502		.0533*
		(.5787)		(.7523)		(.0324)		(.0210)
Edu		.6565		.4746		-.1178		-.0573
		(8.240)		(7.741)		(.1456)		(.0354)
Female		.0257		.0319		-.0022		-.0014
Gender		(.3167)		(.4992)		(.0028)		(.0010)
Hours		.0124		.0105		-.00003		.0013**
		(.1315)		(.1369)		(.0025)		(.0005)
High-Tech		1.003		1.084		.1327		-.0090
		(11.59)		(16.124)		(.1480)		(.0788)
Non-Tech		-.7679		-1.469		.1805		.0572
		(9.947)		(23.40)		.2057		(.0406)
Non-White		.0217		.0089		.0013		-.0003
Race		(.2441)		(.1109)		(.0010)		(.0018)
Organizatio		-.0004		-.1196		-.0519		-.0012
n		(.2904)		(1.807)		(.0115)		(.0216)
Constant	-.1258	.0922	-.9978	2.281	-.1241	.0278	.1311	.1286
	(2.021)	(1.991)	(4.405)	(32.84)	(.2674)	(.2949)	(.0810)	(.1359)
N	2325	1950	1584	1314	2325	1950	2314	1943
F	1.36	.01	.08	0	3.85	.51	6.18	1.81

Notes: The dependent variable is *deterred firm*. Deterred bank loan applications are from firms that *"needed credit, but did not apply because you thought the application would be denied?" Training* is the distance from SBDC in miles as an instrumental variable for training treatment. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Appendix B: Propensity Score Matching, Supplemental Results

Table B1

Training Treatment Effects on Growth Rate of Employment at Young Firms

2008-2009, Firm Year 6

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training	670	492	-.0823	.108	1.12	0
SBA Training	1022	135	-.1110	.235	.85	0
Public Training Only	670	92	.1383	.229	.83	0
Private Training Only	682	183	-.0082	.148	.09	0
Private v Public	105	183	.0134	.143	.11	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .05, ** = .01, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. 4. Dependent variable: $\Delta Employment_f = \frac{employees_{2009} - employees_{2008}}{employees_{2008}}$) 5. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table B2

Training Treatment Effects on Growth Rate of Profit at Young Firms

2008-2009, Firm Year 6

Treatment	Untreated	Treated	ATT[1]	SE[2]	T-stat ATT	Unbalanced[3]
Any Training[4]	725	498	-.0686*	.012	1.87	0
SBA Training	1102	119	-.0926	.085	1.45	0
Public Training Only	725	94	-.0599	.088	.87	0
Private Training Only	737	184	.0071	.081	.13	0
Private v Public	108	205	.0491	.0758	.70	0

Notes: 1.ATT is the average treatment effect on the treated. 2. Standard errors are bootstrapped. Significance is shown as * = .10, ** = .05, two tailed. 3. Unbalanced shows the number of covariates with significantly different means after matching. 4. Female gender, more education, and more owner work hours predicted selection into any training. 5. Dependent variable: $\Delta Profit_f = [\ln(profit_{2009}) - \ln(profit_{2008})]$.

6. Model: second stage, propensity score matched firms, probit selection.

Source: Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Appendix C: Selection into Training for Smaller Outcome Groups

Table C1

First Stage Results: Selection into Training Treatment, For: Growth Rate of Employment 2008-2011

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0086*	.0056	.0057	.0088	.0030
	(.0039)	(.0051)	(.0062)	(.0051)	(.0075)
Credit Risk	-.0324	-.0496	-.0542	-.0184	.0034
	(.0359)	(.0473)	(.0583)	(.0479)	(.0669)
Distance	-.0071**	-.0055	-.0026	-.0090*	-.0062
	(.0026)	(.0038)	(.0038)	(.0036)	(.0053)
Edu	.0802**	.0988*	-.0204	.0466	.1147*
	(.0297)	(.0403)	(.0456)	(.0389)	(.0582)
Female	.0016	.0037**	.0037*	-.0013	-.0023
Gender	(.0010)	(.0012)	(.0015)	(.0014)	(.0018)
Hours	.0013	-.0008	.0010	.0010	-.0008
	(.0009)	(.0013)	(.0013)	(.0013)	(.0015)
High-Tech	-.1267	.0875	.0859	-.3524*	-.4157
	(.1196)	(.1567)	(.1820)	(.1624)	(.2293)
Non-Tech	-.0393	.0271	-.1293	-.0116	-.0475
	(.0931)	(.1220)	(.1501)	(.1205)	(.1778)
Non-White	.0008	.0046***	.0015	-.0029	-.0017
Race	(.0011)	(.0013)	(.0017)	(.0017)	(.0021)
Organization	.0939	.0206	-.0122	.1940**	.2707**
	(.0483)	(.0641)	(.0751)	(.0629)	(.0931)
Constant	-1.0666***	-1.9174***	-1.2772**	-1.6170***	-.3741
	(.2999)	(.4028)	(.4665)	(.3956)	(.5861)
N	1161	1157	762	864	367
Pseudo R^2	.024	.044	.019	.038	.047
Log likelihood	-772.2	-398.4	-275.3	-428.1	-209.4

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement; probit coefficients reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table C2

First Stage Results: Selection into Training Treatment,

For Outcome: Growth Rate of Profit 2008-2011

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0071	.0067	.0027	.0061	.0071
	(.0037)	(.0051)	(.0059)	(.0049)	(.0074)
Credit Risk	-.0534	-.0153	.0014	-.0546	-.0301
	(.0389)	(.0517)	(.0604)	(.0523)	(.0738)
Distance	-.0030	-.0015	.0004	-.0089*	-.0098
	(.0025)	(.0036)	(.0037)	(.0037)	(.0053)
Edu	.0758**	.0632	-.0062	.0463	.1262*
	(.0296)	(.0412)	(.0451)	(.0392)	(.0588)
Female	.0022	.0033*	.0049***	.0011	-.0022
Gender	(.0009)	(.0012)	(.0014)	(.0013)	(.0017)
Hours	.0028**	.0016	.0026*	.0033**	-.0007
	(.0009)	(.0011)	(.0013)	(.0013)	(.0015)
High-Tech	-.2093	-.0036	.0357	-.3311*	-.2558
	(.1222)	(.1715)	(.1890)	(.1594)	(.2361)
Non-Tech	-.1047	.0606	-.1101	-.1672	-.0407
	(.0842)	(.1162)	(.1371)	(.1090)	(.1630)
Non-White	.0003	.0052***	.0016	-.0031	-.0019
Race	(.0013)	(.0015)	(.0019)	(.0019)	(.0024)
Organization	.0558	.0009	-.0588	.1698**	.2653**
	(.0464)	(.0637)	(.0726)	(.0605)	(.0929)
Constant	-.9870***	-2.1552***	-1.4584***	-1.4791***	-.4980
	(.2897)	(.4061)	(.4589)	(.3808)	(.5877)
N	1223	1221	819	921	373
Pseudo R^2	.026	.035	.030	.044	.054
Log likelihood	-804.9	-376.3	-283.1	-440.2	-212.3

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement; probit coefficients reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table C3

First Stage Results: Selection into Training Treatment,

For Outcome: New Bank Loan Applications

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0060*	.0016	.0024	.0079*	.0047
	(.0027)	(.0037)	(.0042)	(.0037)	(.0054)
Credit Risk	-.0154	-.0322	-.0198	-.0069	.0034
	(.0286)	(.0379)	(.0446)	(.0384)	(.0530)
Distance	-.0019	-.0039	-.0005	-.0045	-.0043
	(.0019)	(.0028)	(.0028)	(.0027)	(.0039)
Edu	.1081***	.0844**	.0415	.0751*	.0708
	(.0220)	(.0301)	(.0329)	(.0295)	(.0437)
Female	.0019**	.0032***	.0040***	.0002	-.0021
Gender	(.0007)	(.0009)	(.0010)	(.0010)	(.0013)
Hours	.0017*	.0002	.0006	.0025*	.0012
	(.0007)	(.0009)	(.0010)	(.0010)	(.0012)
High-Tech	-.0448	.2006	.1305	-.2713*	-.3935*
	(.0907)	(.1175)	(.1321)	(.1244)	(.1683)
Non-Tech	-.0984	-.0082	-.1700	-.1179	-.0368
	(.0644)	(.0868)	(.0993)	(.0849)	(.1222)
Non-White	.0003	.0043***	.0009	-.0023	-.0010
Race	(.0008)	(.0010)	(.0013)	(.0012)	(.0016)
Organization	.0568	.0006	.0152	.1746***	.2319***
	(.0350)	(.0474)	(.0526)	(.0461)	(.0692)
Constant	-1.1762***	-1.7747***	-1.5200***	-1.9249***	-.4722
	(.2184)	(.2961)	(.3301)	(.2945)	(.4351)
N	2184	2177	1510	1647	638
Pseudo R^2	.022	.034	.024	.036	.038
Log likelihood	-1431.7	-711.2	-550.1	-747.8	-393.6

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement, probit coefficients reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table C4

First Stage Results: Selection into Training Treatment, For Outcome: New Bank Loan Approvals

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0195**	.0038	.0013	.0182	-.0021
	(.0074)	(.0096)	(.0136)	(.0098)	(.0161)
Credit Risk	-.0112	-.0838	-.0229	-.0951	-.0448
	(.0617)	(.0809)	(.1120)	(.0852)	(.1126)
Distance	-.0098*	-.0220*	-.0062	-.0093	-.0072
	(.0048)	(.0090)	(.0083)	(.0063)	(.0112)
Edu	.1645**	.2065**	.1093	.1396*	.1123
	(.0521)	(.0758)	(.0911)	(.0691)	(.1111)
Female	.0029	.0033	.0049	.0007	-.0033
Gender	(.0019)	(.0023)	(.0032)	(.0026)	(.0034)
Hours	.0020	.0014	.0052*	.0003	-.0041
	(.0014)	(.0015)	(.0021)	(.0023)	(.0022)
High-Tech	-.1101	.1347	.0740	-.3333	-.2629
	(.2009)	(.2741)	(.3325)	(.2604)	(.3981)
Non-Tech	.0283	.2635	-.1276	-.0483	-.0265
	(.1619)	(.2152)	(.2871)	(.2120)	(.3120)
Non-White	.0006	.0069**	.0015	-.0065	-.0001
Race	(.0021)	(.0023)	(.0036)	(.0036)	(.0038)
Organization	.0548	.0396	-.2422	.0798	.2978
	(.0908)	(.1222)	(.1600)	(.1202)	(.1822)
Constant	-1.8881***	-2.3475***	-1.5382	-1.8873*	.3128
	(.5429)	(.7161)	(.9060)	(.7670)	(1.1264)
N	397	396	232	275	138
Pseudo R^2	.058	.116	.088	.060	.066
Log likelihood	-259.2	-139.5	-78.0	-143.6	-70.9

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement; probit coefficients reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table C5

First Stage Results: Selection into Training Treatment,

For Outcome: Deterred Bank Loan Applications

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0057	-.0005	.0006	.0070	.0063
	(.0029)	(.0040)	(.0045)	(.0039)	(.0057)
Credit Risk	-.0113	-.0340	-.0072	-.0072	.0168
	(.0310)	(.0412)	(.0484)	(.0412)	(.0582)
Distance	-.0014	-.0043	.0004	-.0052	-.0053
	(.0021)	(.0031)	(.0031)	(.0029)	(.0042)
Edu	.1083***	.1020**	.0678	.0636*	.0353
	(.0234)	(.0327)	(.0358)	(.0309)	(.0466)
Female	.0021**	.0027**	.0038***	.0007	-.0018
Gender	(.0007)	(.0010)	(.0011)	(.0010)	(.0013)
Hours	.0018*	.0006	.0009	.0025*	.0009
	(.0008)	(.0010)	(.0011)	(.0010)	(.0013)
High-Tech	-.0804	.1829	.1303	-.2833*	-.3970*
	(.0962)	(.1267)	(.1417)	(.1292)	(.1787)
Non-Tech	-.1418*	.0021	-.1786	-.1787*	-.0799
	(.0676)	(.0921)	(.1054)	(.0883)	(.1278)
Non-White	.0003	.0041***	.0008	-.0020	-.0008
Race	(.0009)	(.0011)	(.0013)	(.0013)	(.0017)
Organization	.0565	.0072	-.0047	.1662***	.2384***
	(.0370)	(.0506)	(.0563)	(.0483)	(.0730)
Constant	-1.1611***	-1.7864***	.3556***	-1.7647***	-.3706
	(.2327)	(.3190)	(.3556)	(.3097)	(.4691)
N	1950	1943	1341	1476	574
Pseudo R^2	.024	.035	.025	.034	.034
Log likelihood	-1277.3	-617.6	-479.7	-682.5	-350.8

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement; probit coefficients reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

Table C6

First Stage Results: Selection into Training Treatment,

For Outcome: Forecasting Ability 2004-2009

Treatment:	**Any Training**	**SBA Training**	**Public Only**	**Private Only**	**Private Only**
Control:	**No Training**	**No Training**	**No Training**	**No Training**	**Public Only**
Matching:					
Age	.0063	.0020	.0028	.0081*	.0044
	(.0027)	(.0037)	(.0042)	(.0037)	(.0054)
Credit Risk	-.0141	-.0296	-.0163	-.0064	.0009
	(.0287)	(.0380)	(.0446)	(.0384)	(.0531)
Distance	-.0019	-.0041	-.0007	-.0045	-.0041
	(.0019)	(.0028)	(.0029)	(.0027)	(.0039)
Edu	.1088	.0851	.0419	.0759*	.0707
	(.0220)	(.0301)	(.0330)	(.0295)	(.0437)
Female	.0019	.0033	.0041	.0002	-.0022
Gender	(.0007)	(.0009)	(.0010)	(.0010)	(.0012)
Hours	.0017	.0002	.0006	.0026*	.0012
	(.0007)	(.0009)	(.0010)	(.0010)	(.0012)
High-Tech	-.0447	.2016	.1313	-.2716*	-.3949*
	(.0907)	(.1175)	(.1322)	(.1244)	(.1683)
Non-Tech	-.0968	-.0103	-.1730	-.1150	-.0324
	(.0645)	(.0869)	(.0995)	(.0850)	(.1223)
Non-White	.0003	.0043	.0009	-.0023	-.0010
Race	(.0008)	(.0010)	(.0013)	(.0013)	(.0015)
Organization	.0599	.0029	.0180	.1778***	.2310***
	(.0351)	(.0475)	(.0527)	(.0462)	(.0692)
Constant	-1.2022	-1.8083	-1.5601***	-1.9467***	-.4474
	(.2159)	(.2973)	(.3317)	(.2953)	(.4455)
N	1281	2174	1507	1645	637
Pseudo R^2	.023	.036	.025	.036	.378
Log likelihood	-1429.1	-708.0	-547.2	-747.0	-392.6

Notes: Dependent variable: *training treatment*. Model: probit nearest neighbor propensity score matching with replacement; probit coefficients reported. First stage results vary with the number of respondents. *Age* is the average age of the ownership team in years. *Credit Risk* is a five-point ascending scale of risk. *Distance* is the distance from SBDC in miles as an instrumental variable for training treatment. *Education, Gender, Hours,* and *Race* are averages of the ownership team. *Education* is a six-point ordinal ascending scale. *Hours* is the owners' hours worked in the business per week. *High-Tech* and *Non-Tech* are categorical with *Medium-Tech* as the base state. *Organization* is a four-point ascending scale of complexity. Standard errors are shown in parentheses. Significance is shown as * = .05, ** = .01, *** = .001. ***Source:*** Kauffman Firm Survey full panel [NORC data set], 2004-2011.

The Art Market as Keynes' Beauty Contest with a $10,000 Prize

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Abstract:

To increase primary market sales, do artists alter the content of their work to follow trends? Our survey of U.S. visual fine artists finds that about half do. We compare these artists across demographic, market experience, and motivational measures, to construct a behavioral profile. We also compare trend following behavior indicated by stated and revealed preferences. In Keynes' beauty contest game, when quality is subjective, the winner successfully anticipates the average preference of a group of players, who are also each predicting the average preference. Do arts markets reward this type of behavior? We find they do, with a $10,000 average income premium for professional artists who design content for collectability. This premium holds across four marketplace types. This premium suggests trend appropriation as a dominant strategy across demographic groups. However, appropriation as a dominant strategy suggests an externality to artists who reject this behavior—yet still have their work appropriated—and a disincentive to innovation.

Keywords: Arts Assets, Beauty Contest, Myopia, Level K Reasoning, Content Convergence, NFT

JEL Codes: Z11, D90, L26, B54, D83, G41

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1. Introduction

Artists face a dual role as creators and entrepreneurs. While artworks may be inspired, to make a living, an artist must connect with an audience, signal value, and build a reputation. Over time, arts marketplaces are becoming more open, giving artists more available strategies and more competition. This led us to the research question: Which strategies are effective for artists attempting to signal value?

In American culture, we have several archetypes of The Artist: romantics like Ansel Adams who capture moments of beauty, destructive loners like Jackson Pollack who live to express themselves, storytellers like Diego Rivera who document our collective struggles and aspirations, and fashion leaders like Andy Warhol who set trends. We like to think that artists express unique visions. While postmodern artists use pop-culture references for social commentary, we do not think of The Artist as a follower, appropriator, or cynic. The idea that many artists design the content of their work to appeal to group preferences in the marketplace may challenge our ideal of The Artist. However, history shows that under traditional market structures, artists either acted as court and church politicians, or were beholden to a guild (Becker, 1982).

While American artists today have more freedom of content than ever before, to make a living selling art, they must appeal to buyers and join a marketplace. Keynes (1936) uses the analogy of a “beauty contest” game to describe a dominant strategy for asset trading. Namely, choosing the asset that represents the average most attractive option to a group of investors—who are all trying to anticipate the average preference of the group. This strategy is seen in fads, asset bubbles, and following trends

(Bikhchandani et al. 1992). In our study, we call artist's use of Keynes' strategy "contest behavior."

By considering artists in relation to their marketplace, we find that many types of artists have an incentive to use contest behavior. Emerging artists need to signal value to build a reputation and price level, without history. By incorporating trends in her work, a newcomer can bring a recognizable element to buyers. This gives buyers confidence that the work is serious, timely, and likely to increase in value. For mid-career artists, appealing to group preferences can be an efficient path-of-least-resistance to minimize effort and maximize output. An artist who has established a reputation, price level, and audience may find that inspiration does not come on a schedule. This artist can satisfy his audience by following trends to produce a steady output of work. Late-career artists whose early work was fueled by emotional turmoil may look for new sources of content as their lives become more stable. A late-career artist may be motivated to incorporate trends (especially if he has done so throughout his career) if he fears becoming irrelevant or is inspired by a new generation of artists.

Professional and established artists see the same benefits from trend appropriation as mid-career artists, with one important consideration. Top-tier artists can create barriers to lower-tier artists by appropriating themes from their works. Once an artist is well known, she has the reputation to act as a fashion leader. However, she faces the same challenges as mid-career artists: deadlines, discontinuous creativity, and fickle fans. If an established artist appropriates from lesser-known artists, then she can present new work with minimal creative effort. This forces the lesser-known artists to innovate again or be seen as followers, creating a barrier to top-tier entry for lower-tier artists—who must be recognized before their work appears derivative of higher reputation artists. These costs and benefits create disincentives to innovation and creativity, and incentives to appropriation and contest behavior, at all levels. If a mid-tier artist realizes that others will appropriate his style, forcing him into an accelerating cycle of innovation and appropriation, then he will also realize there is an incentive for him to follow trends and innovate less. If contest behavior is widespread, it may indicate a vicious cycle of disincentives to innovation leading towards content convergence.

Independent dealers represent a large share of primary-market fine-arts buyers and secondary-market sellers, conducting approximately 53% of global sales by value (McAndrew, 2014). In The European Fine Arts Foundation's (TEFAF) 2013 Global Art Dealer Survey, dealers reported challenges accessing new supply in the face of converging buyer preferences (McAndrew, 2014). We offer beauty contest behavior by artists as an explanation for these professional traders' perceived lack of variety. In the year following the TEFAF dealer survey, we survey primary market sellers (artists) about their use of content trends to appeal to buyers. Our survey takes place directly before the emergence of non-fungible token (NFT) markets changed incentives for artists in the secondary market. We observe a baseline level of secondary market awareness without resale royalty rights.

Keynes (1936) theorized that the beauty contest describes behavior in asset markets where the "prospective yield of an asset [is] based [on] existing facts, and future events, [including] the tastes of the consumer" (p.63). He observed the behavior by traders on the New York and London stock exchanges (p.68). Later, Shiller (2015) and others applied the theory to financial markets where it contributes to the formation of bubbles as strategic trader demand converges on one asset. We question if Keynes observed the dominant strategy for trading assets, or the behavior of financial asset traders. Artworks resist the securitization that has become common in financial marketplaces. So, our study tests the robustness of Keynes' theory in a counterpoint asset market. We find, as a group, artists are motivationally and demographically different from Wall Street traders (Green et al. 2009). Yet, both sell assets under the condition of uncertainty of future buyers' tastes. This study asks if artists behave like traders and if the art market rewards this behavior. To the best of our knowledge, we are the first to investigate this question.

Failures of hedonic models, especially over the short-term (Ashenfelter, 2008; Fair, 2012; Vecco and Zanola, 2017) suggest a behavioral solution to art pricing that has been overlooked. Our contribution is showing that the artist's level of strategy is important to their price level. Additionally, we show that a low level of strategy, an attempt to anticipate group trends, is a high enough level to show an economically significant income premium over artists who are not responding to trends. Nagel (1995) denotes this level of strategy k-2, after k-0 being the lowest level of strategy. Our finding is important, because it shows improvement can be made in pricing models without gauging the artists' exact level of market awareness. As in Keynes' game, awareness and anticipation that secondary market participants are also strategic is enough to realize a difference in asset prices. We are able to observe a premium from k-2 behavior outside of a controlled lab in a broadly defined arts asset market.

The remainder of the paper is organized as follows. Section 2 applies the beauty contest analogy to fine arts markets and introduces survey questions we use to reveal contest behavior in artists. Section 3 presents three hypotheses on the prevalence, pay-offs, and profiles of contest behavior users. Section 4 describes the survey and statistical methods. Section 5 provides results. Section 6 discusses implications for arts markets, Keynes' theory, and financial markets, and Section 7 concludes the analysis.

2. Theory and questions

2.1 Arts as assets

While artworks are purchased for enjoyment, they are also traded as speculative investments (Srivastava and Satchell, 2012). In this study we assume artworks are assets (Pownall, 2005). Artworks are stores of value that can produce cash flows for their owners. Collectors can insure, collateralize, and rent out their collections (Pownall and Weihenkamp, 2009). Even when owners do not realize cash flows from artworks during the holding period, artworks are durable goods (like antiques or gold) that are known to appreciate over time, acting as a store of value. Mei and Moses (2002) have constructed a 100-year index that compares returns from investing in art to other assets, finding that artworks have hedging value in a portfolio. Like a zero-coupon bond, investors forego cash flows to hold a stable store of value with negative correlation to stock markets. During the 2008 Global Financial Crisis the prevalence of art backed lending increased (Pownall and Weihenkamp, 2009). Investment in art means that artists attempting to signal value must signal value over time (Stiglitz, 2002). However, art values are a product of social agreement—based in the tastes of a time and place (Mirowski, 1991). Assuming that visual fine artworks are assets, we ask if Keynes' beauty contest game is applicable to asset markets and asset traders beyond the stock market.

2.2 Literature review

There is a literature using hedonic models to predict secondary market prices for individual collectables without a history of repeat sales from their characteristics. Ashenfelter (2008) first uses this method to predict long term prices for aged wine before it is tasted from the weather during the growing season, but not the predictions of critics. However, this model fails to predict short and intermediate term prices in the secondary market before the wine is ready for consumption. This led to many refinements of the hedonic type models including the role of sunshine, influencing collector mood, on auction days (De Silva et al. 2012), the role of authentication and provenance of works (Ginsburgh et al. 2019), and the reputation of sellers in the marketplace (Lennon, and Shohfi, 2021), as well as methods for weighting the models (Vecco, and Zanola, 2017). These models lack the characteristic of awareness described in Keynes' game.

Hedonic models repeatedly fail to predict primary and secondary market prices over a near-term time horizon for arts and collectables (Ashenfelter, 2008; Fair, 2012; Vecco, and Zanola, 2017). In these markets, primary and secondary market prices are largely decoupled (Etro and Stepanova, 2021). This leads to a need to segment the market into short- and long-term sales (Ashenfelter, 2008). Segmentation depends on discerning the varied motivations of collectors who may have social signaling consumption, asset trade, or long-term ownership enjoyment motivations (Burton, and Jacobsen, 1999). Buyers with varied motivations will receive varied utility from the cultural and economic value of art works (Mandel, 2009). We take this literature one step further by considering sellers' beliefs about the motivations of buyers.

Keynes' (1936) *General Theory* describes a strategy for trading assets whose value is, in part, a function of the "tastes of the consumer." He illustrates this strategy with a game called "The Beauty Contest." The players evaluate pictures of women to choose the most beautiful. The winner is the player who chooses the most common choice of all the players (the average of the group). In asset trading, buying the average preference of the group would result in holding the asset with the highest liquidity.

Keynes (1936) describes three degrees of strategy for playing the beauty contest game, which we apply to arts markets. The naïve, first-degree strategy (called k-0 in Nagel, 1995) is picking the photo you find most appealing. For an artist, this is analogous to painting from inspiration without regard for the buyers' tastes. The second-degree strategy, k-1, is picking the photo that you believe the average player would find most appealing. With this strategy the player assumes that the other players are using the naïve strategy. This can be seen as an artist using standard cultural (group specific) conventions of beauty to paint what she believes will resonate with the average buyer. Keynes hypothesized that to win the beauty contest, a player must use third-degree strategy, k-2, to pick the photo that reflects the average preference of the group, with the understanding that the other players are also attempting to anticipate the average preference of the group. An artist can use third-degree strategy by following current trends to paint what he believes dealers believe today's average collector wants. We observe which artists use this strategy with a survey of direct and revealed preference indicators.

2.3 Theory

Since Keynes' time, the beauty contest game has inspired much theoretical systemization, elaboration, and experimentation. We observe the game in a real-world idiosyncratic asset market. Nagel (1995) brings form to the game by conceptualizing it as ascending levels of awareness, starting from level k-0. These players are myopic. Level k-0 includes the naïve players described by Keynes, who do not use theory of mind in neuroeconomic experiments (Coricelli and Nagel, 2009). It also includes players who find the use of the strategy too costly (Stahl and Wilson, 1994). This can be seen in initially zero-priced art entering the marketplace, which has become more common as digital media use increases (Day, 2022). We study this behavior by comparing the income distributions for professional artists to artists with other primary sources of income. Level k-1 still lacks insight about the buyer (Coricelli and Nagel, 2009); the artist has awareness of them-self in the marketplace but assumes all collectors are myopic and do not purchase for resale or signaling value. At level k-2, Keynes' highest level, all collectors are assumed to be strategic, returning buyers and sellers to symmetric levels of awareness. We test this level of awareness because we do not illicit beliefs from sellers about the proportion of strategic buyers in the marketplace. It is not necessary to know if all buyers are strategic to observe that a premium can by realized from engaging with strategic buyers.

K-levels represent a set of expectations artists and primary sellers have about collectors. When an artist is operating at a higher k level, they are considering a larger set of collector types. Keynes' game is binary, strategic or not. Similarly, our survey questions identify strategic behavior at the lowest strategic k-level. Keyne's game is about awareness or myopia at the extensive margin. Nagel (1995) calls this the guessing game because the player is guessing if the other players will be myopic or not. Higher k-level games represent processes of information exposure, learning, and refinement of expectations. These have been studied in controlled laboratory experiments at different k-levels. Our analysis asks if there is a premium for a basic level of strategic awareness over myopathy. Higher k-level models can also be applied to arts markets. Since we measure at the extensive margin, we do not know if there would be increasing or decreasing marginal returns to recognizing more levels of strategy. Applying higher levels to arts asset markets is theoretical, though some survey questions could inform higher levels of awareness[11]

In the arts market as a beauty contest, the first-degree artist creates solely from inspiration. The second-degree artist has an awareness of buyers with unique tastes. At the third-degree, k-2, the artist has an awareness of art as a traded investment and social

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[11] Level k-3 recognizes gains from awareness of and forming expectations around the proportions of player types (Nagel, 1995). Buyer segmentation fills the need presented by hedonic models to understand the proportion of short- and long-term buyers in the marketplace (Ashenfelter, 2008). This leads to theoretical k-level models for guessing the average price, based on the proportions of types of players and their guesses (Nagel, 1995). We analyze several survey questions that point at higher possible levels of awareness. Our study empirically estimates proportions of seller types and their price differences. Higher levels of awareness can be conceptualized stepwise or as continuous processes of refinement. Learning can enter the model in a (level k-4 type) dynamic model where players refine their expectations over time through marketplace participation (Camerer et al. 2004). We investigate level k-4 by comparing strategic premiums for established artists to newcomers.

Level k-5 awareness splits players between engaging in k-3 anticipatory strategy and using less costly heuristics, such as the Pantone color(s) of the year, to play strategically (Allred et al. 2016). At level k-6 highly aware players will recognize uncertainty about their expectations and adopt bounded rationality, adding randomness and error to models (Friedenberg et al. 2015). Higher level models can recognize more player types with varied reference points for making, selling, and buying art (Costa-Gomes, Crawford, and Broseta, 2003). We ask respondents to rank six motivations for selling art. A high-level model will question which player types to include, as in the study by Vasan et al. (2022) on the importance of artist's counts of Twitter followers, previous collectors, and Foundation NFT platform connections to primary market prices.

signaling good. The third-degree strategy, which we call "contest behavior," is a response to the presence of the secondary market and collectors' desire for admiration within their peer group. This paper presents a survey of artists' demographics, behaviors, marketplace experiences, and motivations to test the application of the beauty contest game to characteristic groups of artists and arts asset markets.

2.4 Questions

We directly identify artists using contest behavior with a question that describes contest behavior without describing the beauty contest game: "Do you ever incorporate colors, forms, or themes in your work based on their collectability?" Keynes makes an analogy from a game to the stock market. To extend this analogy to the art market, this question offers a concrete example of our analogy. Lindhjem and Navrud (2011) have found that internet survey participants, given time to contemplate an actual marketplace, respond honestly and accurately to direct behavioral questions. To provide a more robust analysis, we follow up this question with three revealed preference indicators.

We compare results from the direct and revealed preference indicators to check the consistency of our constructed behavioral variable. The first revealed preference indicator, purchasing art as an investment in the past year, shows consideration of secondary market value. The next two indicators are based on artists' stated motivations for collaboration in the past year. These include "collaboration to create a collectable product," and "collaboration to associate myself with a group of artists." Collectability and group association imply that the artist is actively trying to appeal to the average preference of a group that is aware of its ability to construct value through social agreement.

3. Hypotheses

Myopia, awareness and strategy have been long overlooked in empirical models of arts markets. We hypothesize that contest behavior will be associated with higher incomes at the k-2 level of strategy. This is analogous to Keynes' beauty contest game, which Nagel (2017) calls the guessing game, because sellers only need to guess if they are creating for buyers who are myopic or strategic. This is the lowest level of awareness that allows for both strategic buyers and sellers. The seller only needs to recognize that some or all buyers are trend seeking to target them. It is not necessary for the seller to differentiate between resale and signaling motivations for trend seeking buyers. This allows our framework to be applicable to emerging NFT marketplaces which increase the signaling value of collections and primary market purchases by incorporating provenance, display, and social media features.

This study tests three hypotheses, following from Keynes' theory that third-degree strategy is the dominant behavior for trading assets under uncertainty when their value is a function of social taste. If contest behavior is the dominant behavior pattern in these markets, we expect the behavior to be exhibited by a large proportion of sellers. Those using the dominant strategy in the market should receive a premium, while missing out on the premium is a cost of myopia. If the premium is observable, then we expect all types of artists to adopt the behavior, regardless of characteristics.

We use a logistic regression on third-degree strategy from artist characteristics, to test a counterfactual hypothesis that Keynes was describing the characteristic behavior of the asset traders he observed, and not the dominant strategic behavior for asset markets. Together, these hypotheses inform our research question: is Keynes' game applicable beyond the stock market to asset markets or asset traders.

3.1 Prevalence

Since there are incentives for contest behavior, discussed in Section 1, in every tier of the arts market, we expect many artists in the marketplace to choose a contest behavior strategy.

Hypothesis 1: An economically meaningful proportion of sellers in U.S. fine arts primary markets will indicate using contest behavior.

3.2 Premium

To test whether third-degree strategy is the dominant strategic behavior or merely describing the characteristic behavior, we hypothesize that the strategically dominant behavior will lead to an income premium. A characteristic behavior may be exhibited with a high prevalence, but not be associated with a pecuniary benefit.

Hypothesis 2: Artists who use contest behavior will achieve higher average annual income[12] levels when compared to characteristically similar artists who do not use contest behavior.

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[12] In the survey, income level is defined as "*net personal income from selling art you have created*."

3.3 Profile

Since there are incentives for artists to use contest behavior at every career stage, we expect a wide characteristic range of artists to exhibit the behavior. If contest behavior is the dominant strategy in asset markets, and Hypothesis 2 confirms an observable income premium regardless of professional status, gender, or marketplace type, then contest behavior is not expected to be concentrated in any demographic group.

Hypothesis 3: Use of contest behavior will be evenly distributed across characteristic groups and marketplace types.

3.4 Counterfactual

The counterfactual hypothesis is that instead of describing dominant strategic behavior for achieving liquidity in asset markets, contest behavior describes the characteristic behavior of traders in the financial markets that Keynes observed. Keynes (1936) links these concepts by attributing a greater prevalence of contest behavior on Wall Street over the London Stock Exchange to the short-term focus of New York traders. If contest behavior is characteristic of asset traders, not asset markets, then we would expect to see the prevalence of contest behavior in the counterfactual asset market concentrated with the artists who are characteristically similar to the traders in financial asset markets.

Hypothesis 4: Contest behavior will be overrepresented in artists who fit the profile of a stock trader, namely confident, profit-motivated, professional males (Green, et al., 2009).

4. Materials and methods

4.1 Survey

4.1.1 Fine arts markets

The global fine arts market has an annual trade volume of over 58 billion dollars (McAndrew, 2014). Since artworks are typically illiquid assets, most of this volume represents sales of unique works (Pownall, 2005). Arts marketplaces are organized in three tiers: the primary market where works are first sold, the secondary market where works are resold, and the institutional market where known works find homes (Moulin, 1994). This study focuses on the primary market, where artists interact with buyers. However, awareness of the secondary market is a key to Keynes' "third degree" strategy.

There is an age-old debate over what constitutes art: fine-art, decorative-art, folk-art, craft, functional-art, pop-art, popular culture, or garbage (Zolberg, 2010). We did not attempt to define art, or separate art from craft. Instead, we used a marketplace-based approach to survey artists. Survey participants attempted to sell personally created work in U.S. arts marketplaces during the year before the survey. This study includes five marketplace types: gallery, dealer, direct sales, online retail, and social media sites without retail functions (Flanigan, 2019).

4.1.2 Sampling methodology

Survey methodology allows us to examine level k-2 behavior in the context of the marketplace. In 2014, we emailed survey participation requests to 1,624 artists. We attempted to reach a broad representative cross-section of artists by identifying artists from twenty-two directories obtained from online, open studio, regional, and gallery sources. To randomize selection, we sent participation requests to the first 100 artists with U.S. contact information from each list, or the entire list if it contained less than 100 artists[13].

Traditionally, galleries have acted as gatekeepers to participation in arts markets (Moulin, 1994). Recent research shows that female, non-white, and Latino artists are all under-represented in galleries, when comparing gallery exhibitors to the populations of art school graduates and self-identified working artists in the U.S. Census Bureaus' American Community Survey (Jahoda, 2014). This is one reason to look beyond galleries to obtain a representative sample of sellers in U.S. fine arts markets.

The online sample sources included sites open to any artist: Art Fire, Etsy, Sattchi Online, and UGallery, as well as Amazon Art which also accepts listings from galleries and dealers. Regional open studios, and directories, generally limit participation by charging a fee. The regional sources focused on Brooklyn, Detroit, Miami, San Francisco, and Seattle: areas with a high concentration of fine artists by location quotient in the 2013 U.S. Bureau of Labor Statistics Occupational Employment Statistics (OES) estimates (BLS, 2013).

4.1.3 Response rates

Participation requests included a link to an online survey, administered with Survey Monkey. We encouraged responsiveness, and honesty, by ensuring participants' confidentiality, not recording IP addresses, and allowing respondents to skip questions.

[13] To ensure confidentiality, a list of galleries used as sample sources is not included here.

Respondents were identified numerically. Artists had the option to provide an email address to receive updates about the study. Addresses were removed to a separate list after downloading responses and are not included in the final data set. We spoke with many participants about the study motivation, confidentiality, and distribution of results—106 respondents requested results.

The OES estimates for our survey year (BLS, 2014) find about 4,800 full-time professional fine artists in the United States.[14] Since we use a marketplace-based definition of an artist instead of an occupational definition our population estimate is larger. About 40% of our respondents fit the definition of a professional artist, suggesting the population for our sample is closer to 12,000. Out of 1,624 unique participation requests, we received 245 responses, for a 15.1% response rate. Of these, 170 were useful responses, for a 10.5% effective response rate. The rest were incomplete or withdrawals. Our objective was to measure contest behavior; we excluded respondents who skipped all four indicator questions for contest behavior or the income level question, as incomplete.

4.1.4 Respondents

Over the past decade, as the volume of money spent in arts markets increased (McAndrew, 2014) the number of full-time working artists decreased (BLS, 2015). Frank and Cook (1995) describe this dynamic as a "winner-take-all" market return structure. Winner-take-all markets are likely to reward the beauty contest strategy; superstars must

[14] The US Bureau of Labor Statistics (BLS, 2014) Occupational Employment Statistics (OES) population estimate for visual fine artists is low, less than 5,000 artists, because only full-time professional wage-earning artists are included. This estimate excludes artists who are also employed in other professions, and some self-employed artists depending on tax status.

appeal to the average preferences of a large fan base that enjoys the cultural experience of shared preferences. To consider artist's information about the market structure they participate in, we asked artists about their knowledge of recent arts marketplace statistics and price trends, length of time in the marketplace, and consumption of arts market publications.

We characterized artists' degree of institutional acceptance by their participation in juried competitions, frequency of critical reviews, and attitude toward galleries. Finally, we considered a range of marketing activities artists engage in, including blogging, hosting open studios, teaching informally, traveling to meet with collectors, traveling to exhibitions, and interacting with their audiences on social media. These questions were used to assess contest behavior prevalence and likelihood across many dimensions before focusing on key groups for analysis.

Respondents were categorized in groups by demographics, marketplaces, motivations, and actions. In addition to basic demographics, and previously described marketplace groups, we asked artists to rank their *"motivations for making art*[15]*."* Frank and Saeyoon (2011) find that as labor markets, arts markets are long right-tail markets characterized by excess entry and low median returns. If artists derive utility from creativity, then motivation may lead to an excess supply of people attempting to earn a living as artists. We categorized respondents by their top two motivations, including *aesthetics, continuing a cultural tradition, enjoyment of the process, expression, social commentary, and a way to make a living*. We elicit individual artist incomes with the

[15] Motivations surveyed for selling art: *aesthetics, continuing a cultural tradition, enjoyment of the process, expression, social commentary, a way to make a living*.

question: *"Over the past year, which of the following five ranges describes your net personal income from selling art you have created?"* (the ranges are defined in Section 4.2.3).

While artists compete in a heterogeneous marketplace, using characteristic group questions and dummy variables allowed us to compare outcomes for similar types of artists. We defined five groups of artists for analysis: *professional vs. marginal, newcomer vs. established, and high-persistence low-returns.* Professional artists indicated that creating art was their profession and primary income source, whereas marginal artists chose artist as their profession but not their primary income source. Newcomers have less than 10 years of marketplace experience; established artists have at least 10 years of experience and above median incomes. High-persistence low-returns artists have at least 10 years of experience with below median returns.

4.1.5 Survey construction

The survey used 56 questions to test our hypotheses and categorize artists for analysis. Questions were designed to be as straightforward as possible. During the development of the survey the authors gave drafts to artist friends, and based on their feedback, the survey was edited for clarity. The IRB of the authors' home institution approved the survey. A data set with identifiers removed and the complete survey text are available from the authors.

The survey contained question types: yes or no, multiple choice, check all that apply, ordinal ranking, scaled ranking, and open-ended. This allowed us to approach concepts from multiple perspectives and consider respondents' consistency. To avoid priming, we asked attitudinal questions before quantitative questions. We ended with the *"net income in the past year"* question. This was the most personally sensitive question we asked. By waiting until the end to ask about returns, we hoped the respondents would be comfortable enough to answer honestly. The open-ended questions gave respondents an opportunity to fully communicate their thoughts and informed us of the surveys' limitations.

4.1.6 Limitations

We identified several limitations of the study; participants pointed out others. Self-selection of respondents is always a consideration in survey research. Lower-tier artists may be flattered by recognition and respond at higher rates; higher-tier artists may be less likely to share details with researchers. From inquiries by respondents, we know that a few well-known artists participated. Four percent of respondents were in the wage tier reported as the 90th percentile by the BLS (2013), which only includes full-time professional artists in its analysis. Since we included any artist with sales, our rate of higher-income respondents appears reasonable.

Though we sampled from select areas, we surveyed artists from 27 U.S. states. It is likely that sampling from online marketplaces allowed us to expand our geographic reach. We considered that sampling from online marketplaces could lead to sellers in these marketplaces being overrepresented. While less than 50% of the sample was drawn from online marketplaces, 85% of respondents participated in them. Nearly all the respondents participated in multiple marketplace types.

Respondents criticized the binary gender choice. We also left out concepts of race and ethnicity. If we included more demographic variables, we may have found additional differences in behavior prevalence and returns.

4.2 Statistical methods

4.2.1 Prevalence

We identify contest behavior using four indicator questions. 1) *"Do you ever incorporate colors, forms, or themes in your work based on their collectability?"* 2) *Did the respondent purchase art for "investment" in the past year?* 3) *Was the respondent's motivation for collaboration in the past year "to create a collectable product?"*4) *Was the respondent's motivation for collaboration in the past year "to associate myself with a group of artists?"*

Artists who answered "yes" to at least one indicator question were categorized as using contest behavior with a binary "contest" variable. Indicator questions two, three, and four were only given to the sub-sets of artists who purchased art or collaborated in the past year. Prevalence from these indicators is reported for the entire sample and for artists who purchased art or collaborated in the past year.

4.2.2 Models

We test for robustness of our contest behavior indicator by constructing four models specifying variations on our definition of contest behavior. 1) The *stated model* uses only indicator question 1, the direct ask. 2) The *revealed model* uses only indicator questions 2, 3, and 4, the revealed preference indicators. 3) The *restricted model* uses only the respondent's top motivation for collaboration (see section 4.1.4) 4) The *expanded model* uses the respondent's top two motivations for collaboration. Both the *stated* and *revealed* models are *expanded* models.

4.2.3 Premium

We measure an income premium for contest behavior by differencing the average incomes of characteristically similar groups of artists based on their use of contest behavior.

$$Premium = \overline{income}_{characteristic\ group,\ \ contest\ behavior} - \overline{income}_{characteristic\ group,\ \ no\ contest\ behavior}$$

We confirm significance of differences in average incomes using a t-test. Asking for *"net personal income"* controls for heterogeneity of materials costs and business activities. Average incomes are determined from the survey question *"Over the past year, which of the following five ranges describes your net personal income from selling art you have created?"* We take the income level for each respondent as the midpoint of the range they selected. The five income ranges[16] correspond to the income quintiles reported for fine artists in the U.S. Bureau of Labor Statistics (BLS, 2013) Occupational Employment Statistics. We used ranges to increase the response rate.

After determining a behavior premium for all sampled artists, we repeat the analysis using the following characteristic groups: dealer sales, direct sales, gallery sales, online sales, social media sales, established, newcomers, high-persistence low-returns,

[16] Income bins: below $19,000, $19,000 - $29,999, $30,000 - $44,999, $45,000 - $65,000, above $65,000

professional, marginal, non-profit motivation, and travel to meet with collectors. We further split the professional artist group by gender. By controlling for select characteristics, we attempted to maintain a sub-group size of at least thirty respondents per comparison group.

4.2.4 Distributions

Distributions of returns in arts markets are left tail heavy (Frank and Saeyoon, 2011). In addition to the t-test, we test for contest behavior significantly changing the shape of the income distribution for characteristically grouped artists using median, rank sum, and distribution tests. The median test, also known as the Mood's test, is a non-parametric median test to compare the distribution midpoints. The test compares the median *net personal income from selling art* to the median return for each behavioral group. The rank sum test, also known as the Mann-Whitney u-test, combines a median and distribution test to determine if return distributions for the behavioral groups are likely drawn from the same population. Finally, we compare the shape of the income distributions between the behavioral groups, with and without contest behavior, using a two-sample Kolmogrov-Smirnoff (K-S) distribution test.

4.2.5 Profile

Using a logistical (logit) regression, we attempt to predict the likelihood of contest behavior from artist characteristics. Following Keynes' example of the beauty contest on stock exchanges, we begin with a demographic profile of a typical Wall Street trader (Green et al. 2009). If these characteristics are significant, it will suggest that artists who fit the demographic profile of a stock trader are more likely to use contest behavior than other artists. Next, we model a best-fit profile of an artist who uses contest behavior following from the theoretical incentives for artists to use the behavior. In constructing the final profile, we consider factors including demographics, marketplaces, motivations, experience, information, institutional acceptance, interactions with collectors, and marketing activities.

5. Results

5.1 Prevalence

We identified artists using contest behavior from four indicators discussed in Section 2. Table 1 presents the number and percentage of artists categorized under each indicator for the expanded and restricted models described in Section 4.2.2. The motivation-based indicator questions were only asked to respondents who collaborated or purchased art in the past year. The "conditional percent" reports the percent indicated for contest behavior given collaboration or purchase. "Percent unique" shows the percent of artists responding positively to an indicator question who are categorized as exhibiting contest behavior solely from that indicator.

At 51% and 47%, the proportion of artists exhibiting contest behavior under at least one indicator is slightly higher than the proportion of professional artists in the marketplace for both the expanded and restricted models. This supports Hypothesis 1: that an economically significant proportion of sellers in fine arts marketplaces use Keynes' third-degree beauty contest strategy. Alternately, the revealed indicator percentage in the restricted model (21%) could be seen as a lower bound for contest behavior.

Table 2 presents the number and percent of artists indicated as using contest behavior, in characteristic groups, for each model described in Section 4.2.2. Established artists, and those who had traveled to meet personally with collectors in the past year, exhibited the highest proportions of contest behavior. Marginal artists and those with high-persistence and low-returns (HPLR) had the lowest proportions.

Established and HPLR artists have over 10 years of seller experience. However, established artists are in the top three income tiers, while HPLR artists are in the bottom two. Marginal artists want to be seen as professional artists but do not derive most of their personal income from selling their art. This suggests that, while not the whole story, contest behavior is an important factor in making a living from making art. Professional artists (who do earn most of their income from selling art) exhibited an above average prevalence of contest behavior use in each model, with a 9.14 percentage point greater than average prevalence in the expanded model. Table 2 supports Hypotheses 3, that contest behavior is broadly used by many segments of artists and in a variety of marketplace types.

5.2 Premium

Figure 1 presents the absolute and percent differences in average income levels between artists using contest behavior and those not using the behavior. All groups analyzed except for established artists (with 10+ years of experience and above median income) received an income premium when using level k-2 behavior. This confirms

Hypotheses 2, that using contest behavior results in a significantly higher annual income level.

Artists who traveled to meet personally with collectors in the past year saw the highest premium associated with contest behavior at 136%. These artists may be especially effective at using contest behavior given their receptivity to knowing their audience.

Established, and artists selling to art dealers, had the lowest percent premiums at -10% and 11% respectively. Since dealers select works they expect to sell quickly (Hutter et al., 2007), contest behavior may be redundant for artists with dealer relationships if dealers are selecting artists based on fit with current demand trends. Similarly, sales by established artists may be less sensitive to strategic behaviors if these well-known artists are already receiving top-tier prices for their works. These artists could be seen as the trend leaders that less established artists are emulating.

Figure 2 shows that the income distributions of artists using contest behavior have different shapes than those of artists not using the behavior. While both are long-right-tail distributions, the income distributions for artists using contest behavior have less clustering at the low end, and greater percentages of artists with mid-range incomes.

The differences in income distributions have statistical as well as graphical significance. Table 3 presents the significance of differences in means, medians, distributions, and shapes, confirming Hypothesis 2 for many characteristic groups, including professional artists.

5.3 Profile

Table 4 presents the estimated logit model of contest behavior including variables of individual characteristics that describe an average Wall Street trader (Green et al. 2009). Each model discussed in Section 4.2.2 is presented. The marginal effects (MFX) show the increase in probability of contest behavior for each characteristic. The estimation results do not confirm that an artist with the characteristic profile of an average Wall Street trader predicts contest behavior. Thus, our results do not support the counterfactual Hypothesis 4, that Keynes observed the characteristic behavior of asset market participants, not an optimal strategy for trading assets.

Table 5 presents an estimated logit model including artist characteristics that significantly predict contest behavior use or non-use. We are reporting the best-fit model after testing various logit models of characteristics that theoretically could predict behavior from artist incentives discussed in Section 1, such as newcomer, participation in marketplaces with conspicuous consumption, and process and aesthetic motivations for creating art. We also modeled the contest behavior likelihood from characteristics that implied increased opportunities to use the behavior, or interest in marketing activities including reading publications about arts markets, knowledge of recent market price trends, and various interactions with artists and collectors such as blogging, teaching, hosting open studios, and creating customized works.

Our reported model is able to significantly predict contest behavior from artist characteristics associated with incentives and opportunities for using the behavior and allows us to describe a profile of artists engaging in contest behavior: being an established artist, making sales through social media sites without a retail interface, and traveling to meet personally with collectors. We report the Bayesian information criterion (BIC) for each model discussed in Section 4.2.2. In addition to the gains in statistical significance of the incentive-based profile (Table 5) over the trader characteristic profile (Table 4), we find a lower BIC for each model in the incentive-based profile compared to its' counterpart in the trader characteristic profile. The expanded model shows the largest gain in information efficiency with a BIC difference of 25.4 below the expanded model in the trader characteristic profile. Within the incentive-based profile, the revealed preference model exhibited the best performance, with the lowest BIC and the highest proportion of correctly classified artists.

6. Discussion

6.1 Characteristics

We find the persistence of, and differences between, behavioral premiums across groups informative and consistent with the theoretical incentives for contest behavior adoption by group. A main characteristic predicting the positive likelihood of using contest behavior is sales experience in the marketplace, while a main characteristic predicting lower likelihood of using contest behavior is the artist having a primary source of income other than selling art. However, it is possible that there is a missing factor that is correlated with both the use of contest behavior and income but is invariant to the characteristic group differences.

There is also the question of endogeneity with regards to the characteristics in our incentive-based logit profile reported in Table 5. It makes sense that there would be positive reinforcement between contest behavior and the income premium associated with the behavior shown in Figure 1. It is less clear if the use of contest behavior could inspire other behaviors such as persistence, choice of marketplace type, and meeting with collectors.

We see the use of contest behavior as a strategy for overcoming information asymmetry in marketplaces without gatekeepers. This is supported by the high income premiums associated with the behavior in the social media, online, and direct sales marketplaces. The survey investigates several types of communications with collectors besides travel, including blogging, personal social media interaction, and hosting open studios. None of these communication behaviors were associated with contest behavior. It seems plausible that "going the extra mile" to meet personally with collectors is indicative of a type of artist who has greater willingness to mix their vision with current trends, to give the market what it wants.

Established artists, with above median incomes and over 10 years of experience, present an interesting case. We find that established artists have a greater likelihood of using contest behavior but are the only group to exhibit a negative income premium from this behavior. There are several possible explanations for this finding. Theoretically, average artists are the most likely to benefit from strategic behavior. Even with strategy, the lowest quality artists will have difficulty finding buyers. Similarly, artists with the highest quality − or name recognition − will find buyers with the highest willingness to pay regardless of strategy. Since established artists represent the top half of the income distribution, this group would include most artists at the far right of the distribution whose incomes are not sensitive to strategic behavior.

Despite not realizing an observable premium in the current period, contest behavior may have helped many established artists reach their position in the arts market. This could explain our observation of increased likelihood of use. Hutter et al. (2007) find that artists' careers follow a similar trajectory with income levels plateauing around age 70. Since established artists have over 10-years-experience, this group contains most of the older respondents. If older artists' price levels are less sensitive to strategic behavior, this could reduce an observable behavior premium for established artists. If these older artists did observe an income premium from the behavior in earlier career stages, they may continue using the behavior at higher rates without an observable premium in the current period.

We do not find that gender or overconfidence predict the use contest behavior. Compromise, or awareness of group preferences, could be seen as stereotypically feminine behaviors, while strategy and competitiveness could be seen as stereotypically masculine behaviors. Our study contributes to the growing body of literature that finds behavioral gender differences are greater within gender than between genders (Sent and van Staveren, 2019). Gender differences are typically less apparent within a specific domain, especially amongst experts in that domain. Instead, we find that non-professional artists, who do not rely on arts markets for their primary income, have the agency to eschew contest behavior and content compromise.

6.2 Incentives

If the beauty contest analogy describes asset trading under uncertainty, as Keynes states, then artists should, at least partially, respond to their market as a beauty contest. In applying the beauty contest to arts markets, we see that artists at all levels have theoretical incentives to use Keynes' third-degree strategy. For example, newcomers, who may have few available marketing strategies, can use contest behavior to signal context and value, while professional artists can use contest behavior to signal continued relevance and to meet demand. Our empirical results demonstrate that on average, arts markets reward contest behavior by many groups of artists, in all types of marketplaces. This shows that, in addition to theoretical incentives, artists have an observable financial incentive to use contest behavior.

We find that artists with varied motivations, across demographic groups, respond to these incentives—the behavior is prevalent across many characteristic groups—while in most cases membership in a particular group is not a significant predictor of behavior. The empirical findings that artists with other sources of income (marginals) are less likely to use contest behavior, and artists whose primary income source is selling their personally created art (professionals) are more likely to use contest behavior, are consistent with the hypothesis that the income premium from using contest behavior is an observable financial incentive and a learned behavior.

Both the established and high-persistence low-returns (HPLR) groups consist of artists with at least 10 years of marketplace experience. However, established artists use contest behavior at higher than average rates and HPLR artists use contest behavior at lower than average rates. Between these groups, established artists have above median incomes and HPLR artists have below income profits. This suggests that the ability to recognize financial incentives, and willingness to compromise enough to use them, separates artists with high and low earnings over the long term. In this case, we are not concerned with the issue of causality since the process of recognizing, responding to, and being rewarded by incentives in the marketplace implies a feedback process. Observation of the behavior and sales of established artists could motivate behavior adoption by newcomers.

6.3 Content convergence

Contest behavior, defined here as incorporating observed trends in content, is a description of herd behavior. When artists who follow trends have higher average incomes than those who don't, then the market-returns structure incentivizes appropriation. Having shown that artists respond to incentives in a way that leads to contest behavior, we offer contest behavior as an explanation for the lack of variety in fine arts marketplaces observed by art dealers in the TEFAF (2013) Global Art Dealer Survey. TEFAF survey respondents described a convergence of buyer preferences and a shortage of available works to supply these preferences. However, the observations of excess entry and many artists in low wage tiers show that there is never a true shortage in arts markets. Instead, there is a shortage of works dealers want to buy—those with high liquidity and minimal risk.

6.4 Contributions

This study contributes a 56-question marketplace-based survey of 170 U.S. visual fine artists covering demographics, information, motivations, marketplaces, and entrepreneurial activities (Flanigan, 2019). We use the survey to answer two critical questions that arise from Keynes' description of the beauty contest game in *The General*

Theory. Is the game applicable to asset markets beyond the stock market? Is Keynes observing the behavior of asset markets or asset traders?

We also challenge naïve views of the Artist as an inspired or tragic archetypal figure and introduce artists as entrepreneurs and strategic asset traders. In doing so we find a cost to myopy in the loss of the behavioral premium. This tests the k-level theory at the lowest symmetric level, with buyers and sellers both behaving strategically and sharing awareness of the same market trends. Our findings establish returns to awareness empirically in a specific asset market.

With nearly half of surveyed artists exhibiting “contest behavior” in the previous year, we find that Keynes’ beauty contest game applies to arts markets. Artists who use contest behavior have an observable financial incentive informing their creative decision; artists who use contest behavior have significantly higher average incomes than those who do not. In a likelihood model for contest behavior, we find that artists with greater than 10,000 hours of marketplace experience, and above median incomes are more likely to use the behavior, while artists with other primary income sources are less likely to use the behavior. Other factors including demographics, marketplaces, and motivations do not affect artists’ likelihood of using contest behavior. This counterfactual asset market suggests that Keynes was indeed observing a strategy for increasing liquidity by responding to incentives in asset markets. Keynes was not simply observing the behavior of stock-market traders.

While prior studies (Velthuis, 2003; Hutter et al. 2007; De Silva et al. 2012) have focused on small groups of galleries in single major cities, we contribute to the study of the market for visual fine arts by using a marketplace-based definition of an artist to survey a broad range of sellers in a national marketplace. The survey data set is available for further analysis. The take-away for artists from our analysis is that half their competitors are designing content to appeal to current trends and the marketplace appears to reward this behavior. For art dealers attempting to increase their inventory of on-trend works at low risk, our study suggests they seek out artists who travel to meet their customers. Our take-away for collectors is that they have considerable power in a demand driven market. When more collectors are willing to take risks on off-trend works, then there will be more content variety supplied in galleries and art fairs.

6.5 New markets

We expect contest behavior to become increasingly important to understanding behavior in global arts and collectibles markets which have adopted NFT platforms since 2019.[17] The blockchain is a more indelible and public version of the online ledger market organizing method observed by Lennon and Shohfi (2021) to be successful at replacing formal auctions and contracts in the illicit market for collectable whisky. The public sales ledger attached to an individual work allows for segmentation of sales between short-term repeat trade and long-term collection, the point of failure found by Ashenfelter (2008) and others (Vecco, and Zanola, 2017; Etro, and Stepanova, 2021) in hedonic asset pricing. The blockchain ledger integrates the asset with its provenance. Ginsburgh et al. (2019) find that removing uncertainty around provenance increases an artist's price level

[17] In 2021, the NFT market accounted for 17% of the sales volume in global arts markets and was especially important to new and high net worth collectors, with 74% purchasing at least one NFT work (McAndrew, 2022). At the asset level, an NFT is a public contract conferring rights in real time. It is important to note that purchasing an NFT can confer rights to a physical object.

by 60%. When these major sources of asymmetric information in arts markets are mitigated, artist strategy and awareness remain as important behavioral components of price appreciation.

Our study shows that artist's awareness of trends is rewarded, even at the lowest strategic k-level, when they are not directly incentivized. NFT marketplaces directly incentivize artist participation in secondary markets by giving artists resale royalty rights, a goal that has long been out of reach for most visual fine artists in decentralized markets (Salisbury, 2019). Artist awareness of the secondary market is now explicitly rewarded and may itself be commodified when artists participate in both the primary and secondary markets. We have suggested that higher k-level thinking by artists and collectors leads to content convergence. NFT markets accelerate the contest behavior fueled movement towards content conversion by allowing artists to mint multiple numbered editions, while maintaining the uniqueness of works through the individual blockchain ledger. Following the April 16, 2021 minting of the work "Reborn" by well-known visual artist Vexx in the Nifty Gateway marketplace, the artist directly entered the secondary market by purchasing the three lowest priced editions and gifting them to large scale collectors.

This is an example of an artist with awareness of the secondary market, responding to incentives to protect their price level while also reentering the provenance ledger and recognizing engaged collectors. In online galleries and public ledgers, the signaling value from owning an on-trend work greatly increases. In traditional auctions, the collector is recognized when the work is sold, and may be again if the collection is leased out. In NFT marketplaces, online galleries are combined with social media features so that value from conspicuous consumption is realized on an ongoing basis, greatly increasing the implicit incentives for contest behavior.

7. Conclusion

For the collector, owning a work is a membership in an exclusive club; and owning a large collection increases their social signaling clout. Conspicuous consumption on social media, popularized by unboxing and haul videos, confers social asset value to consumption goods, further blurring lines between consuming and collecting. In this environment, contest behavior and higher k-level thinking are growing in importance and applications. We present theory and evidence that can explain the movement towards content conversion in arts marketplaces. We have established a behavioral premium at the most extensive margin of awareness. New types of marketplaces and networks present opportunities for future research into higher k-levels of strategy.

Keynes describes the beauty contest as arising from traders' short-term focus. The result is art collectors and investors with highly correlated portfolios. In arts, this results in a narrow visual representation of each time period and artists without a short-term focus being overlooked. In finance this results in systemic risk. Traders in financial markets are typically overconfident, profit-driven men. Our analysis finds that all types of traders will use contest behavior when they have an observable financial incentive to do so—even at a personal cost, as in the case of artists motivated by personal expression or continuing cultural tradition. This suggests that as the diversity of participants in financial markets increases, beauty contest behavior will remain a dominant feature of stock markets, unless the incentives and compensation structures of these markets are changed to reward a longer-term investment horizon.

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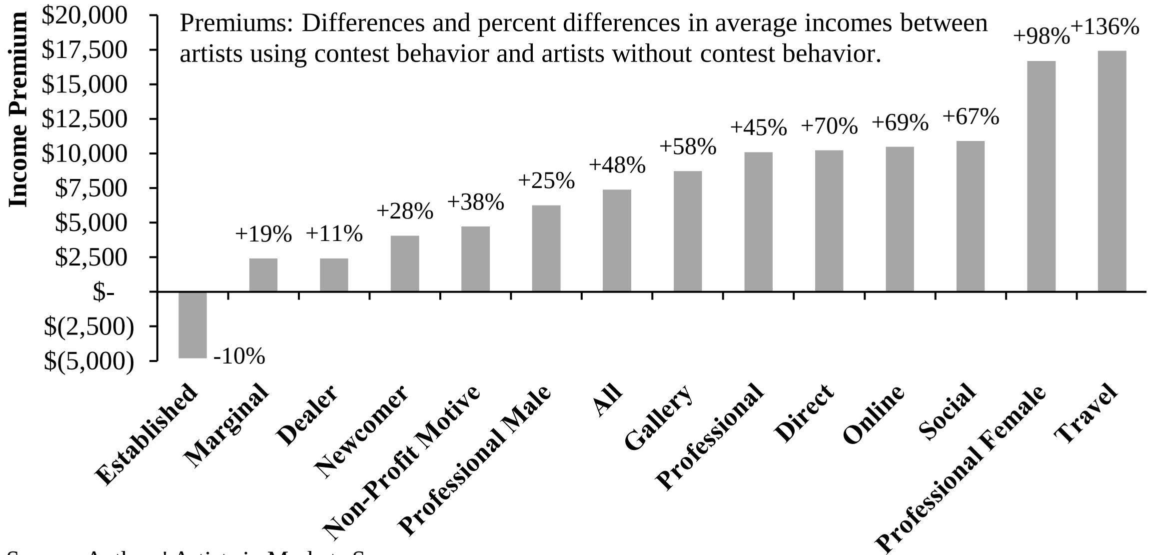
Figures

Figure 1

Average income premiums by group for contest behavior in U.S. fine arts marketplaces, expanded model

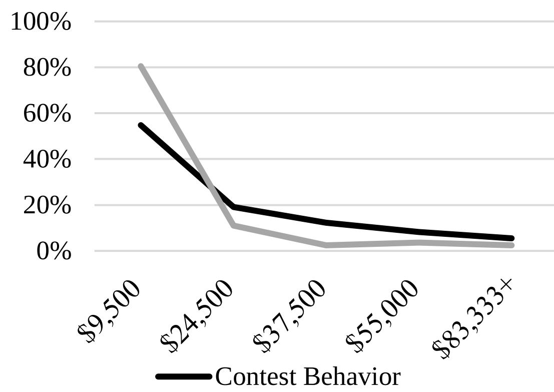


Source: Authors' Artists in Markets Survey

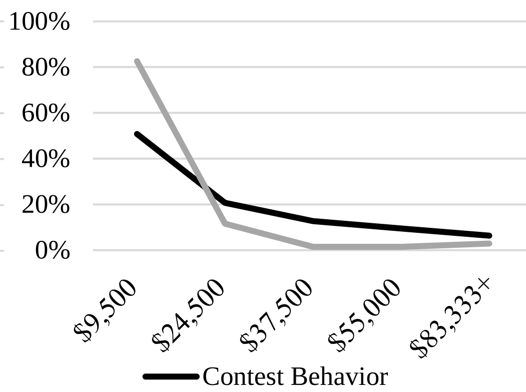
Figure 2

Differences in artist income distributions within groups by contest behavior, expanded model

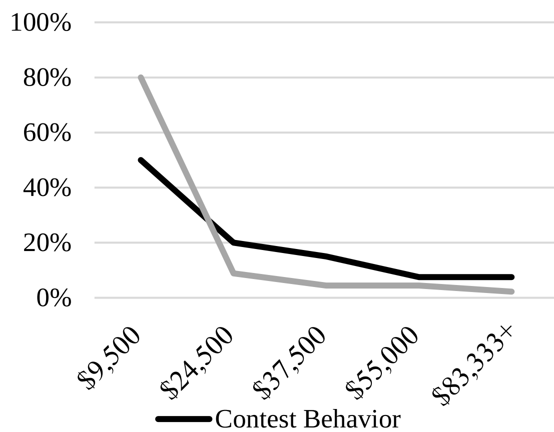
All Artists



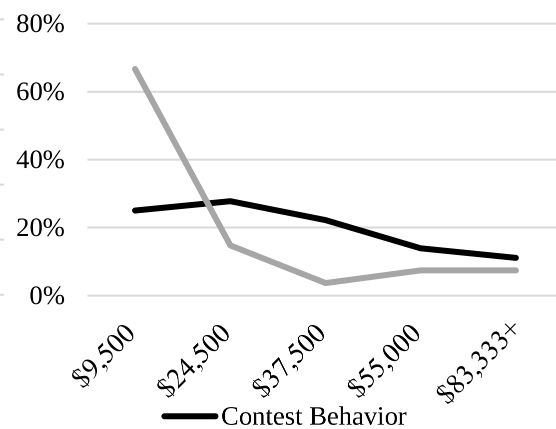
Artists with Gallery Sales



Artists with Online Sales



Professional Artists



Tables

Table 1

Prevalence of Contest Behavior in U.S. Fine Arts Markets

	Expanded Model				Restricted Model			
Variable	Count	Percent of sample	Conditional percent	Percent unique	Count	Percent of sample	Conditional percent	Percent unique
Collaborate	66	38.82 (.0375)	-	-	66	38.82 (.0375)	-	-
Purchase	97	61.39 (.0389)	-	-	97	61.39 (.0389)	-	-
Indicator Variables								
Associate (Collaborate)	25	14.71 (.0272)	37.88 (.0602)	48.00 (.1020)	12	7.06 (.0197)	18.18 (.0478)	66.67 (14.21)
Collectable (Collaborate)	21	12.35 (.0253)	31.82 (.0578)	19.05 (.0878)	12	7.06 (0197)	18.18 (.0478)	16.67 (.1124)
Invest (Purchase)	14	8.86 (.0227)	14.43 (.0359)	50.00 (.1387)	14	8.86 (.0227)	14.43 (.0359)	50.00 (.1387)
Theme	60	37.50 (.0384)	-	61.67 (.0633)	60	37.50 (.0384)	-	71.67 (.0587)
Contest Behavior Variables								
Contest	87	51.18 (.0385)	-	-	79	46.70 (.0384)	-	-
Revealed (Contest)	50	29.41 (.0350)	57.47 (.0533)	54.00 (.0712)	36	21.18 (.0314)	45.57 (.0564)	52.78 (.0844)
Stated (Contest)	60	37.50 (.0384)	70.58 (.0497)	61.67 (.0633)	60	37.50 (.0384)	77.92 (.0476)	71.67 (.0587)

Notes: Standard errors are in parentheses. Conditional percent shows the percent with variable behavior given the parenthesized variable. Percent unique is the percent of respondents with the indicated behavior not categorized with contest behavior using another indicator. Source: Authors' Artists in Markets Survey.

Table 2

Prevalence of Contest Behavior by Group in U.S. Fine Arts Markets

Model			Total Sample		Contest Behavior					
			(1) Expanded		(2) Restricted		(3) Stated		(4) Revealed	
Group	Count	Percent	Count	Percent	Count	Percent	Count	Percent	Count	Percent
All	170	100.00	87	51.18 (.0385)	79	46.47 (.0384)	60	37.50 (.0384)	50	29.41 (.0350)
Dealer sales	43	27.04 (.0353)	28	65.12 (.0735)	26	60.47 (.0754)	20	47.62 (.0780)	19	44.19 (.0766)
Direct sales	116	71.17 (.0356)	66	58.90 (.0462)	59	50.86 (.0466)	47	41.23 (.0463)	38	32.76 (.0438)
Established	35	21.60 (.0324)	26	74.29 (.0462)	23	65.71 (.0814)	20	60.61 (.0864)	12	34.29 (.0814)
Gallery sales	139	85.80 (.0275)	73	52.52 (.0425)	66	47.48 (.0425)	51	37.50 (.0417)	42	30.22 (.0391)
High-persistence, low-returns	72	46.16 (.0400)	29	40.28 (.0582)	26	36.11 (.0570)	19	26.39 (.0523)	17	23.61 (.0504)
Newcomer	52	30.59 (.0354)	25	48.08 (.0700)	24	46.15 (.0689)	18	38.30 (.0717)	15	28.85 (.0634)
Online sales	88	54.66 (.0394)	45	51.14 (.0536)	41	46.59 (.0535)	37	42.53 (.0533)	21	23.86 (.0457)
Marginal	60	37.27 (.0382)	22	36.67 (.0627)	19	31.67 (.0606)	17	28.33 (.0567)	12	20.00 (.0521)
Non-profit motivation	98	60.49 (.0385)	42	42.86 (.0502)	39	39.80 (.0497)	28	29.17 (.0466)	27	27.55 (.0454)
Professional	63	38.89 (.0384)	38	60.32 (.0621)	33	52.38 (.0634)	28	45.90 (.0643)	19	30.16 (.0583)
Professional men	36	22.22 (.0328)	19	52.78 (.0844)	17	47.22 (.0844)	14	41.18 (.0857)	8	22.22 (.0703)
Professional women	27	16.67 (.0294)	19	70.37 (.0896)	16	59.26 (.0964)	14	51.85 (.0980)	11	40.74 (.0964)
Social media sales	48	30.19 (.0365)	33	68.75 (.0676)	28	58.33 (.0719)	21	43.75 (.0724)	20	41.67 (.0719)
Travel to collectors	42	25.77 (.0344)	33	78.57 .0641	29	69.05 (.0722)	23	54.76 (.0777)	20	47.62 (.0780)

Notes: Standard errors are in parentheses. Model (1) uses all indicators and top two motivations. Model (2) uses all indicators and top motivation. Model (3) uses only the stated preference indicator. Model (4) uses only the revealed preference indicators and top two motivations. Source: Authors' Artists in Markets Survey.

Table 3

Significance of income distribution differences by contest behavior within groups in US fine arts marketplaces

Model	Expanded				Restricted			
Test P-Value	Mean	Rank-Sum	Median	Distribution	Mean	Rank-Sum	Median	Distribution
Group								
All	.010**	.001***	.001***	.013*	.012*	.002**	.002**	.029*
Dealer sales	.694	.325	.711	.796	.544	.258	.481	.788
Direct sales	.004**	.000***	.000***	.004**	.006**	.001***	.001***	.012*
Established	.593	.694	.481	1.00	.746	.823	.411	.997
Gallery	.007**	.000***	.000***	.006**	.003**	.000***	.000***	.006**
Newcomer	.324	.115	.079	.602	.258	.082	.055	.484
Online sales	.011*	.004**	.004**	.046*	.017*	.004**	.004**	.044*
Marginal	.407	.388	.395	1.00	.417	.524	.568	1.00
Non-profit motivation	.070	.035*	.035	.522	.117	.155	.290	.953
Professional	.106	.025*	.072	.066	.078	.020*	.049*	.060
Professional men	.465	.181	.668	.377	.297	.119	.392	.343
Professional women	.085	.059	.040*	.256	.135	.099	.069	.314
Social media sales	.074	.103	.171	.738	.103	.139	.211	.830
Travel to meet with collectors	.036*	.020*	.045*	.192	.025*	.027*	.014*	.205
Model	Stated				Revealed			
Test P-Value	Mean	Rank-Sum	Median	Distribution	Mean	Rank-Sum	Median	Distribution
Group								
All	.002**	.001***	.001***	.029*	.523	.171	.109	.638
Dealer sales	.307	.213	.104	.788	.405	.875	.302	.991
Direct sales	.001***	.000***	.000***	.012*	.832	.467	.341	.986
Established	.935	.797	.567	.997	.430	.450	.801	.999
Gallery	.000***	.000***	.000***	.006**	.847	.409	.282	.961
Newcomer	.403	.246	.230	.484	.185	.128	.119	.746
Online sales	.036*	.011*	.008**	.044*	.816	.483	.405	.998
Marginal	.507	.805	.906	1.00	.172	.117	.102	.806
Non-profit motivation	.036*	.242	.367	.953	.409	.058	.038*	.540
Professional	.034*	.009**	.013*	.060	.976	.744	.907	1.00
Professional men	.343	.226	.350	.343	.854	.754	.799	1.00
Professional women	.030*	.018*	.014*	.314	.807	.911	.851	1.00
Social media sales	.047*	.055	.080	.830	.492	.659	.813	.964
Travel to meet with collectors	.027*	.044*	.013*	.205	.678	.566	.635	1.00

Notes: Incomes are binned to quintiles. Expanded model uses stated and revealed indicators with top two motivations. Restricted model uses stated and revealed indicators with top motivation. Stated model uses only the stated indicator. Revealed model uses only the revealed behavior indicators. P-values and significance are shown; * = .05, ** = .01, *** = .001. Means test is a t-test. Rank-sum test is a Wilcoxon and Mann-Whitney test. Median test is a Mood's test. Distribution test is a 2-sample Kolmogorov-Smirnov test. Source: Authors' Artists in Markets Survey.

Table 4

Likelihood of Contest Behavior from Trader Characteristic Profile

Logistic Regression on Contest Behavior								
Model	Expanded		Restricted		Stated		Revealed	
	MFX	Coef.	MFX	Coef.	MFX	Coef.	MFX	Coef.
Variable								
Confidence	.00 (.026)	0.00 (.103)	.02 (.025)	.08 (.104)	.02 (.024)	.09 (.115)	.01 (.025)	.02 (.112)
Male	-.01 (.082)	-.04 (.331)	-.00 (.080)	-.02 (.328)	.04 (.073)	.18 (.346)	-.08 (.072)	-.41 (.355)
Professional	.09 (.089)	.34 (.359)	.04 (.088)	.15 (.358)	.08 (.084)	.36 (.375)	.01 (.087)	.05 (.395)
Profit Motivation	.27* (.123)	1.18 (.634)	.22 (.127)	.919 (.564)	.25 (.136)	1.06 (.555)	.07 (.135)	.33 (.565)
Constant		-.17 (1.14)		-1.10 (1.16)		-1.92 (1.29)		-1.02 (1.24)
BIC	237.020		240.499		223.007		214.619	
Log likelihood	-106.29		-107.58		-98.88		-94.64	
Observations	159		159		156		159	
P – value of model	.1101		.3132		.0868		.7335	
Pseudo R^2	.0342		.0216		.0395		.0105	
Correctly classified	55.35%		57.23%		66.03%		71.07%	

Notes: Expanded model uses stated and revealed indicators with top two motivations. Restricted model uses stated and revealed indicators with top motivation. Stated model uses only the stated indicator. Revealed model uses only the revealed behavior indicators. Base states for marginal effects are: confidence at mean, female, not professional, not profit motivated. MFX show the percentage point increase in probability of contest behavior when switching from the base state, holding other variables in the base state. They are not additive due to interactions. Significance: * = .05, ** = .01, *** = .001. The logit coefficient is interpreted qualitatively. BIC is the Bayesian information criterion. The reported P-values are the significance of each variable for predicting contest behavior in the logit model. Source: Authors' Artists in Markets Survey.

Table 5

Likelihood of Contest Behavior from Artist Characteristics

Logistic Regression on Contest Behavior								
Model	Expanded		Restricted		Stated		Revealed	
	MFX	Coef.	MFX	Coef.	MFX	Coef.	MFX	Coef.
Variable								
Established	.21* (.100)	.89 (.457)	.17 (.102)	.70 (.424)	.25* (.103)	1.06* (.429)	-.03 (.088)	-.16 (.451)
Social	.19* (.090)	.78* (.391)	.11 (.092)	.43 (.373)	.03 (.090)	.11 (.387)	.15 (.085)	.68 (.387)
Travel	.32*** (.085)	1.42*** (.434)	.26** (.090)	1.08** (.396)	.20* (.094)	.83* (.390)	.23* (.090)	1.04** (.396)
Constant		-.67** (.229)		-.69** (.226)		-1.07*** (.241)		-1.37*** (.258)
BIC	212.555		222.309		210.170		201.189	
Log likelihood	-96.15		-101.03		-94.99		-90.47	
Observations	158		158		156		158	
P – value of model	.0000		.0010		.0020		.0097	
Pseudo R^2	.1211		.0748		.0725		.0593	
Correctly classified	64.56%		63.92%		67.95%		72.78%	

Notes: Expanded model uses stated and revealed indicators with top two motivations. Restricted model uses stated and revealed indicators with top motivation. Stated model uses only the stated indicator. Revealed model uses only the revealed behavior indicators. Base states for marginal effects are: not established, no social media sales, and no travel to meet with collectors. MFX show the percentage point increase in probability of contest behavior when switching from the base state, holding other variables in the base state. They are not additive due to interactions. Significance: * = .05, ** = .01, *** = .001. The logit coefficient is interpreted qualitatively. BIC is the Bayesian information criterion. The reported P-values are the significance of each variable for predicting contest behavior in the logit model. Source: Authors' Artists in Markets Survey.

Conclusion

These studies show that young firms can benefit from supportive public policies. When faced with local credit supply shocks, young firms often exit financial markets due to owner beliefs despite being credit worthy. This leads to inefficiencies in commercial bank financing that can stall economic innovation and employment growth. This study suggests public policy intervention to reduce inefficiency and support innovation. Young firms would benefit from increased public counter cyclical lending programs to smooth the effects of credit supply shocks. I also suggest increased transparency in commercial credit scoring and lending criteria.

I find that Public entrepreneurship training programs are not effective in supporting young firm survival, growth, and financing. I suggest that the Small Business Administration undertake large scale surveys including panel surveys to better understand the needs of young firms. These surveys should lead to the creation of more flexible and targeted training programs.

My study demonstrates market incentives for content convergence in arts and cultural production. Mass market appeal in the arts can have social benefits. Participation in shared art can increase empathy across cultures. It is important for policymakers to understand these market incentives so that public funding for arts can be used to support emerging artists, diversity in the arts, and the continuation of traditional cultural products.