Costly Entrepreneurship

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Abstract

We document how entrepreneurship can impose personal costs on small business owners by analyzing personal and business administrative credit data. As compared to non-entrepreneurs with similar creditworthiness, entrepreneurs experience an 11.47% increase in personal credit default rates after incorporating the business, and delinquencies remain elevated for five years. In addition, entrepreneurs who default on their business loans experience a higher default rate on their personal credit accounts and an increase in personal bankruptcy rates. Our results are primarily driven by entrepreneurs that borrowed more on their personal accounts than their business accounts after incorporating their business. We use natural disasters as a shock to business cash flows to mitigate endogeneity concerns with business defaults. Our results highlight how entrepreneurship can have a long-lasting impact on the personal credit of some small business owners.

Keywords: Entrepreneurship, Personal Credit, Bankruptcy

JEL Classification: G51, L26, D14, G21

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1 Introduction

Policymakers and economists largely view entrepreneurship with a positive lens, given that entrepreneurship has been a reliable and robust engine of economic growth and employment. For example, in 2019 in the U.S, 770k establishments were created and firms less than 5 years old generated 7.5 million new jobs. Entrepreneurship can also lead to Schumpeterian creative destruction in which old capital, technology, and processes are replaced by new ones, and incumbent firms are replaced by new entrants (Smith, 1937; King and Levine, 1993). However, failure rates for small businesses are very high. For example, in 2019, 21.6% of the establishments shut down within a year of business start (Figure 1). Entrepreneurship is a very risky endeavor, but we do not have much direct evidence on the impact of entrepreneurship on the personal finances of the business owners.

In case of a business failure, the *incorporated* business owners benefit from limited liability, that limits the financial risk to the entrepreneur. Thus, these business owners may not suffer personal financial losses beyond their equity. However, many small business owners utilize personal credit (Fonseca and Wang, 2022) or personal assets as collateral to finance their business (Schmalz, Sraer, and Thesmar, 2017), and individual personal creditworthiness plays an important role for entrepreneurship (Herkenhoff, Phillips, and Cohen-Cole, 2021). Therefore, it is unclear whether the legal separation is sufficient to mitigate any negative spillover of business cashflow shocks to the entrepreneur's personal credit. Our paper studies the personal costs from business failures, and we provide the first direct evidence on the long-term impact of entrepreneurship on the personal credit of entrepreneurs.

Using the universe of credit bureau data on business owners' personal credit, we first document several new correlations between personal credit outcomes and business formation rates. We then show that new business starts, unconditional on success or failure of the business, adversely impacts the personal credit outcomes of the entrepreneur compared to other matched consumers with similar creditworthiness who have never started a business.

We find that the monthly personal credit default rates (90+ DPD, i.e., personal loans past-due for more than 90 days) increase by 20.5% among entrepreneurs within a year of business start. We notice that these rates remain 15.4% more than the matched non-entrepreneurs (2.25 ppt for entrepreneurs and 1.95 ppt for matched non-entrepreneur consumers) five years after the business start. We find qualitatively similar effects for personal bankruptcy rates.

Next, we disentangle these effects based on the success/failure of the business. In our case, we utilize data on incorporated limited-liability new businesses. As mentioned above, the legal separation may insulate small business owners from the negative spillover of business cash flow shock. Interestingly, we see that is not the case. Individuals who default on business loans are more likely to default on personal loans and file for personal bankruptcy. For example, we find that personal credit delinquency rates increase from 3 ppt a year before the business credit default to as high as 12 ppt within three months of business default. These personal credit default rates remain as high as 4 ppt five years after the default on business credit. However, personal credit delinquency rates remain between 2 ppt to 3 ppt for matched business owners that are not delinquent on their business loans and individuals who never started a business. We use natural disasters as an exogenous shock to business cash flows and notice consistent results on personal delinquency rates. We find that the impact on personal defaults is much stronger for failed entrepreneurs who borrowed more on their personal accounts after starting the business. Thus, we provide the first evidence on the personal costs of entrepreneurship.

In our analysis, we match the Secretary of State (SoS) data with Small Business Finance Exchange (SBFE) data and the universe of consumer credit data provided by Equifax. We utilize the business incorporation date from SoS to create an monthly panel for all the businesses incorporated between January 2012 to December 2016. For these businesses, we identify business credit information and business characteristics data from SBFE for the period between January 2012 to December 2019. The anonymized credit bureau data on the universe of U.S. consumers provides us with information on business owner's personal credit history including credit scores and all credit accounts. Therefore, we can compare the personal credit outcomes of an entrepreneur with a similar non-entrepreneur matched on observable credit information, income, and location. We follow the entrepreneurs and a matched set of individuals that do not start a business (non-entrepreneur sample) in the two-years before business start and for five years after the business starts. Entrepreneurs and non-entrepreneurs are matched in the month before business start using an exact match on county of residence, personal income, credit scores-levels and slope, and the individual's age.

Within a matched entrepreneur non-entrepreneur pair, we find that on average, in a given month, after starting a business, entrepreneurs are 0.195% more likely to have a personal account 90 days past due. In the month before business start, the average DPD levels of a individual was 1.7%, suggesting an average increase of 11.47% for entrepreneurs following business start. The difference persists even five years after business start. We also find that on average, there is a 0.099% increase in bankruptcy filings in a given month compared to baseline level of 6.0% of consumers with bankruptcy filings in a given month.

To understand if the increased personal defaults are driven by business performance, we classify our sample of new business owners as successful (unsuccessful) if they do not (do) observe business delinquencies (90+ DPD) within 36 months of business start. As discussed before, it is not clear if we should observe any spillover from business to personal credit, especially for the incorporated businesses.[1] However, we find a significant increase in personal delinquencies of entrepreneurs. We see personal delinquencies rise 3.39% after there is a business delinquency, compared to an unconditional mean 90+DPD rate of 4.70%, i.e., a 72.12% increase above the mean. The effect is strongest in the first year when personal

[1] It is possible that the decision to incorporate may be driven by the underlying quality of business and thus future performance. For example, low skilled people who are not sure about the quality of business ideas may choose to incorporate firms to avoid any possible negative spillover on the personal side. However, Levine and Rubinstein (2017) show that "smart and illicit" have a much greater tendency to become *incorporated* business owners and tend to earn more compared to self-employed people who start an *unincorporated* business. They show that the choice of a business's legal form primarily reflects the ex-ante nature, not its ex-post performance.

delinquencies rise 6.20%, and slowly reduce over time. We find similar results for personal bankruptcy filings after business delinquency. We also find that non-prime borrowers, renters, low income, and individuals with less than a college see a greater impact on personal defaults when their business defaults.

To understand the reason for the negative impact on personal credit, we test if excess borrowing on personal balance sheet exacerbates the spillover effect of business delinquencies. Previous research shows that personal creditworthiness is important for entrepreneurship (Hurst and Pugsley, 2011; Robb and Robinson, 2014; Herkenhoff, Phillips, and Cohen-Cole, 2021; Fonseca and Wang, 2022). We find a larger spillover effect of business delinquencies on personal credit for business owners who raise more personal debt during the course of the business. Overall, our paper presents the first evidence on the personal costs of entrepreneurship.

The rest of the paper proceeds as follows. Section 2 documents our contribution to the literature. Section 3 describes our data and empirical methodology. Section 4 presents the main empirical results . Section 5 concludes.

2 Literature Review

Our paper contributes to three main strands of the literature. Firstly, we contribute to the link between personal credit and entrepreneurship. Previous work has shown how personal credit affects entrepreneurship rates, while we focus on the impact of business creation on consumer credit. Hurst and Pugsley (2011) use wealth as a proxy for access to capital markets and show that business entry rates are uncorrelated to personal wealth, except for very wealthy individuals. On the contrary, Bellon, Cookson, Gilje, and Heimer (2021) show that large cash windfalls from shale drilling increase business formation rates but do not affect the duration of business ownership. In a similar vein, increased student debt (Krishnan and Wang, 2019) and lack of housing collateral (Schmalz, Sraer, and Thesmar, 2017) hinders entrepreneurship rates. Herkenhoff, Phillips, and Cohen-Cole (2021) show that bankruptcy flag removal from personal credit files increases access to credit and the likelihood of starting a business. We add to this growing literature by documenting the negative impact of business ownership on personal creditworthiness, especially among business owners with delinquent business debt. Robb and Robinson (2014) find that many startups receive debt financing through the personal balance sheets of the entrepreneur. We show that the spillover effect on the personal balance sheet is confined to business owners with a greater share of borrowing on their personal balance sheet. To the best of our knowledge, we are the first to show that an entrepreneur's personal credit outcomes deteriorate after starting a business and with business default.

Second, we contribute to the emerging literature on entrepreneurship that documents how debtor rights (Cerqueiro and Penas, 2017), creditor rights (Ersahin, Irani, and Waldock, 2021), business bankruptcy flag removal (Cahn, Girotti, and Landier, 2021), career risks (Gottlieb, Townsend, and Xu, 2021), and home equity (Jensen, Leth-Petersen, and Nanda, 2021) impacts entrepreneurship rates. Finally, we also contribute to the large literature on financing and growth that highlights the importance of external and internal credit for growth of small businesses (Rajan and Petersen, 1994; Hubbard, 1997; Carpenter and Petersen, 2002; Berger, Bouwman, and Kim, 2017). Contemporaneous work by Fonseca and Wang (2022) show that small businesses borrow on personal balance sheets when small business credit conditions tighten.

3 Data and Methodology

3.1 Data Sources

We obtain our data from Equifax. All the data are used purely for academic purposes, and they contain completely anonymized information. The credit bureau's trade line-level data provide comprehensive, anonymized records of the various lines of credit opened by every U.S. consumer (see Chava, Ganduri, Paradkar, and Zhang (2021) for details). Equifax also provides the secretary of state (SoS) business registration records, including business incorporation date. We use bureau-created linkage keys to connect each business to its business owners. We extract the personal credit data from the bureau's consumer database for these business owner. The personal credit data includes residential zip code, credit score, individual-level credit attributes like total balance, and individual-level performance attributes that measure the consumer's credit standing like 90 days past due (DPD).

The Small Business Finance Exchange (SBFE) database provides business credit information for small businesses. To identify the performances of these businesses after the business start, we use the business key linkage file provided by Equifax to match it to business credit files provided by SBFE. We use the business delinquency flag (90+DPD) to classify delinquent and not-delinquent businesses. In addition, we observe various business credit data, including business credit card balance and business term loans and firmographic characteristics, including industry (SIC4 code) and location of the business (zip code). Our final dataset includes all incorporated companies between January 2012 to December 2016. For these businesses, we observe personal and business credit from January 2010 to December 2019.

3.2 Methodology

To test if entrepreneurship can have a long-term impact on business owners' credit, we match the entrepreneurs' pre-incorporation personal credit information with non-entrepreneurs' personal credit information. For all individuals who start incorporated businesses between January 2012 to December 2016, we firstly identify non-entrepreneurs who 1) reside in the same county, 2) in the same income band, 3) have a similar credit score (in same 20 points credit score bin), 4) have similar age (in same 5 years individual age band) in the month before incorporation. Then, for these exactly matched entrepreneur-non-entrepreneur pairs, we calculate the Euclidean distance using 1) credit score (a month before business start) and

2) slope credit score (-24 to -1 month relative to business start). For each entrepreneur, we keep the non-entrepreneurs with the smallest Euclidian distance. This matching strategy helps us control various observable differences in the personal credit of entrepreneurs and non-entrepreneurs before the business starts.

In our first set of tests, we estimate the impact of business start on personal credit outcomes using the following specification:

$$Y_{i,p,t} = \alpha_i + \beta \text{Entrepreneur}_i \times \text{Post}_t + \gamma_{p,t} + \epsilon_{i,p,t} \tag{1}$$

where Y is personal credit delinquency dummy, equal to 100 if individual (entrepreneur or non-entrepreneur) i belonging to a pair p of matched entrepreneur and non-entrepreneur observe 90+ DPD in month t. Similarly, we define personal bankruptcy dummy. Our sample is based on businesses started between January 2012 and December 2016 and follows the individual in the two years before business start and five years after. We run an event-style regression with a stacked panel where we define the event based on month of business start. We include individual fixed effects (α_i), pair-month fixed effects ($\gamma_{p,t}$), and our coefficient of interest is the β on a dummy variable for *Entrepreneur* interacted with *Post*. We double cluster standard errors by business owner's residence county and incorporation event-month.

Within entrepreneurs, we further test the impact of business delinquency on personal credit using the following regression specification:

$$Y_{i,p,t} = \alpha_i + \beta \text{Business Default}_i \times \text{Post}_t + \gamma_{p,t} + \epsilon_{i,p,t} \tag{2}$$

where Y is the personal credit delinquency/personal bankruptcy of the entrepreneur i belonging to a pair p of matched entrepreneurs with and without business delinquencies in month t. Our sample is based on businesses started between January 2012 and December 2016 and follows the individual in the two years before the first business delinquency and five years after. We include individual fixed effects, pair-time fixed effects, and our coefficient of interest is the β on a dummy variable for *Business Default* interacted with *Post* where

Business Default is defined as an entrepreneur with a business delinquency.

3.3 Summary Statistics

In Table 1, we present personal financial characteristics from the consumer credit panel, both before and after our matching procedure.

Panel A of shows that, on average, entrepreneurs are more creditworthy - higher credit score (713 vs. 697), higher income ($4776/mo vs. $3647/mo), lower delinquencies (90+DPD) (1.7% vs. 2.4%), lower bankruptcy rates (6.2% vs 6.6%), have higher credit balance ($213k vs. $75k), have higher monthly debt ($2,318 vs. $1,158), and higher debt-to-income ratios (0.41 vs. 0.27). These suggest that, in general, entrepreneurs have a stronger financial position than the general population. After matching, however, the observable characteristics across these groups are comparable. This is true not just on credit score, income, and age on which we matching the groups but also on all other personal characteristics. In Panel B, we provide a similar comparison across entrepreneurs who face a business delinquency within three years of business start and entrepreneurs without a business delinquency.

4 Results

4.1 Business Starts

To the best of our knowledge, our paper is the first to combine the universe of business and consumer credit bureau data. Thus, we first provide descriptive statistics on the patterns observed in our novel dataset. We start by documenting the type of individuals that start a new venture (Section 4.1.1), followed by the impact of the business start on the individuals' personal outcomes (Section 4.1.2).

4.1.1 Who Starts Businesses?

Figure 2 plots the business starts in our merged business-consumer credit panel scaled by the number of consumers in the credit panel in a given year. As expected, there is sharp decline in number of businesses started during the financial crisis, and business start rates recover after 2015. Appendix Figure IA1 shows heterogeneity in business starts across gender, race, and education levels. On average, men start more businesses, as do individuals with higher levels of formal education. Interestingly, we notice patterns in business starts across race have flipped in recent years. Before 2014, white individuals were more likely to start a business. Since then, there has been a steady increase in business starts by minorities, with the current level far exceeding that of white individuals.

Figure 3 denotes where entrepreneurs are most active in the U.S. We plot the average annual new business starts in a county scaled by county population. We observe interesting patterns. Unsurprisingly, large cities such as New York City, Los Angeles, Chicago, San Francisco, etc., see high business growth. However, we also see high growth across urban and rural areas in Florida, Colorado, Utah, and Oregon. In the appendix (Figure IA2), we show that businesses in the agricultural sector do not drive these results. We also observe very similar patterns in high-tech business starts across the country.

Next, we study how the likelihood of starting a business varies across individuals' characteristics. Figure 4a plots business starts along with household income. We see a strong positive correlation between the two - richer households are more likely to start businesses.[2] Figure 4b shows that consumers with a house have a higher likelihood of starting a business, consistent with the idea that collateral makes borrowing and business start easier (see Schmalz, Sraer, and Thesmar (2017)). In the Appendix Figure, we see that business starts also increase with the mortgage balance. Similarly, Figure 4c shows a strong positive correlation between likelihood of starting a business and the consumer's debt-to-income levels.

Figure 4d and Figure 4e show an inverted U-shaped relationship between business start

[2] We find similar results using individual instead of household income (Appendix Figure IA1)

and consumer credit score and consumer age respectively. Borrowers with a credit score between 640-780 are most likely to start a business, with the likelihood dropping at higher and lower scores. Furthermore, we observe the likelihood of starting a business is highest among 35-40 year olds, with business starts dropping strongly among the oldest.

4.1.2 Impact of Business Starts on Personal Credit

We start by looking at whether an entrepreneur's personal credit is affected by a business start. With access to detailed credit bureau data that links both the personal and business credit of small business owners, we study the impact of new business start on personal credit outcomes.

Figure 5 presents the personal credit outcomes of entrepreneurs as compared to a matched set of consumers that do not start a business (non-entrepreneurs sample). We follow the two groups two years before the business starts and five years after. Entrepreneurs and non-entrepreneurs are matched on observables in the month before the business start. The consumers who start businesses are matched non-entrepreneurs on the county, income, credit scores, and age. Details on the matching are described in Section 3.1.

Figure 5a plots the personal delinquency rates (90+ DPD rate). Before starting the business, we note that both groups of consumers are on a similar path, with credit conditions improving and personal delinquency rates dropping. After the start of the business, the personal DPD of entrepreneurs continues to drop for a couple of months before increasing. Within a year of business start, entrepreneurs are more likely to have a personal DPD, and the difference persists even five years after the business start.

In Table 2 we test this relationship more formally and estimate regression equation (1). Column 1 of Table 2 shows that on average, in a given month, after starting a business, entrepreneurs are 0.195% more likely to have a personal account 90 days past due. In the month before the business started, the average DPD level of consumers was 1.7%, suggesting an average increase of 11.47% for entrepreneurs following business start.

In Column 2, we study the effect of business start over the years. As our aggregate figure suggests, immediately after the business starts, personal delinquency rates fall, suggesting improved personal outcomes. However, entrepreneurs have higher delinquencies from the second year, with the rate increasing over time. Five years after the business start, entrepreneurs are 0.342% more likely to have personal delinquency, equivalent to 20.11% of the unconditional mean.

To ensure there are no differential pre-trends among the group of entrepreneurs and non-entrepreneurs, we estimate a dynamic version of Equation 1 in Figure 6. We observe no differential pre-trends. In the first two quarters after business start, we observe a significant decline in personal delinquency rates for entrepreneurs compared to the non-entrepreneurs. However, this effect is short-lived. After two quarters, personal delinquency rates of entrepreneurs increases significantly and stays elevated for the next five years.

Figure 5b shows the corresponding path for personal bankruptcy filing. The dependent variable takes a value of 100 in the first month the individual files for bankruptcy. We see that, as with delinquencies, bankruptcy rates are dropping in the months preceding the business start, but rise for entrepreneurs after the business incorporation. New bankruptcy filings continue to stay elevated even five years after the business start.

Column 3 and 4 of Table 2 look at personal bankruptcy filings. The dependent variable takes a value of 100 if the borrower has a bankruptcy filing on their credit report. On average, there is a 6.0% likelihood having a bankruptcy filing on record. Column 3 shows that, on average, the likelihood of having a bankruptcy filing rises by 0.099% after a consumer starts a business. As with delinquencies, Column 4 shows that the likelihood of filing for a bankruptcy increases with time, and by the fifth year, the entrepreneur is 0.368% more likely to have filed for bankruptcy, equivalent to 6.13% of the unconditional mean.

In Internet Appendix Figure IA4, we provide trends for other personal credit outcomes of the borrower. IA4a shows that there is a sudden decrease in credit scores for entrepreneurs on business start. In Figure IA4b, we observe that the utilization of revolving accounts, which was on a downward trend before the business start, increases significantly for the group of entrepreneurs. This shows that when a consumer starts a business, personal credit is an important source of financing, with increased drawdown by borrowers on their existing accounts. Simultaneously, entrepreneurs are opening new accounts, primarily in the form of new non-mortgage accounts, as seen in Figure IA4c. While we also see a small growth in the number of new mortgages (Figure IA4d). These results suggest increased personal borrowing upon business start.

Thus, overall, we see a worsening of personal credit conditions through increased delinquency rates and bankruptcy filings. One possible reason for these worsening outcomes could be the additional borrowing, observed primarily in non-mortgage accounts of entrepreneurs after the business start. We test this formally in Section 4.4.

Lastly, we examine heterogeneity in borrower delinquency and bankruptcy outcomes based on borrower characteristics. The goal is to understand whether personal credit of certain types of borrowers are more negatively affected when a new business is formed. These differences could have significant policy implications, such as which type of entrepreneurs need support.

Panel B of Table 2 follows the procedure in Equation 1 but includes an additional interaction term based on borrower characteristics in each column. We notice that the impact on the personal side is worst for borrowers with less than a college degree and older entrepreneurs. However, we see no differences in outcomes across other borrower financial conditions. In addition, Internet Appendix Table IA1 shows that homeowners, high-income borrowers, and older borrowers are more likely to file for bankruptcy, suggesting some discrepancy in which borrowers file for bankruptcy even conditional on delinquency.

4.2 Business Failures

In the previous section, we show that business starts can have a negative impact on the owner's personal credit. However, there are two main concerns with these analyses. First, the business start is not exogenous. Thus, even if we match entrepreneurs and non-entrepreneurs on observable characteristics, there could be inherent differences across them that lead to business starts and worse personal outcomes. Second, we do not know what leads to worse personal outcomes or which entrepreneurs suffer after the business start. To address these issues, we analyze the sample of entrepreneurs and focus on the impact of business distress on personal outcomes.

4.2.1 Impact of Business Delinquency on Personal Credit

Ex-ante, it is not apparent that we should observe any spillover from business to personal credit. Incorporated businesses (our sample) create a legal separation between personal assets and the business's assets. Thus, business failure could be limited to the business side without directly impacting the owner's personal finances. However, there could be conditions under which business failure impacts the owner. Firstly, the business failure could directly impact the business owner's income and personal credit outcomes. Furthermore, if business owners borrow using personal credit facilities to finance the business (as anecdotes about small business financing would suggest and as observed in our results in Section 4.1.2), we may expect worsening of personal credit conditions along with deteriorating business finances. Therefore, we are especially interested in this indirect channel, which could serve as a double whammy for small business owners if their business fails.

Figure 7 studies the personal delinquencies and bankruptcy rates of three groups - a) non-entrepreneurs, b) entrepreneurs who have no delinquencies within 36 months of business start (successful entrepreneurs), and c) entrepreneurs that see delinquency within 36 months of business start (failed entrepreneurs).[3] We match the entrepreneur groups (failed and successful entrepreneurs) using county of residence, income, the month of business start, and credit score. The consumers who start businesses are also matched to non-entrepreneurs on the county, income, credit score, and age. Details on the matching are described in Section

[3]Our results are insensitive to the choice of timing of business delinquency. We choose 36 months to retain a sufficiently large number of consumers that can be tracked post business delinquency.

3.1.

Figure 7a looks at the rate of consumer defaults as measured by the 90+ days past due (90+DPD) for the three groups above. We see a large increase in personal delinquencies of an entrepreneur even before their business defaults, with rates increasing almost a year before there is a business account that is 90+ DPD. The delinquency rates continue to rise after business failure, peaking at around three months after business failure and then dropping. However, even five years after the business failure event, personal DPDs of entrepreneurs are 1 ppt higher (compared to a baseline of 3% for successful entrepreneurs and non-entrepreneurs).

As an alternate measure of personal default, we study bankruptcy filings of consumers in Figure 7b. Not all loan defaults lead to personal bankruptcy, which is the last resort outcome for financially impaired borrowers. However, we notice a similar trend when measuring personal default using bankruptcy filings. Again, we see a significant jump in personal bankruptcy rates for consumers whose businesses are delinquent, with *new* personal bankruptcy filings of failed entrepreneurs above the rate of both non-entrepreneurs and successful entrepreneurs multiple years after business default.

We formally analyze the impact of business failure on personal creditworthiness using equation (2). Table 3 presents the results. In Panel A, we look at personal delinquencies (Columns 1 and 2) and personal bankruptcy (Columns 3 and 4) in the window around the first time a business has a delinquent account. Column 1 shows that personal delinquencies rise 3.39% after business delinquency, compared to an unconditional mean 90+DPD rate of 4.70%, i.e., a 72.12% increase above the mean. The effect is strongest in the first year when personal delinquencies rise 6.19% and slowly reduce over time. However, 5 years after the business delinquency, personal delinquency is still 1.24% higher than similar entrepreneurs who did not have business delinquency.

To understand the exact timing of the impact on personal credit, we estimate a dynamic version of Equation 2 in Figure 8. In the quarters before a business delinquency, we observe personal delinquency rates of struggling entrepreneurs increase relative to entrepreneurs whose businesses face no default. The difference peaks in the quarter after business delinquency and remains elevated even five years after, compared to the pre-business-delinquency levels.

In Column 3 of Table 3, we show that entrepreneurs whose businesses face delinquency are 3.23% more likely to face personal bankruptcy. This compares to an unconditional mean of 8.45% of entrepreneurs who have a bankruptcy filing at a given point in time. Unlike delinquencies, we see in Column 4 that personal bankruptcy rates increase over time. This could be because bankruptcy flags remain on record for 7 years after consumer files for bankruptcy while DPDs are discharged. Lastly, we look at heterogeneity in borrower delinquency outcomes based on borrower characteristics in Panel B of 3. The goal is to understand whether certain types of borrowers are more negatively affected personally when their business is in trouble. We see that non-prime borrowers, renters, low income, or individuals with less than a college degree face a business default, they have a larger negative impact on personal credit. We explore the reasons for this in Section 4.4

4.3 Exogenous Variation in Business Failure

As mentioned earlier, business starts or failures are not exogenous events. Omitted variables such as an entrepreneur's ability or skill could affect both the likelihood of business failure and their personal financial outcomes. While we try our best to match entrepreneurs on observable characteristics, inherent ability or skill is not observable.

We, thus, identify exogenous shocks that lead to business failure to address this identification challenge. In particular, we focus on the increased likelihood of a business failing in regions that face an unexpected natural disaster shock. In this paper, we focus on damages from hurricanes. Of the 258 U.S. weather disasters since 1980, hurricanes have caused the most damage totaling over $945 billion, with an average cost of almost $21.5 billion per event. They are also responsible for the highest number of deaths - 6,593 between 1980 and

2020.[4]

We first document that regions that face these large natural disaster shocks see increased business failure. In turn, these failures lead to worse personal credit outcomes by comparing personal outcomes of individuals who were or were not operating a business when the hurricane strikes. Our exclusion restriction is that business owners' personal credit is differentially affected compared to a matched non-entrepreneur only due to the impact of the natural disaster.

To study this, one can estimate the following 2-stage regression,

$$\text{Business Default}_{i,c,t} = \alpha_1 + \beta_1 \text{Natural Disaster}_{t-1,c} + \epsilon_{i,c,t}$$
$$Y_{i,p,c,t} = \alpha_i + \beta \widehat{\text{Business Default}}_{i,c,t} \times \text{Post}_t + \gamma_{p,t} + \epsilon_{i,p,c,t}$$

where Y is the personal credit outcome of the entrepreneur i belonging to a pair p of matched entrepreneurs with and without business delinquencies in county c and month t. We include individual fixed effects, pair-time fixed effects, and our coefficient of interest is the β on a dummy variable for *Business Default* interacted with *Post* where *Business Default* is the predicted value from the first stage regression. Natural disaster measures the level of property damaged caused by hurricanes in a given county c in month t.

However, in this version, we present the reduced form estimates in Table 4. Here, we estimate the following the specification :

$$Y_{i,p,cR,cB,t} = \alpha_i + \beta \text{Natural Disaster}_{cB} \times \text{Post}_t + \gamma_{p,t} + \epsilon_{i,p,cR,cB,t} \tag{3}$$

where Y is personal credit delinquency dummy, equal to 100 if individual i residing in county cR and operating a business in county cB observe 90+ DPD in month t. We match entrepreneurs living in the same county cR on income, credit score, age, and industry. The sample is restricted to individuals who reside in the same county but operate businesses in different counties, and hence face differential business cash flow shocks due to the hurricane.

[4]Office for Coastal Management - https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

Our sample is based on businesses started between January 2012 and December 2016 and follows all entrepreneurs in the one year before the hurricane and two years after. We run an event-style regression with a stacked panel where we define the event based on month of the hurricane in a county.

In Column 1 of Table 4, we find that within a pair of entrepreneurs residing in the same county, individuals whose businesses are in a location affected by the hurricane see personal default rates increasing by 0.45%, compared to an unconditional mean delinquency rate of 1.25%, or 36.00% above the mean. In Column 2, we see that the impact of the shock increases in the first year and slowly subsides.

To ensure there are no differential pre-trends among the group of entrepreneurs that do or do not get hit by a hurricane in the business county, we estimate a dynamic version of Equation 3 in Figure 9. We observe no differential pre-trends. However, after the hurricane, personal delinquency rates of affected entrepreneurs increases sharply and stays elevated for the next year.

4.4 Channels

Having established that business delinquencies and failures lead to worse personal outcomes, we focus on the reason for these spillovers. As highlighted earlier in the paper, incorporated firms are shielded on the personal side from business losses. Yet, we see a negative spillover. To understand why, we turn to the source of financing for the small business.

Business owners can borrow either business credit or personal credit to finance the start and growth of a small business. Thus, even though delinquencies on business debt do not impact the consumer, the increased borrowing on personal credit could have negative consequences if the business fails.

To disentangle this, we look at the personal and business borrowings of entrepreneurs in the months around the start or failure of a business. We then interact the growth in personal and business (total) debt with business delinquency and study the impact of these on personal delinquency rates.

Table 5 presents the results. In Panel A, we look at the growth in personal and total (business + personal) borrowings of the entrepreneur in the first year of business start. Column 1 suggests that, entrepreneurs who have higher personal borrowings have worse personal outcomes upon business delinquency. Column 2 suggests a similar trend based on total borrowings of the entrepreneur. However, when we run a horse race of the two measures, we see that personal debt growth explains the entirety of the negative impact on personal outcomes. In Panel B, we measure debt growth in the months leading to the business delinquency. We observe similar patterns. Overall, these results suggest that the negative impact of business failure is correlated with increased personal borrowing by the business owner.

However, the choice to borrow on the business vs. personal side is endogenous. We are concerned that business feasibility or individual entrepreneur ability or skill may impact the composition of personal and business debt as well as personal credit outcomes. Thus, we need a quasi-random variation in business financing coming from personal credit. For this purpose, we use a credit supply shock that impacts the small business credit access. As small business credit becomes harder to access, entrepreneurs have to finance business investment and growth through personal credit. We plan to use this variation to study the impact on personal credit outcomes.

5 Conclusion

In this paper, we provide the first direct evidence on how entrepreneurship impact the personal finances of business owners. New business formations help individuals transition from formal employment to self-employment and help create new jobs in the economy. However, the large exit probability of new businesses is not costless for business owners. We find that entrepreneurs experience increased personal credit default rates and personal bankruptcy rates within a year of incorporating their business, compared to non-entrepreneurs with similar creditworthiness. The personal costs are more for entrepreneurs who default on their business loans. We show that entrepreneurs that borrowed more on their personal accounts when incorporating their business suffer more. Overall we document that entrepreneurship can have a long-term negative impact on the personal credit of some small business owners.

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Figure 1: Exit Rates By Age

This figure plots the rate of establishment exit by establishment age in 2019. Source: Business Dynamic Statistics (BDS)

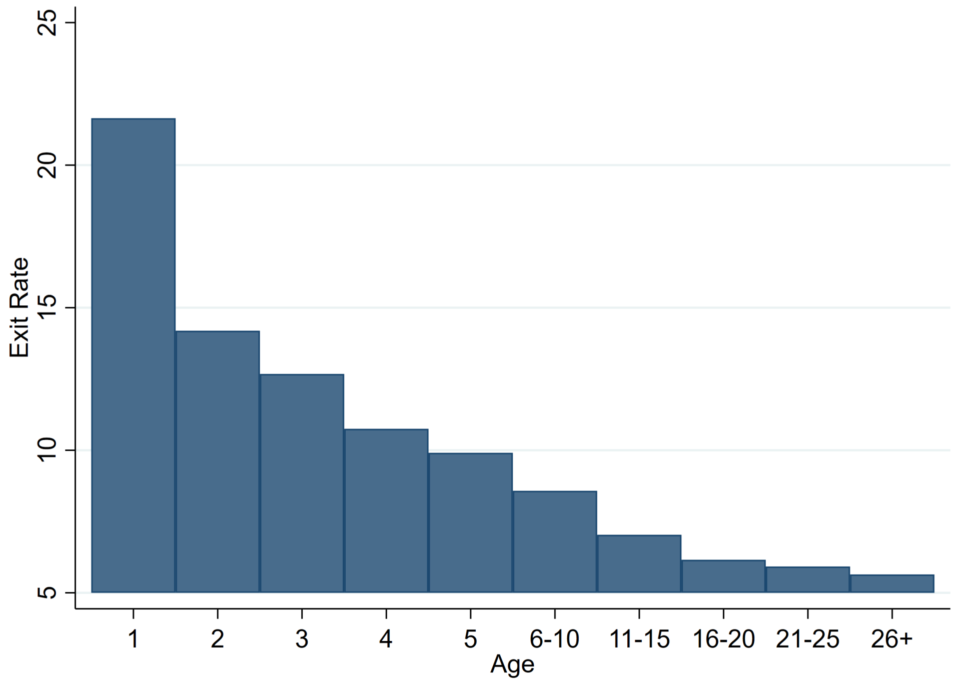


Figure 2: Business Starts By Year

This figure plots the number of business starts in the merged Equifax business-consumer credit panel scaled by the number of consumers in the credit panel in a given year.

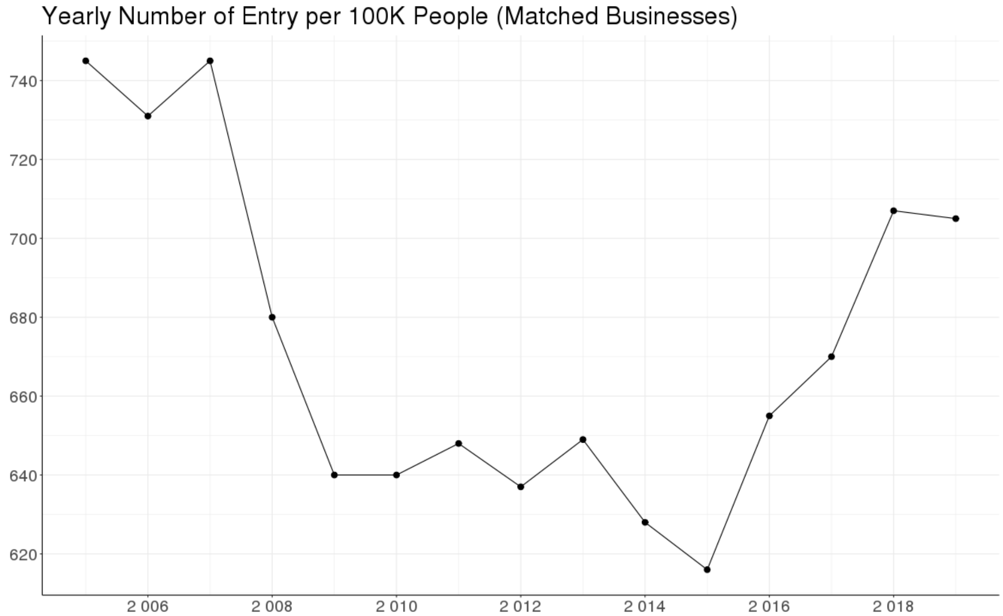


Figure 3: Business Starts per 100k population

This map plots the average number of business starts in a county between 2005 and 2019 scaled by the county population in 2010. We split the business start rates into terciles.

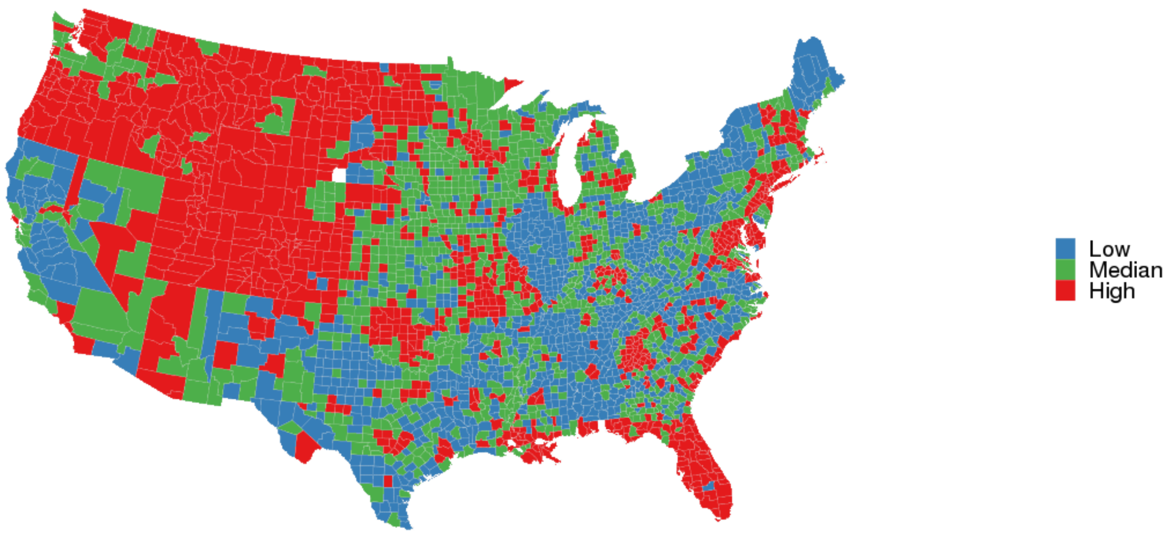
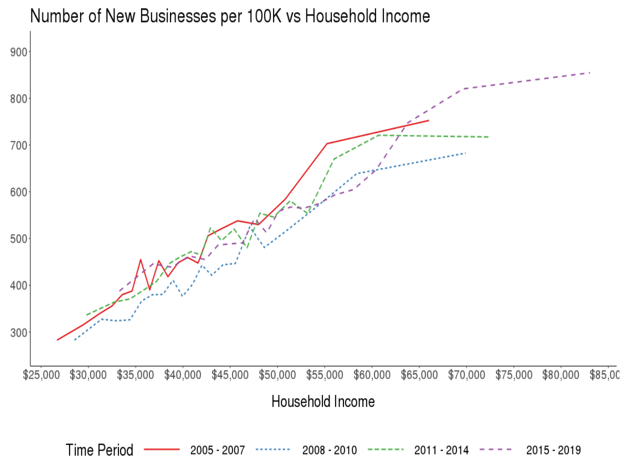
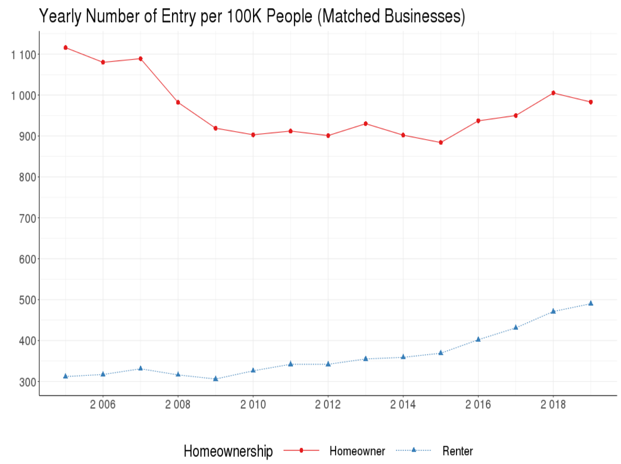


Figure 4: Business Starts By Borrower Characteristics

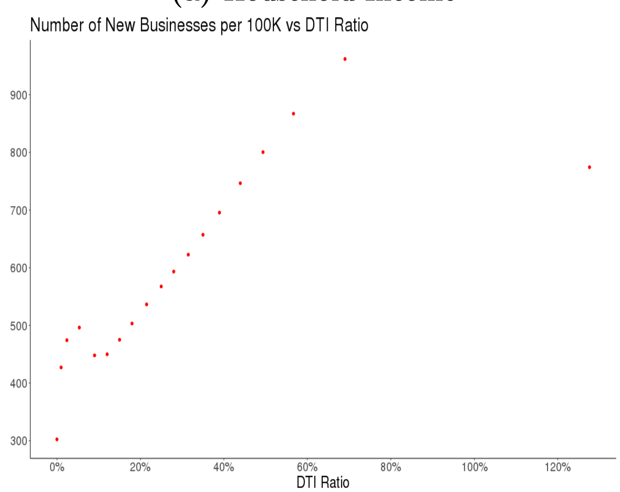
This figure plots the business start rate across borrower characteristics. Household income, home ownership, debt-to-income, credit scores and age are obtained from the Equifax consumer panel.



(a) Household Income

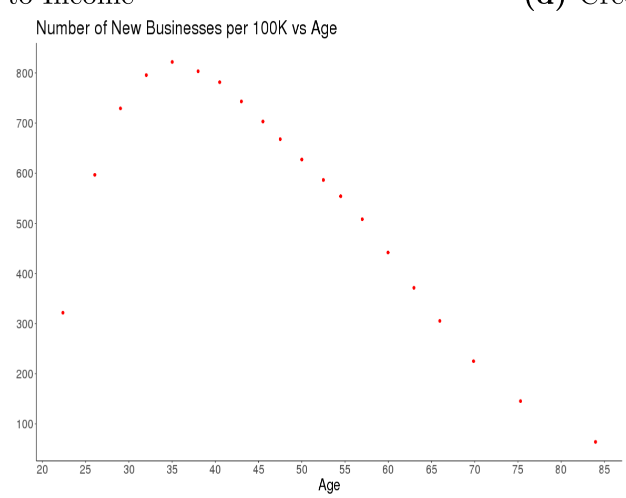


(b) Home ownership



(c) Debt to Income

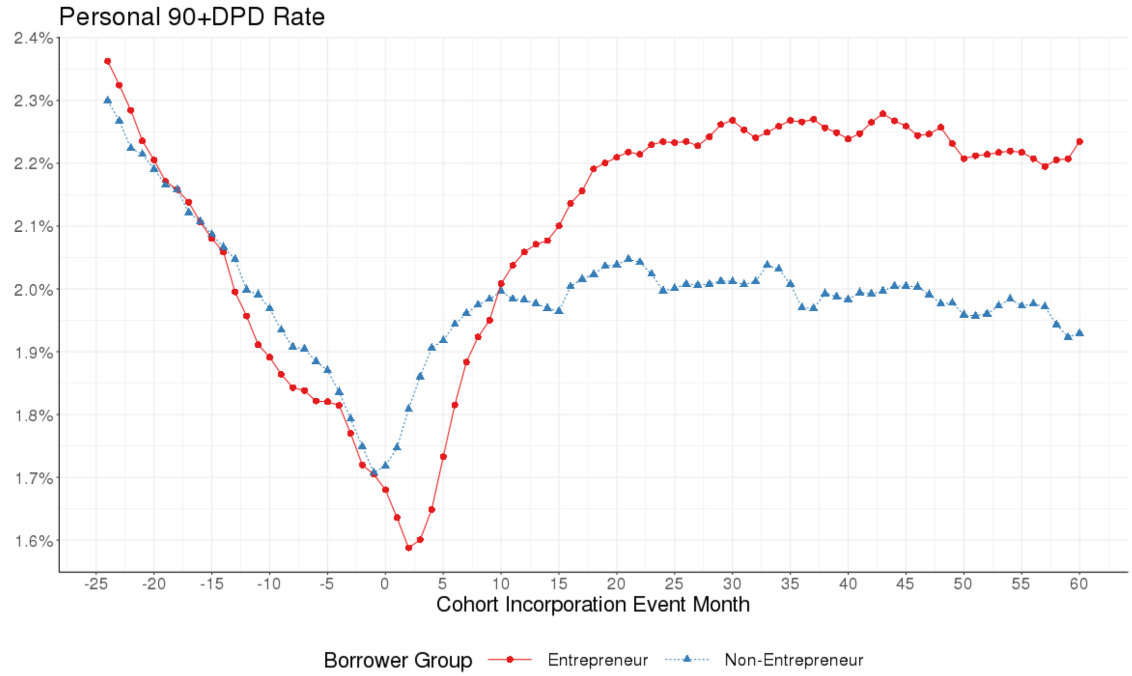
(d) Credit Score



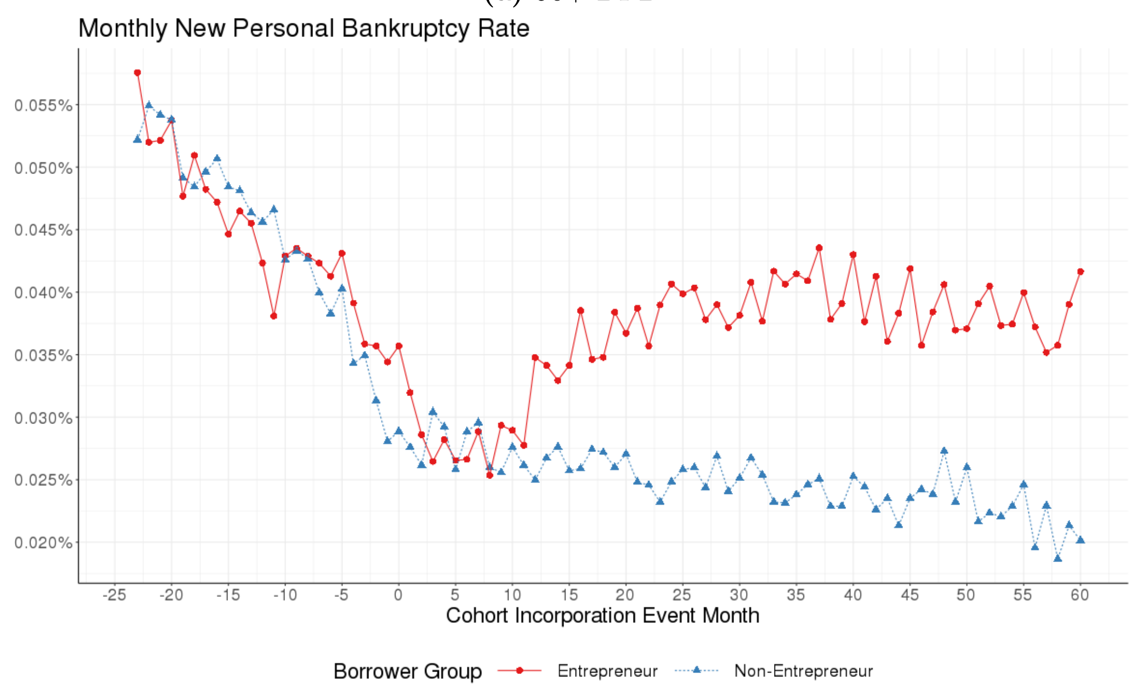
(e) Age

Figure 5: Personal Credit Outcomes of Entrepreneurs and Non Entrepreneurs

This figure plots the average monthly personal 90 days past due (90+DPD, Panel A) and new bankruptcy filings (Panel B) for entrepreneurs and non-entrepreneurs matched as described in Section 3.2. We track the individuals in the two years prior to business start and five years after.



(a) 90+ DPD



(b) Personal Bankruptcy

Figure 6: Personal Credit Dynamics Around Business Start

This figure plots the regression coefficients based on

$$Y_{i,p,t} = \alpha_i + \Sigma_{q=-8}^{q=-2}\beta_q \text{Entrepreneur}_i \times \mathbf{1}_q + \Sigma_{q=0}^{q=19}\beta_q \text{Entrepreneur}_i \times \mathbf{1}_q + \gamma_{p,t} + \epsilon_{i,p,t}$$

where Y is personal credit delinquency dummy, equal to 100 if individual (entrepreneur or non-entrepreneur) i belonging to a pair p of matched entrepreneur and non-entrepreneur observe 90+ DPD in month t, quarter q. Our sample is based on businesses started between January 2012 and December 2016 and follows the individual in the two years before business start and five years after. We run an event-style regression with a stacked panel where we define the event based on month of business start. We include individual fixed effects (α_i), pair-month fixed effects ($\gamma_{p,t}$). We double cluster standard errors by business owner's residence county and incorporation event-month.

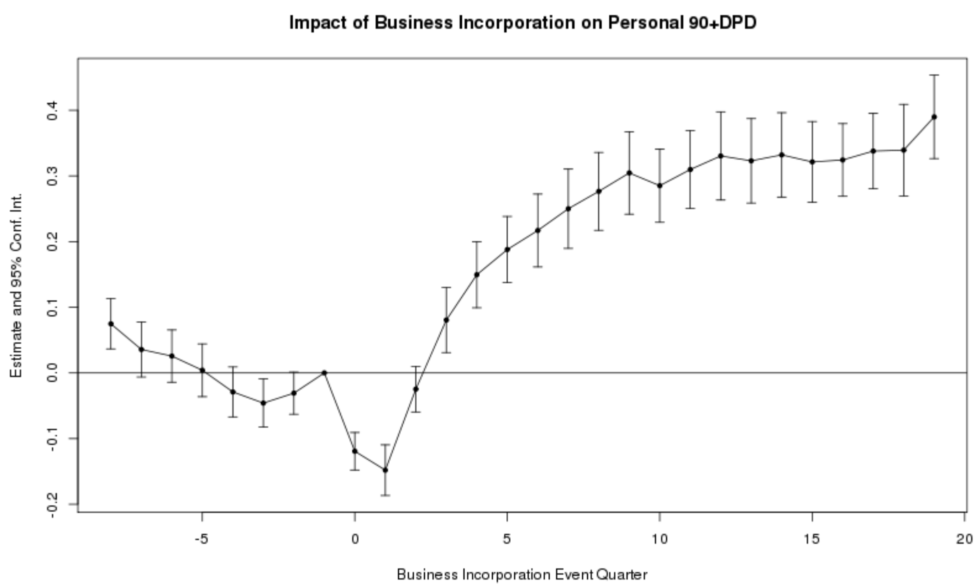
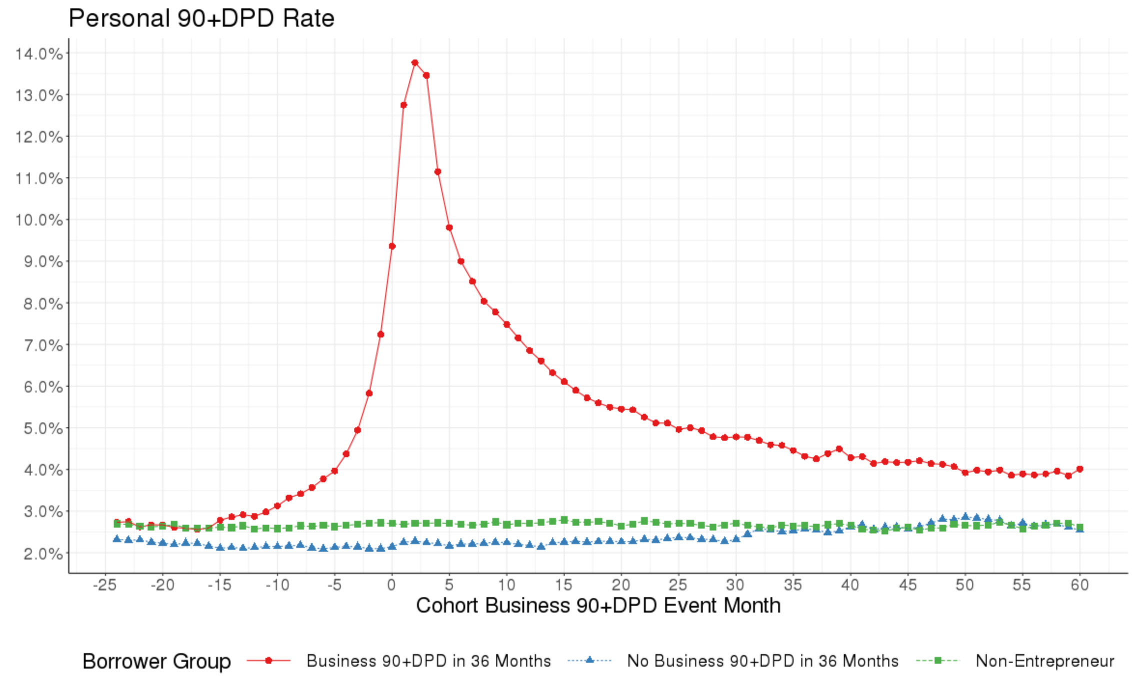
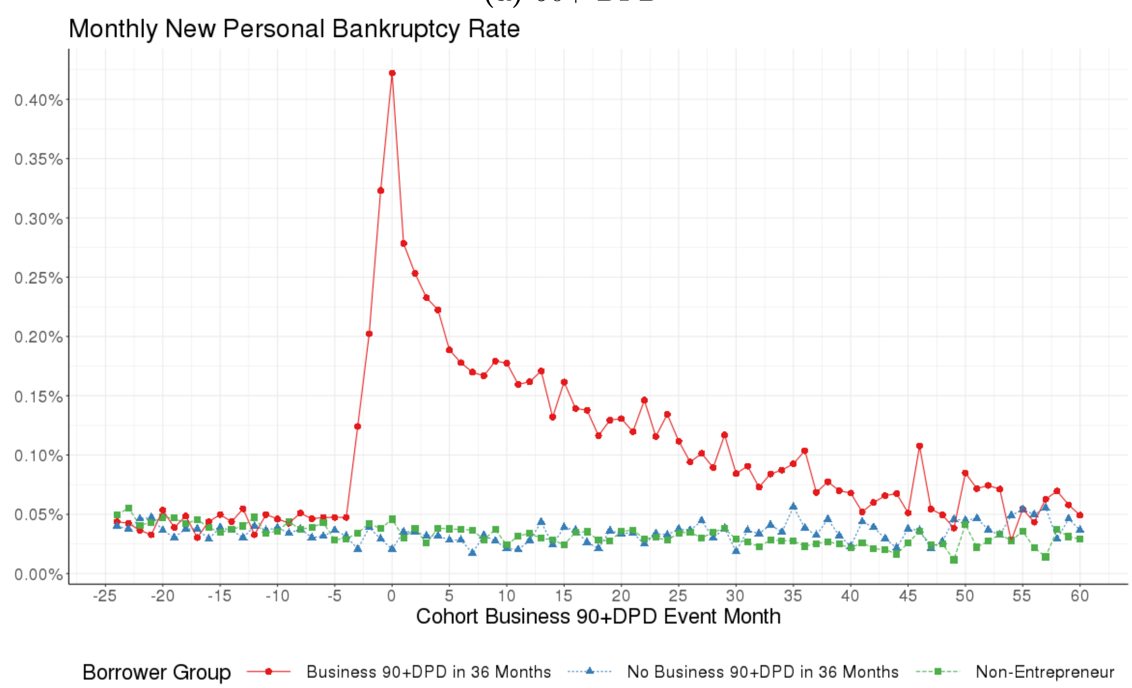


Figure 7: Personal Credit Outcomes of Successful and Failed Entrepreneurs

This figure plots the average monthly personal 90 days past due (90+DPD, Panel A) and new bankruptcy filings (Panel B) for entrepreneurs with a business delinquency, entrepreneurs without business delinquencies, and non-entrepreneurs matched as described in Section 3.2. We track the individuals in the two years prior to the first business delinquency and five years after.



(a) 90+ DPD



(b) Personal Bankruptcy

Figure 8: Personal Credit Dynamics Around Business Delinquency

This figure plots the regression coefficients based on

$$Y_{i,p,t} = \alpha_i + \Sigma_{q=-8}^{q=-2} \beta_q \text{Business Default}_i \times \mathbf{1}_q + \Sigma_{q=0}^{q=19} \beta_q \text{Business Default}_i \times \mathbf{1}_q + \gamma_{p,t} + \epsilon_{i,p,t}$$

where Y is personal credit delinquency dummy, equal to 100 if an entrepreneur i belonging to a pair p of matched entrepreneurs with and without business defaults observes 90+ DPD in month t, quarter q. Our sample is based on businesses started between January 2012 and December 2016 and follows the individual in the two years before the first business delinquency and five years after. We run an event-style regression with a stacked panel where we define the event based on month of business default. We include individual fixed effects, pair-month fixed effects, and industry-month fixed effects. We double cluster standard errors by business owner's residence county and incorporation event-month.

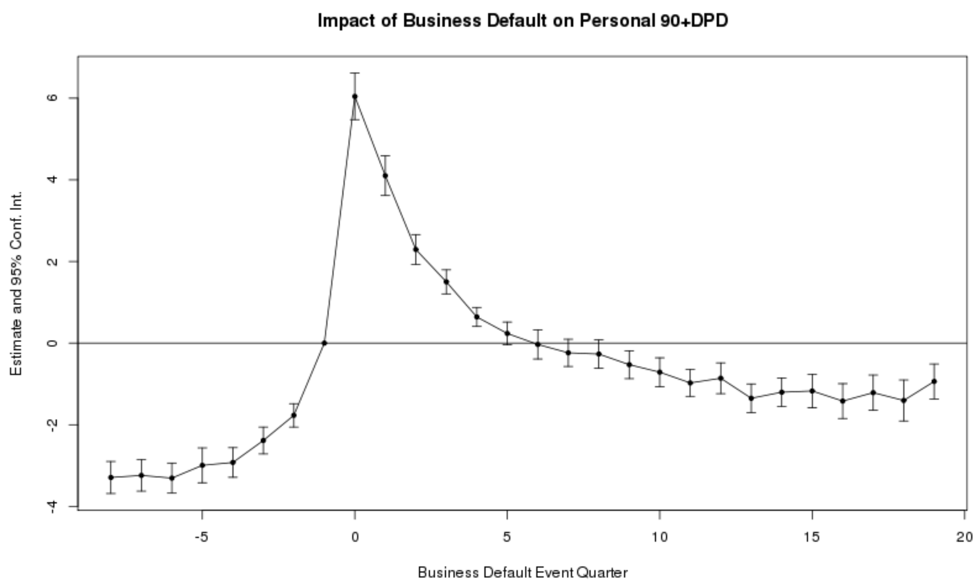


Figure 9: Personal Credit Dynamics Around Natural Disaster Shock

This figure plots the regression coefficients based on

$$Y_{i,p,t} = \alpha_i + \Sigma_{q=-4}^{q=-2}\beta_q \text{Hurricane}_i \times \mathbf{1}_q + \Sigma_{q=0}^{q=7}\beta_q \text{Hurricane}_i \times \mathbf{1}_q + \gamma_{p,t} + \epsilon_{i,p,t}$$

where Y is personal credit delinquency dummy, equal to 100 if an entrepreneur i observes a 90 days past due (90+ DPD) on any personal account. Our sample contains pairs p of entrepreneurs who reside in the same county and have similar observable prior to incorporation but operate businesses in different counties. Further details are described in Section 3.2. Our sample is based on businesses started between January 2012 and December 2016 and follows the individual in the year before a hurricane strikes the business county and follows them for two years after the hurricane. We run an event-style regression with a stacked panel where we define the event based on month of hurricane. We include individual fixed effects, pair-month fixed effects, and industry-month fixed effects. We cluster standard errors by business owner's residence county.

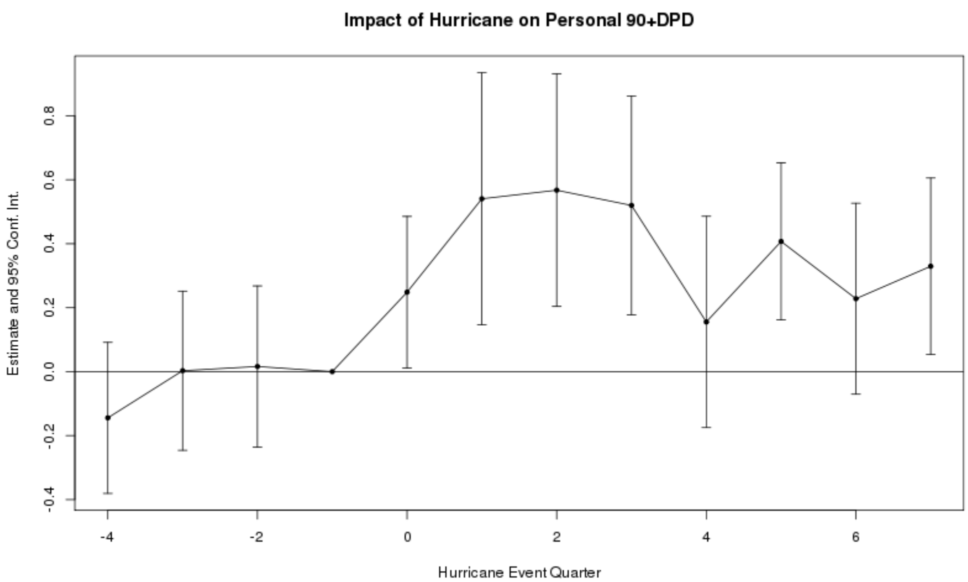


Table 1: Summary Statistics - Personal Financial Information

This table presents personal credit characteristics between January 2012 and December 2016. Columns 1 and 2 provide the means before matching and Column 3 and 4 compare the individuals after matching (matching procedure described in Section 3.2). In Panel A, we compare entrepreneurs to individuals who did not start a business (non-entrepreneur). We use a 1% random sample of non-entrepreneurs before matching to generate statistics for the Column 2. Panel B presents personal characteristics of entrepreneurs who observed a business default (90+ DPD) within three years of business start compared to the entrepreneurs without a business default.

Panel A - Entrepreneur vs. Non-Entrepreneur

	Before Matching		After Matching	
	Entrepreneur (1)	Non-Entrepreneur (2)	Entrepreneur (3)	Non-Entrepreneur (4)
Number of Observations	1,310,076	1,398,271	1,277,405	1,277,405
Matched Characteristics				
Credit Score	713	697	714	714
Monthly Income	4,776	3,647	4,796	4,254
Borrower Age	45	52	45	45
Other Characteristics				
Personal 90+DPD	0.017	0.024	0.017	0.017
Personal Bankruptcy	0.062	0.066	0.062	0.058
# Mortgage Accounts	0.75	0.39	0.76	0.6
# Non-Mortgage Accounts	6.6	4.8	6.7	5.9
Revolving Utilization	0.32	0.29	0.32	0.31
Total Balance	213,398	74,699	216,449	141,789
Homeowner Indicator	0.74	0.53	0.74	0.67
Monthly Debt	2,318	1,158	2,322	1,650
Debt-to-Income Ratio	0.41	0.27	0.41	0.33

Panel B - Entrepreneur with vs. without Business Default

	Before Matching		After Matching	
	Entrepreneur with Business Default (1)	Entrepreneur without Business Default (2)	Entrepreneur with Business Default (3)	Entrepreneur without Business Default (4)
Number of Observations	153,210	1,156,866	83,836	83,836
Matched Characteristics				
Credit Score	661	720	685	691
Monthly Income	4,028	4,874	4,401	4,516
Borrower Age	44	45	44	44
Other Characteristics				
Personal 90+DPD	0.038	0.015	0.021	0.019
Personal Bankruptcy	0.1	0.056	0.087	0.08
# Mortgage Accounts	0.6	0.77	0.67	0.72
# Non-Mortgage Accounts	6.2	6.6	6.6	6.7
Revolving Utilization	0.42	0.3	0.39	0.37
Total Balance	171,110	218,985	206,405	215,199
Homeowner Indicator	0.64	0.75	0.69	0.71
Monthly Debt	2,255	2,326	2,368	2,387
Debt-to-Income Ratio	0.47	0.4	0.44	0.44

Table 2: Impact of Business Start on Personal Credit

This table presents the results based on Equation 1. The data are stacked event-month panel between January 2010 and December 2019, and contain information in the two years before and five years after business start. *Entrepreneur* is a dummy that takes a value of one if an individual starts a new business between January 2012 and December 2016. *Post* takes a value of one in the months after the business start and is zero otherwise. In Panel A, the dependent variable in Columns 1 and 2 are 100 if the consumer has an account that is 90 days past due (90+DPD). In Columns 3 and 4, the dependent variable is 100 if there is a bankruptcy filing observed on the individual's credit file. In Panel B, the dependent variable is a 90+ DPD on the entrepreneur's personal account. *Non-prime* borrowers are individuals with a credit-score below 680. *Renter* takes a value of one if the individual has had no past or current mortgages. *Low Income* and *Young* borrowers are individuals with below median income and age respectively. We classify individuals without a college degree as *Below College*. We include individual as well as cohort-event-month fixed effect where the event is the start of the business and a cohort is a pair of matched entrepreneurs and non-entrepreneurs (details in Section 3.2). Standard errors are double clustered at the business owner's residence county and incorporation event-month level.

Panel A - Personal Credit Outcomes

	Personal 90+DPD		Personal Bankruptcy	
Event - Business Start	(1)	(2)	(3)	(4)
Entrepreneur × Post	0.195***		0.099***	
	(0.020)		(0.032)	
Entrepreneur × 1 Year Post		-0.062***		-0.032*
		(0.013)		(0.017)
Entrepreneur × 2 Year Post		0.197***		-0.016
		(0.025)		(0.025)
Entrepreneur × 3 Year Post		0.290***		0.090**
		(0.028)		(0.034)
Entrepreneur × 4 Year Post		0.322***		0.209***
		(0.031)		(0.044)
Entrepreneur × 5 Year Post		0.342***		0.368***
		(0.027)		(0.048)
Adjusted R^2	0.232	0.232	0.805	0.805
Observations	190,500,514	190,500,514	202,909,214	202,909,214
Individual fixed effects	✓	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓	✓

Panel B - Heterogeneity by Borrower Characteristics

	Personal 90+DPD				
Event - Business Start	(1)	(2)	(3)	(4)	(5)
Entrepreneur × Post	0.187***	0.238***	0.179***	0.164***	0.227***
	(0.009)	(0.017)	(0.014)	(0.021)	(0.021)
Entrepreneur × Post× Non-Prime	0.030				
	(0.057)				
Entrepreneur × Post× Renter		0.009			
		(0.036)			
Entrepreneur × Post× Low Income			0.036		
			(0.034)		
Entrepreneur × Post× Below College				0.063***	
				(0.021)	
Entrepreneur × Post× Young					-0.070***
					(0.022)
Adjusted R^2	0.232	0.232	0.233	0.232	0.232
Observations	190,500,441	190,348,072	190,244,266	190,358,519	190,500,500
Individual fixed effects	✓	✓	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓	✓	✓

Table 3: Impact of Business Delinquency on Personal Credit

This table presents the results based on Equation 2. The data are stacked event-month panel between January 2010 and December 2019, and contain information in the two years before and five years after a business delinquency for businesses started between January 2012 and December 2016. *Business Default* is a dummy that takes a value of one the first time a business is 90 days past due on any of its credit accounts. *Post* takes a value of one in the months after the business default and is zero otherwise. In Panel A, the dependent variable in Columns 1 and 2 are 100 if the consumer has an account that is 90 days past due (90+ DPD). In Columns 3 and 4, the dependent variable is 100 if there is a bankruptcy filing observed on the individual's credit file. In Panel B, the dependent variable is a 90+ DPD on the entrepreneur's personal account. *Non-prime* borrowers are individuals with a credit-score below 680. *Renter* takes a value of one if the individual has had no current or past mortgages. *Low Income* and *Young* borrowers are individuals with below median income and age respectively. We classify individuals without a college degree as *Below College*. We include individual, industry (SIC-4)- month, as well as cohort-event-month fixed effect where the event is the first time a business delinquency is observed and a cohort is a pair of matched entrepreneurs with and without a business delinquency (details in Section 3.2). Standard errors are double clustered at the business owner's residence county and incorporation event-month level.

Panel A - Personal Credit Outcomes

	Personal 90+DPD		Personal Bankruptcy	
Event - Business Delinquency	(1)	(2)	(3)	(4)
Business Default × Post	3.386***		3.227***	
	(0.206)		(0.196)	
Business Default × 1 Year Post		6.196***		1.870***
		(0.255)		(0.128)
Business Default × 2 Year Post		2.662***		3.248***
		(0.112)		(0.206)
Business Default × 3 Year Post		1.897***		4.031***
		(0.138)		(0.234)
Business Default × 4 Year Post		1.370***		4.409***
		(0.129)		(0.296)
Business Default × 5 Year Post		1.242***		4.239***
		(0.172)		(0.342)
Adjusted R^2	0.186	0.189	0.787	0.788
Observations	7,742,217	7,742,217	8,471,592	8,471,592
Individual fixed effects	✓	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓	✓
SIC4 × Event Month fixed effects	✓	✓	✓	✓

Panel B - Heterogeneity by Borrower Characteristics

	Personal 90+DPD				
Event - Business Delinquency	(1)	(2)	(3)	(4)	(5)
Business Default × Post	2.548***	2.864***	2.328***	2.588***	2.814***
	(0.196)	(0.190)	(0.179)	(0.237)	(0.208)
Business Default × Post× Non-Prime	1.939***				
	(0.224)				
Business Default × Post× Renter		1.862***			
		(0.246)			
Business Default × Post× Low Income			2.280***		
			(0.213)		
Business Default × Post× Below College				1.393***	
				(0.240)	
Business Default × Post× Young					1.215***
					(0.182)
Adjusted R^2	0.186	0.187	0.188	0.186	0.186
Observations	7,731,003	7,720,064	7,714,357	7,736,820	7,731,003
Individual fixed effects	✓	✓	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓	✓	✓
SIC4 × Event Month fixed effects	✓	✓	✓	✓	✓

Table 4: Impact of Hurricane on Personal Delinquency

This table presents the results based on Equation 3. The data are stacked event-month panel. Our sample is based on businesses started between January 2012 and December 2016 and follows all entrepreneurs in the one year before a hurricane and two years after. *Hurricane* is a dummy that takes a value of one if the business's county is struck by a hurricane in our sample. *Post* takes a value of one in the months after the hurricane and is zero otherwise. The dependent variable is 100 if the consumer has an account that is 90 days past due (90+ DPD). We include individual, industry (SIC-4)-month, cohort-event-month, and business-county fixed effects where the event is each hurricane and a cohort is a pair of entrepreneurs who reside in the same county and are matched on observable but operate business in different counties (details in Section 3.2 and 4.3). Standard errors are clustered at the business county.

	Personal 90+DPD	
	(1)	(2)
Hurricane × 1 Year Post	0.451***	
	(0.136)	
Hurricane × 2 Year Post	0.279**	
	(0.116)	
Hurricane × 1 Quarter Post		0.248**
		(0.121)
Hurricane × 2 Quarter Post		0.541***
		(0.201)
Hurricane × 3 Quarter Post		0.567***
		(0.185)
Hurricane × 4 Quarter Post		0.520***
		(0.174)
Hurricane × 5 Quarter Post		0.155
		(0.168)
Hurricane × 6 Quarter Post		0.407***
		(0.125)
Hurricane × 7 Quarter Post		0.228
		(0.152)
Hurricane × 8 Quarter Post		0.330**
		(0.141)
Adjusted R^2	0.128	0.128
Observations	18,425,180	18,425,180
Individual fixed effects	✓	✓
Cohort × Event Month fixed effects	✓	✓
SIC4 × Event Month fixed effects	✓	✓

Table 5: Business Failure - Impact of Personal Debt on Outcomes

This table presents the results based on Equation 2. The data are stacked event-month panel between January 2010 and December 2019, and contain information in the two years before and five years after a business delinquency for businesses started between January 2012 and December 2016. *Business Default* is a dummy that takes a value of one the first time a business is 90 days past due on any of its credit accounts. *Post* takes a value of one in the months after the business default and is zero otherwise. The dependent variable is 100 if the consumer has an account that is 90 days past due (90+ DPD). In Panel A, we define growth in personal and total (business +personal) debt as the respective change in borrowings in the first year after business start. In Panel B, we define growth in personal and total debt as change in borrowings in the year before the first business delinquency. We include individual, industry (SIC-4)- month, as well as cohort-event-month fixed effect where the event is the first time a business delinquency is observed and a cohort is a pair of matched entrepreneurs with and without a business delinquency (details in Section 3.2). Standard errors are double clustered at the business owner's residence county and event-month level.

Panel A - Personal Debt Growth around Incorporation Event Month [-1, +12]

	Personal 90+DPD		
	(1)	(2)	(3)
Business Default × Post	3.327***	3.279***	3.328***
	(0.208)	(0.205)	(0.207)
Business Default × Post× Personal Debt Growth	0.384***		0.465**
	(0.110)		(0.199)
Business Default × Post× Total Debt Growth		0.345***	-0.084
		(0.112)	(0.204)
Adjusted R^2	0.211	0.211	0.211
Observations	7,195,664	7,195,664	7,195,664
Individual fixed effects	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓
SIC4 × Event Month fixed effects	✓	✓	✓

Panel B- Personal Debt Growth around Business Failure Event Month [-12, -1]

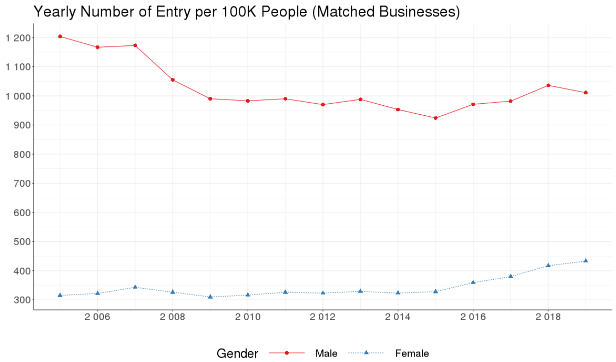
	Personal 90+DPD		
	(1)	(2)	(3)
Business Default × Post	3.431***	3.365***	3.451***
	(0.212)	(0.212)	(0.218)
Business Default × Post× Personal Debt Growth	0.621***		1.019***
	(0.098)		(0.241)
Business Default × Post× Total Debt Growth		0.553***	-0.427*
		(0.098)	(0.225)
Adjusted R^2	0.206	0.206	0.206
Observations	7,252,221	7,252,221	7,252,221
Individual fixed effects	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓
SIC4 × Event Month fixed effects	✓	✓	✓

Internet Appendix for Costly Entrepreneurship
Chava, Gopal, Singh, and Zhang

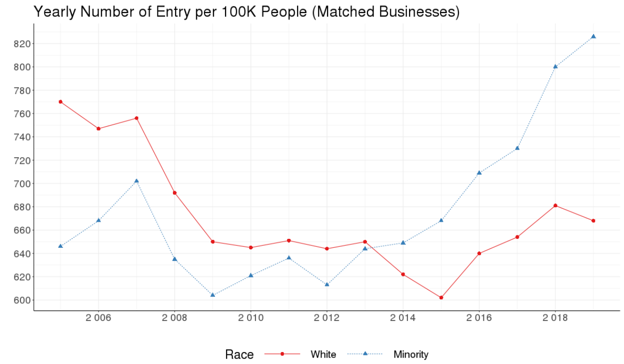
Online Publication Only

In this appendix, we provide evidence supporting our main results reported in the paper.

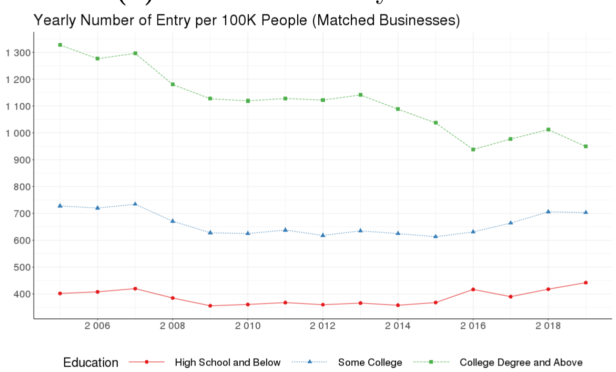
Figure IA1: Business Starts by Borrower Characteristics



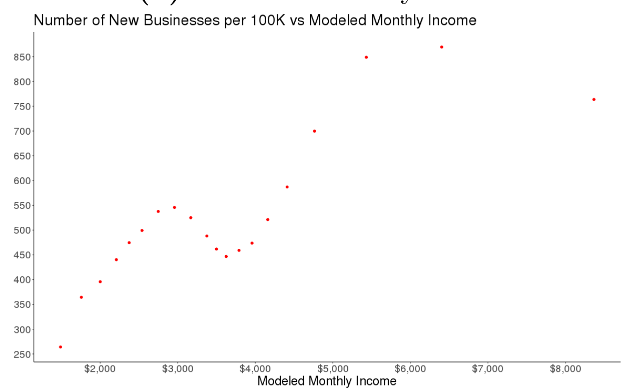
(a) Business Start by Gender



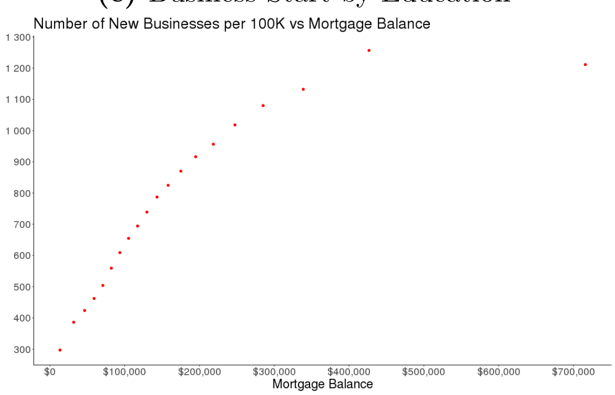
(b) Business Start by Race



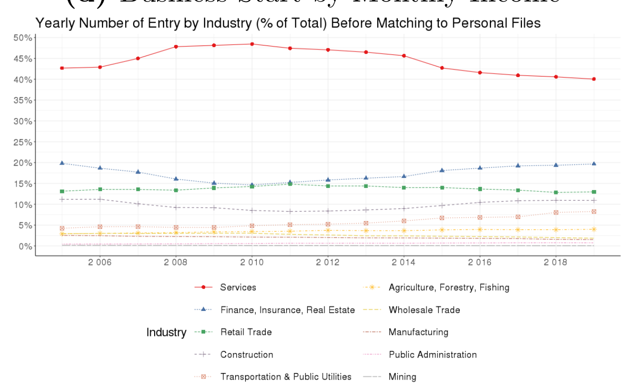
(c) Business Start by Education



(d) Business Start by Monthly Income



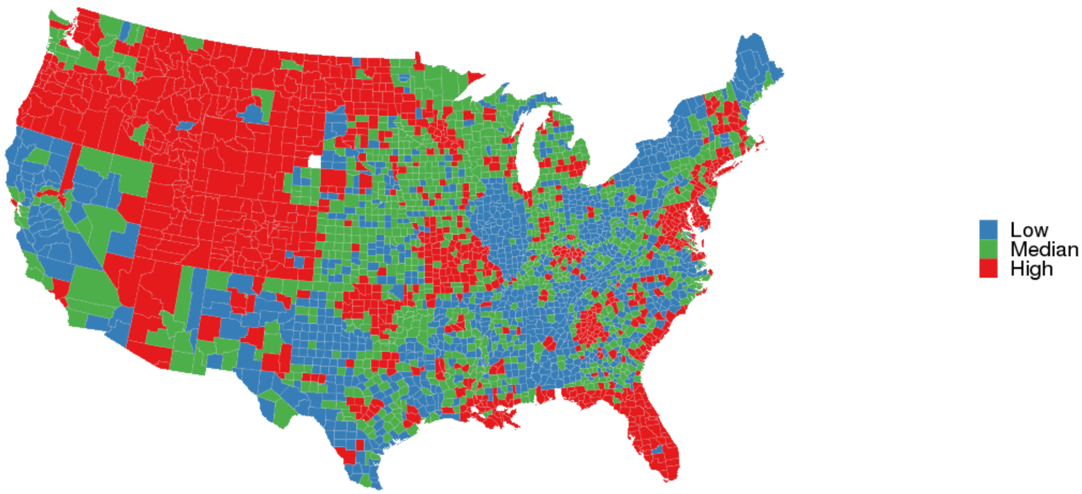
(e) Business Start by Mortgage Balance



(f) Business Starts by Industry

Figure IA2: Business Starts

Yearly Number of Entry per 100K People Excluding Agriculture Industries (2005 - 2019)



Yearly Number of Entry per 100K People in High Tech Industries (2005 - 2019)

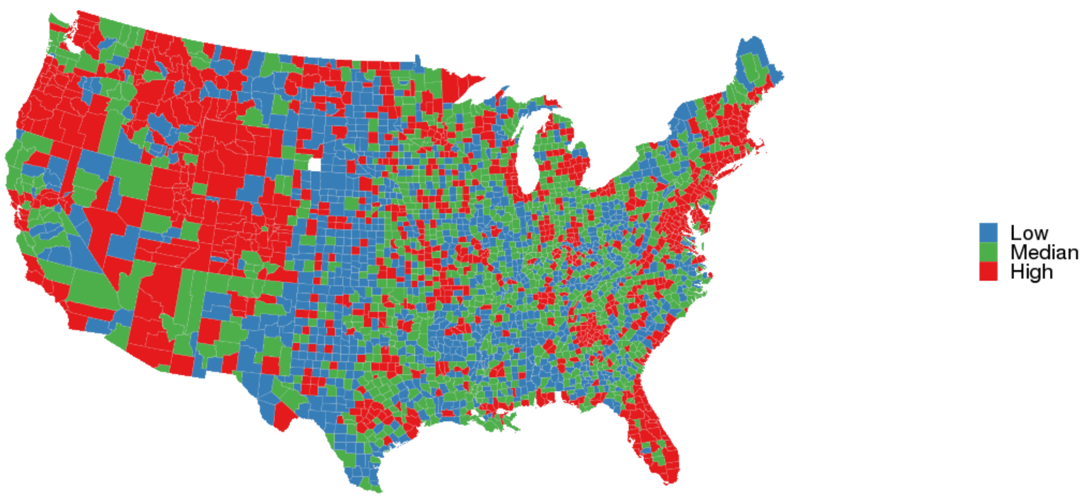


Figure IA3: Business Starts by Firm Size

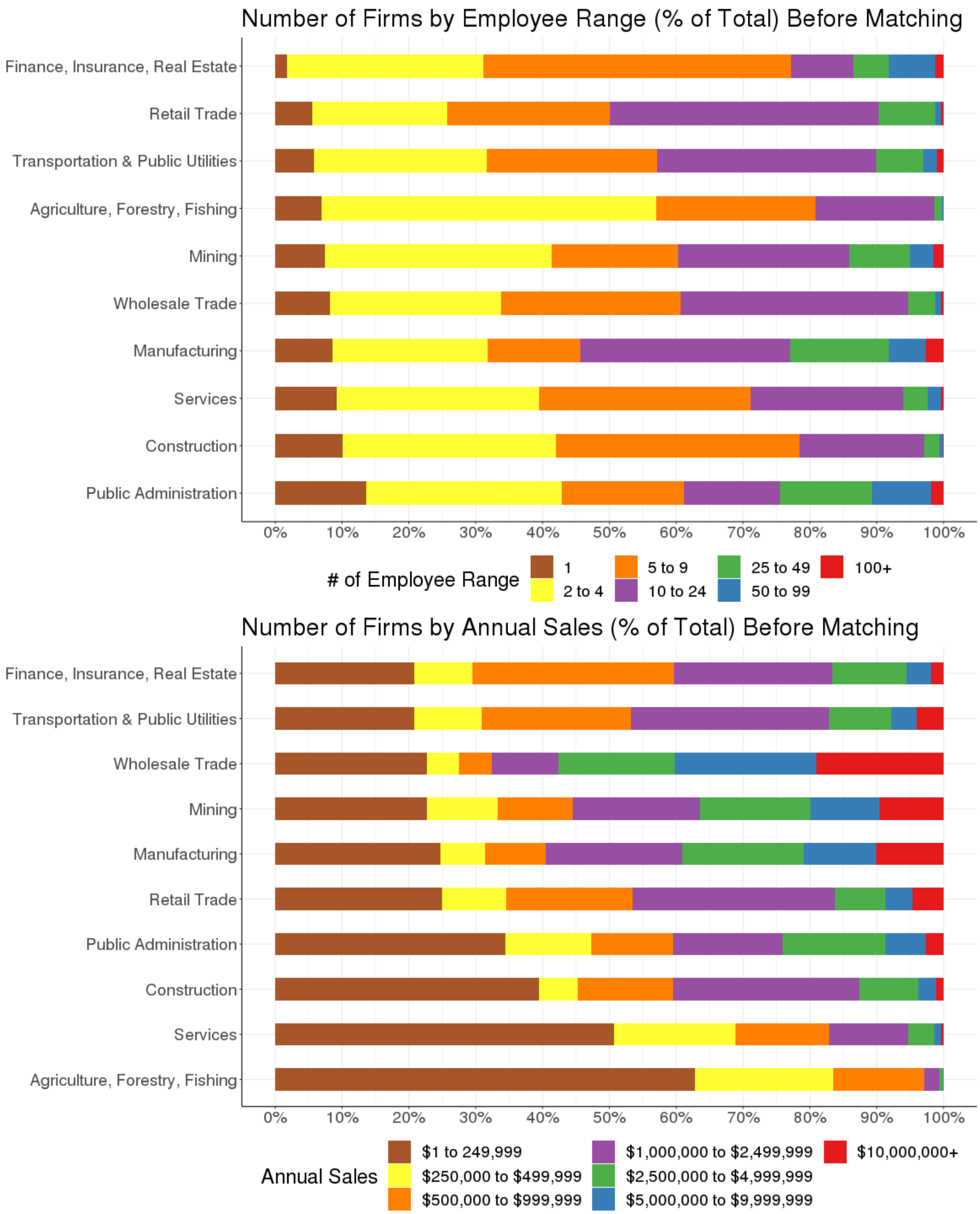
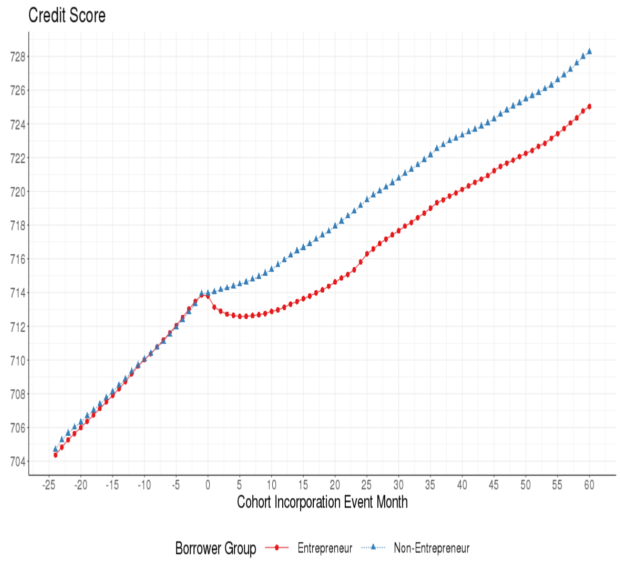
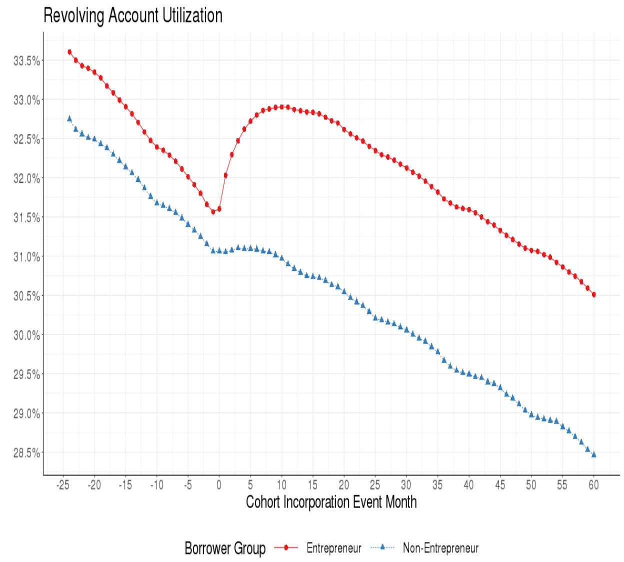


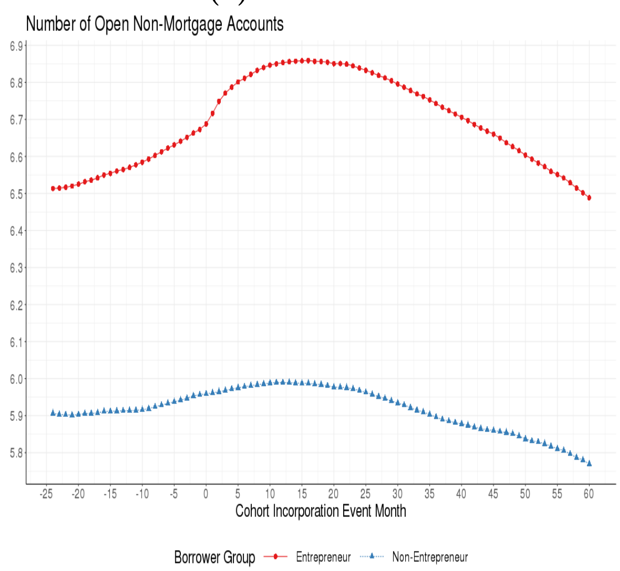
Figure IA4: Other Personal Credit Outcomes of Entrepreneurs and Non Entrepreneurs



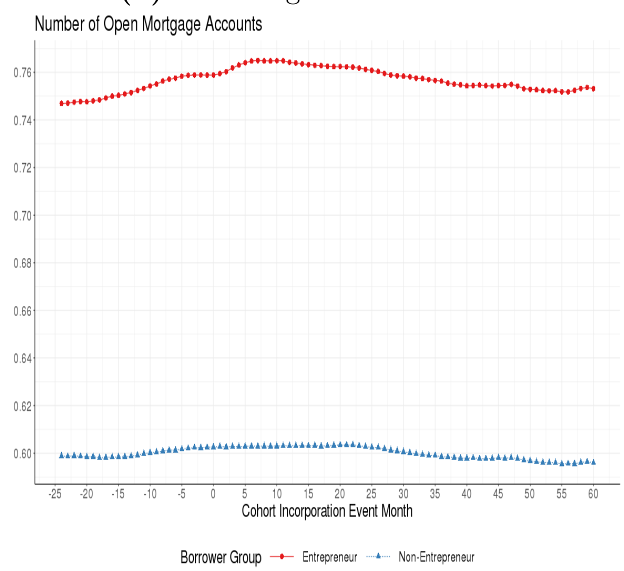
(a) Credit Score



(b) Revolving Utilization Rate

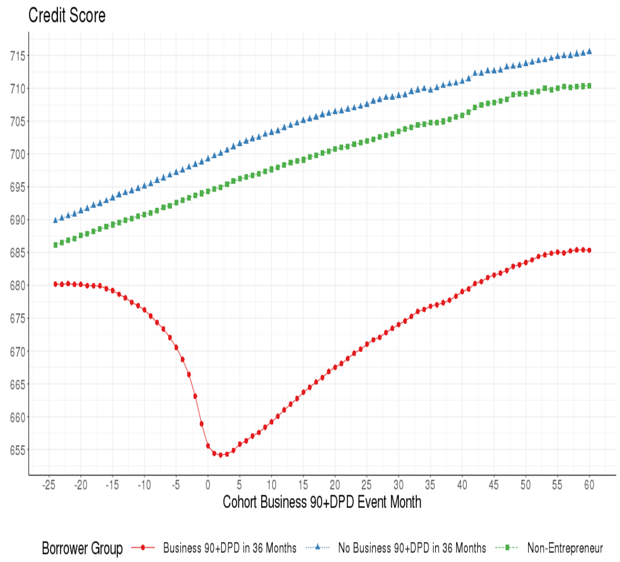


(c) Open Non-Mortgage Balance

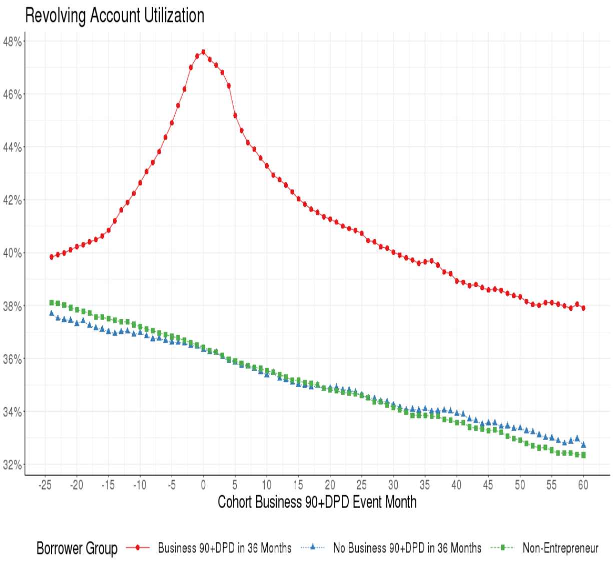


(d) Open Mortgage Accounts

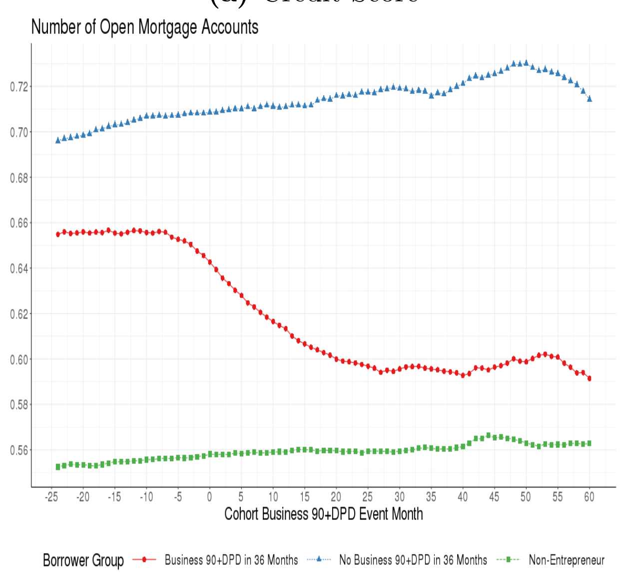
Figure IA5: Other Personal Credit Outcomes of Successful and Failed Entrepreneurs



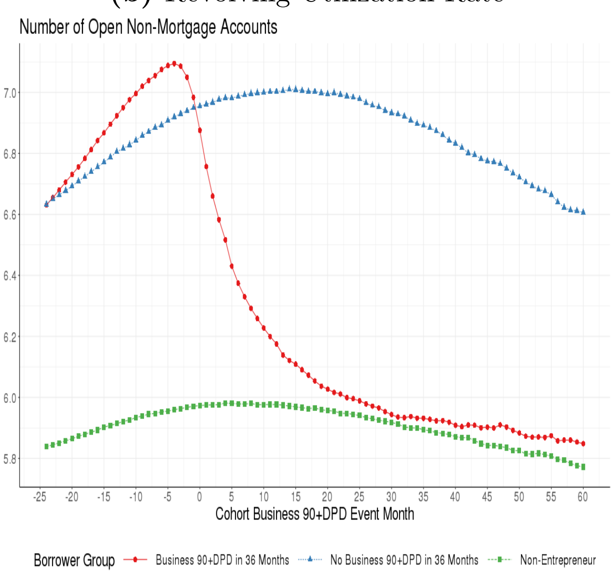
(a) Credit Score



(b) Revolving Utilization Rate



(c) Open Mortgage Accounts



(d) Open Non-Mortgage Balance

A Tables

Table IA1: Impact of Business Start on Personal Bankruptcy - Heterogeneity

	Personal Bankruptcy				
	(1)	(2)	(3)	(4)	(5)
Entrepreneur × Post	0.151***	0.110***	0.114***	0.114***	0.186***
	(0.025)	(0.033)	(0.020)	(0.037)	(0.044)
Entrepreneur × Post× Non-Prime	-0.165**				
	(0.063)				
Entrepreneur × Post× Renter		-0.369***			
		(0.058)			
Entrepreneur × Post× Low Income			-0.256***		
			(0.050)		
Entrepreneur × Post× Below College				-0.032	
				(0.047)	
Entrepreneur × Post× Young					-0.182***
					(0.047)
Adjusted R^2	0.805	0.806	0.807	0.805	0.805
Observations	202,909,143	202,182,341	201,427,645	202,759,448	202,909,165
Individual fixed effects	✓	✓	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓	✓	✓

Table IA2: Impact of Business Failure on Personal Bankruptcy - Heterogeneity

	Personal Bankruptcy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Business Default × Post	3.646***	3.728***	3.939***	2.854***	3.326***	3.308***	2.994***	3.791***
	(0.204)	(0.242)	(0.240)	(0.262)	(0.240)	(0.286)	(0.241)	(0.219)
Business Default × Post× Non-Prime	-0.887**							
	(0.379)							
Business Default × Post× Renter		-1.450***						
		(0.420)						
Business Default × Post× Low Income			-1.222***					
			(0.357)					
Business Default × Post× Below College				0.609				
				(0.373)				
Business Default × Post× Young					-0.173			
					(0.281)			
Business Default × Post× Single						-0.189		
						(0.344)		
Business Default × Post× Female							0.845**	
							(0.395)	
Business Default × Post× Minority								-1.605***
								(0.335)
Adjusted R^2	0.787	0.788	0.788	0.787	0.787	0.787	0.787	0.788
Observations	8,459,667	8,430,283	8,409,365	8,465,526	8,459,667	8,471,592	8,429,523	8,471,592
Individual fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Cohort × Event Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
SIC4 × Event Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓