Essays on Firm Dynamics

by

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Dedication

To my parents Anhua Xu and Jinxiang Zhu, who have a deep worship for the old Chinese saying “knowledge changes people’s fate”. Without their long-term complete and enthusiastic support, both mentally and financially, I could not “flee as a bird to my mountain”.

To my old brother Jiangshan Xu, who presented me my first Economics book, “Principles of Economics” written by Gregory Mankiw, in the summer when I finished high school. It was also the time when I became (temporarily) captive to the “illusion” that economics is so simple, while so powerful.

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Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

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Abstract

Firm size distributions and firm dynamics have important implications for macroeconomic outcomes, particularly aggregate productivity through effects on allocation of human and physical capital. This dissertation evaluates the mediating role of firm size distribution on the allocation of human capital over the business cycle, and identifies the drivers behind firm dynamics across regions.

Over eight million jobs were lost in the Great Recession, creating widespread economic hardship. The first chapter documents a novel and robust empirical regularity, that highly concentrated local labor markets experienced larger employment declines during the Great Recession. I provide an explanation using a model with heterogeneous firms where recessions arise as an aggregate consequence of idiosyncratic firm shocks. My model predicts a larger decline in expected employment when the market has a higher initial concentration level. The key idea is that relatively small firms are unable to absorb the large number of workers that get displaced when relatively big firms are hit by idiosyncratic shocks, as the absorption is limited by decreasing returns to scale (at the firm) and an upward-sloping labor supply (in the local labor market). I undertake a series of empirical tests to rule out alternative explanations, and show that large employment losses in concentrated labor markets are not driven by highly concentrated industry-locations being hit harder during the Great Recession, having thinner labor markets, having more large firms, or having high firm leverage ratios.

In the second chapter, I explore the drivers of new-firm creation, focusing on unintended consequences of unemployment insurance on the propensity of unemployed individuals to form new businesses. Exploiting staggered changes in benefit generosity across states and over time, I find that higher unemployment insurance (UI) benefits lower the probability that an unemployed person will become self-employed and delay such a transition. These effects are concentrated in the formation of unincorporated business. The negative effects are smaller in states offering a self-employment assistance program that allows the unemployed to collect benefits while starting their own business.

The last chapter studies how the adoption of product line exception (PLE) to successor non-liability, a plausibly exogenous mechanism that introduces a friction into the corporate transactions market, affects firm acquisitions and growth. We find that adoption of PLE has a negative effect on the propensity of being acquired, and a positive effect on closure rate, especially among manufacturing establishments. In line with the predictions of our theoretical model, we find stark differences in effects across young vs older firms. In particular, the probability of acquisition, as well as closure, increases for young manufacturing establishments after PLE is adopted. In contrast, the impact on older establishments is more in line with the overall effects (lower acquisition and higher closure propensity), albeit statistically insignificant. Firm level regressions show slower growth, greater exit and lower entry rates following adoption of PLE for manufacturing firms. Together, these results suggest that the friction from adoption of PLE has material effects in the manufacturing sector including reduction in reallocation of assets through acquisitions, shift in the focus of corporate transactions to younger incumbents, and reduction in firm growth, entry and survival.

Chapter I

Employment Decline during the Great Recession: The Role of Firm Size Distribution

1.1 Introduction

The Great Recession created the largest decline in employment in the United States since the Great Depression: From 2006 to 2010, private sector employment fell by 8 million. Strikingly, there was significant variation in the extent of employment decline *across* regions *within* the same industry. For example, the inter-quartile change in employment in "computer and electronic product manufacturing" was −33.73% to −8.59% across commuting zones. Understanding the drivers of this large variation is crucial to explaining the large drop in employment during this turbulent time.

This chapter explores how the initial firm size distribution (summarized by the HHI measure of concentration) affects employment change of local labor markets. A number of salient anecdotal examples suggest that when workers cluster in one or a few firms, the local economy is subject to larger employment fluctuation in general, and larger employment declines in the face of adverse shocks. For example, the nation's oldest General Motors assembly plant, in operation since 1919, was in Janesville, Wisconsin. However, this plant shut down in the midst of the Great Recession, with a ruinous impact on the local economy (Goldstein 2018).[1] Many of the displaced workers were not able to find new jobs because there were few other manufacturing firms nearby.

I document a strong positive relation between the pre-crisis concentration level of the

[1]For details on how this GM plant shutdown affected the local community see *Janesville: An American Story* by Amy Goldstein.

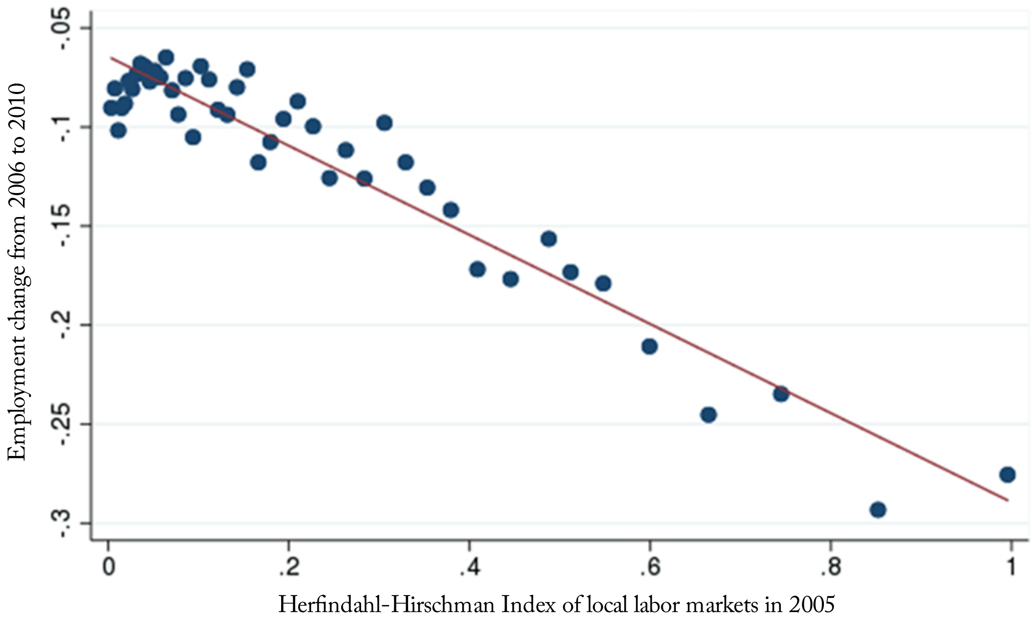


Figure 1.1: Binned scatterplot of the employment growth rate from 2006 to 2010 and the Herfindahl-Hirschman Index (HHI) of local labor markets in 2005.

This graph plots the raw relation between the concentration level in the year 2005 and the employment growth rate from 2006 to 2010 (2006 is the peak year for aggregate employment before the crisis, and aggregate employment bottomed out in 2010). There are about 51,500 total observations, with one observation representing a commuting zone (CZ)-industry (three-digit NAICS code) cell. These observations are grouped in 50 equal-sized bins (about 1,000 CZ-industry cells in each bin) based on the concentration level (HHI). I compute the mean of HHI and employment growth rate within each bin, then create a scatter plot of these 50 bins. The concentration index, measured by HHI, uses the employment shares of establishments in the industry and commuting zone. The line represents fitted values from a linear regression.

local labor market and the magnitude of employment decline during the Great Recession. Figure 1.1 shows this raw relation using the binned scatter of industry-by-commuting zone (CZ) cells, which are used as the definition for local labor markets.[2] Across these bins, Figure 1.1 shows that highly concentrated local labor markets had larger declines

[2]Specifically, using the U.S. Census Bureau's Longitudinal Business Database (LBD), I calculate the Herfindahl-Hirschman Index (HHI) of concentration and the employment change for each three-digit NAICS code industry in each commuting zone. This yields over 50,000 industry-location cells for my analysis. Commuting zones (CZs) were developed by Tolbert and Sizer (1996), and have been commonly used as a geographic basis for defining local labor markets in the literature (e.g., Autor, Dorn, and Hanson 2013). I exclude agriculture (NAICS code below 200) and the public sector (NAICS above 900). Hence, there are about 80 industries. Then, I group these observations into 50 equal-sized bins based on the quantiles of concentration levels.

in employment during the Great Recession.

To understand and explain this correlation, I set up a model of employment declines arising from stochastic firm-level shocks alone, building on a standard firm dynamics framework. While I acknowledge that the aggregate and industry-level shocks may have played important roles during the Great Recession, the goal of my model is to explain within-industry, cross-location patterns. Accordingly, my model builds on a growing literature that shows idiosyncratic firm shocks played a crucial role during the Great Recession (e.g., Bloom et al. 2018; Schaal 2017; Arellano, Bai, and Kehoe Forthcoming; Carvalho and Grassi 2019).[3] The initial firm-size distribution is determined by realizations of firm-level productivity draws. Employment is then adjusted based on the realization of firm-specific productivity shocks and resulting new wage levels. Averaging realized employment across scenarios leads to the expected new employment level and employment growth rate accordingly.

My analytical and simulation results show that expected employment is lower in areas with initially high concentration levels measured by HHI.[4] The key idea is that in the scenario that relatively big firms are hit by negative shocks, small firms nearby have limited ability to absorb the large number of displaced workers, a result that is driven by decreasing returns to scale and an upward-sloping local labor supply curve. In particular, as smaller firms attempt to absorb workers because of a decrease in wage, the marginal product of additional workers falls as a result of diminishing returns to scale, and the wage to be paid for hiring additional workers increases due to an upward-sloping local labor supply. Thus these two parameters – the degree of decreasing returns to scale and the elasticity of local labor supply – play an important moderating role on restricting the capacity of smaller firms to absorb displacements from larger ones. Total employment drops disproportionately more in this scenario, and hence, on average, total employment falls more in highly concentrated areas.

I confirm the negative correlation between initial concentration and employment de-

[3]Two recent papers provide specific examples of idiosyncratic firm shocks during the Great Recession: Chodorow-Reich (2013) documents that firms linked to banks that suffered larger losses reduced employment more; Garcia-Appendini and Montoriol-Garriga (2013) find that clients of cash-rich suppliers got access to a larger amount of trade credit and subsequently performed better during the Great Recession. Because shocks to banks and cash holding of upstream suppliers are arguably exogenous to the linked firms, they could be considered as idiosyncratic firm shocks.

[4]One question is whether concentration measured using HHI sufficiently captures the salient feature of the firm size distribution, or other moments or measures may have additional explanatory power. I show analytically and through simulations that HHI is a nearly sufficient statistic in the sense that this measure by itself captures the influence of firm size dispersion on local employment responsiveness to adverse shocks.

cline documented in Figure 1 using fixed effects regression specifications, and confirm that the observed negative correlation is robust to the inclusion of fixed effects for region and industry. In the most rigorous specification (including both commuting zone and industry fixed effects), I find that an industry-region labor market in the 75th percentile of HHI has a 5.46% larger decline in employment, relative to a labor market in the 25th percentile of HHI.

An important concern with this negative correlation is that highly concentrated CZ-industry cells might have larger employment losses not because of limited absorptive capacity of relatively small firms as in my model, but because of other factors unrelated to concentration levels. Although this alternative interpretation is impossible to rule out in the abstract, I identify and address several specific alternative stories. For example, idiosyncratic industry shocks might explain this negative correlation; that is, industries that were more strongly impacted by the recession, such as those producing durable goods, could also incidentally have higher local labor market concentration levels. Any such incidental correlation between severity of the recession shock and average concentration levels for specific industries is controlled for by the inclusion of industry fixed effects. Similarly, if some regions experienced stronger shocks and incidentally had more concentrated labor markets, any potential bias is controlled for by the region fixed effects.

Giroud and Mueller (2017) document that highly levered firms experienced greater distress during the Great Recession; therefore if firms located in highly concentrated local labor markets had high leverage ratios, this could provide an alternative explanation for the observed result. Moretti (2010) conjectures that a thick market (i.e., one with many potential employers) may protect workers and firms from idiosyncratic shocks; then, if concentration levels were negatively correlated to labor market thickness, the observed result may be explained by factors related to labor market thickness. I add industry- and region-specific controls to address each of these alternative explanations related to firm leverage and labor market thickness, and find the effect of initial local industry concentration on employment decline remains robust and economically significant.

An interesting question when interpreting my empirical finding is whether people who lose jobs in one industry find work in another industry or location; thus the employment decline in an industry-CZ cell might not necessarily mean an increase in non-employment. To address this question, I analyze data aggregated to the CZ level instead of the industry-CZ level. The idea is that if laid-off workers could switch from a highly concentrated industry to another local industry, then the (weighted) local-level HHI should not affect aggregate employment changes at the CZ level. However, my empirical results indicate that the weighted HHI has a significant negative impact on the employment growth rates at the CZ level, suggesting that switching industries within location does not offset the decline in employment observed in the industry-CZ-level regressions. Further, I directly investigate the effect of initial concentration on the changes in total non-employment (unemployment plus the number of people who are out of the labor market) in each industry-CZ cell. The results show that non-employment increases more in highly concentrated cells during the Great Recession, confirming that the baseline finding of decline in employment reflects a rise in non-employment.

Motivated by predictions from my theoretical model, I investigate the effects of concentration on the changes in wages and output, the heterogeneous effects across sectors, and the role of concentration during the recovery period. Consistent with the model, I find that wages and output declined more in highly concentrated industry-CZ cells during the Great Recession. However, in sectors with low labor supply elasticity, employment dropped less, while wage level declined more, when compared with sectors with high labor supply elasticity. The intuition is that in low-elasticity sectors, displaced workers were more likely to remain in the workforce (as they are less sensitive to wage decline) instead of dropping out of the labor force (or moving to other markets) when faced with adverse shocks; thus, in markets with lower labor supply elasticity, wage levels adjust down more with lower declines in employment. Moreover, highly concentrated markets recovered slower after the Great Recession. The unambiguous prediction of the model regarding employment gains from positive shocks arises from the same channels driving the baseline prediction for greater employment declines from adverse shocks – during a recovery when larger firms (in a concentrated market) are hit by positive shocks and attempt to hire more workers, decreasing returns to scale and the upward-sloping labor supply curve limit their ability to expand, so, on average, highly concentrated areas had a slower recovery pace.[5]

The negative relation between local labor market concentration and employment growth rate this chapter explores has not been empirically documented or theoretically predicted, to my knowledge. Many papers analyzing local labor markets focus on describing the general pattern of concentration levels, or exploring the relation between the

[5] Similarly, Baqaee and Farhi (2019) show that nonlinearities, shaped by the microeconomic details such as elasticities of substitution, network linkages, returns to scale, and the extent of factor reallocation, magnify negative shocks and attenuate positive shocks; however, they do not study firm size distributions.

monopsony power of employers and wage levels (see, for example, Azar, Marinescu, and Steinbaum 2017; Azar, Marinescu, Steinbaum, and Taska 2018; Benmelech, Bergman, and Kim 2018; Lipsius 2018). Berger, Herkenhoff, and Mongey (2019) and Jarosch, Nimczik, and Sorkin (2019) consider the importance of non-atomistic firms and build quantitative models to study the effect of market power on wages; the former uses a classical general equilibrium framework, while the latter builds on a search model. In my model, however, the core predictions do not rely on the monopsony power of these firms, as I assume firms are price-takers in both product and labor markets.[6] I provide a microfoundation for a structural relation between HHIs of local labor markets and declines in employment in the face of adverse shocks. Moreover, I take the core idea of the model to the search-matching framework, showing the intuition still holds in an environment with searching frictions (see Appendix C for the details).

My model depicts business cycles as arising from idiosyncratic firm shocks and is related to the literature on granularity (Gabaix 2011; Di Giovanni and Levchenko 2012; Di Giovanni, Levchenko, and Mejean 2014; Carvalho and Grassi 2019). In this literature, idiosyncratic firm shocks are not averaged out due to the fat-tailed firm size distribution, and substantially contributes to the aggregate volatility. In contrast, I examine the impact of size-distribution dispersion on the level of employment growth rate rather than its fluctuation, and I model recession (recovery) as arising from firm-specific shocks with a *nonzero* mean.[7]

This chapter also relates to the literature on the causes of declines in employment during the Great Recession. Mian and Sufi (2014) explore the impact of demand shocks; they find that employment declined more in nontradable than in tradable sectors in response to a decline in local housing net worth losses, suggesting an important role

[6]Adding monopsony power is likely to strengthen the results of my model. In particular, if labor markets with low concentration levels have perfect competition, and those with high concentration levels could be described by the Cournot model with oligopsonistic competition, then total employment declines even more in highly concentrated areas after negative idiosyncratic shocks compared with the case in the perfect competition model. When small firms are hit, big firms use their market power to keep wages low and add only a few workers (in the other scenario, in which big firms are hit, total employment declines slightly less than in the perfect competition model because large firms lose their market power). However, in general, the role of monopsony power also depends on the magnitude of idiosyncratic shocks, and adding monopsony power to the model does not increase the effect of concentration levels significantly from the simple simulation result. Hence, the main model assumes firms are price-takers in both product and factor markets.

[7]Gabaix (2011) shows that fluctuation of employment/output growth rates is mechanically higher in markets with high HHI when faced with a zero mean firm-specific shock; however, it is not obvious why the level of growth rate is lower without building a model. Appendix Figure A.2 documents a strong positive relation between the standard deviation of employment growth rates and HHI, consistent with the finding in Gabaix (2011).

of the demand channel in explaining employment decline. Another strand of literature highlights the supply channel; that is, firms had to cut more jobs due to limited access to new credit, and financially constrained firms were less likely to engage in labor hoarding (e.g., Chodorow-Reich 2013; Garcia-Appendini and Montoriol-Garriga 2013; Giroud and Mueller 2017). This chapter documents a novel channel, arguing that local labor market concentrations were instrumental in modulating the transmission of negative shocks into local market employment losses during the Great Recession. I address alternative stories empirically, and find that the contribution of the local labor market concentration channel is robust and economically significant.

To motivate the empirical analysis, Section 1.2 presents a model with heterogeneous firms facing idiosyncratic shocks. Section 1.3 describes the data and measurements of variables, and provides summary statistics. Section 1.4 provides primary estimates of the effect of pre-crisis HHI on employment losses during the Great Recession. Section 1.5 shows how concentration affects changes of wage levels and output. Section 1.7 investigates the role of HHI during the recovery period. Section 1.8 concludes.

1.2 Theoretical Framework

In this section, I build a model to show how the pre-crisis HHI could have affected the employment growth rate during the Great Recession. I start from a simple model with two firms to more easily illustrate the intuition. Then, I provide a rigorous proof with N firms. After that, I conduct a simulation confirming the analytical solution and showing that HHI is a nearly sufficient statistic for firm size distribution under the model setting.

1.2.1 A Model with Two Firms

The basic setting is a simple perfect competition model with heterogeneous firms subject to idiosyncratic firm-specific shocks, similar to the setting used in Hopenhayn (1992) and Hopenhayn (2014). Hopenhayn (2014) argues that this kind of model is equivalent to the one of monopolistic competition (Melitz 2003) that is commonly used in the literature. The difference is that decreasing returns to scale in this chapter's model come from the production function, while it comes from the demand side in Melitz (2003).

Suppose there is one area: A1. There are two firms located there: firms B and C. Assume there are two periods: −1 (before the crisis) and 0 (during the crisis). Firms are price-takers in both product and factor markets. There is only one input: labor.[8] In period –1, firms receive a firm-specific productivity draw z_i, and then maximize the profits by choosing the labor ($L_{i,-1}$). The production function displays diminishing marginal returns to the only input labor: $Y_{i,-1} = z_i L_{i,-1}^{\alpha}$, where $\alpha < 1$, i indexes firm i (firm B or C).

At the beginning of period 0, each firm faces an unexpected stochastic productivity shock.[9] With the same probability s, the firm is hit by the shock, leading to a new productivity level $z_i' = \mu z_i$, with $0 \leq \mu < 1$ in the downturn and $\mu > 1$ in the recovery.[10] Firms adjust labor ($L_{i,0}$) given the new wage and new realization of productivity level in period 0. For simplicity, I abstract from entry which is supported by Coles and Kelishomi (2011), who show that job creation by new firms is insensitive to business cycles.

Let us begin from period –1. After receiving the productivity draw z_i, firm i chooses labor $L_{i,-1}$ to maximize profit.

$$\pi_{i,-1} = z_i L_{i,-1}^{\alpha} - W_{-1} \cdot L_{i,-1}$$

W_{-1} indexes the wage level that is given for each firm. Based on the first-order conditions ($z_i \alpha L_{i,-1}^{(\alpha-1)} = W_{-1}$), I can derive:

$$\frac{L_{i,-1}}{L_{j,-1}} = \frac{z_i^{1/(1-\alpha)}}{z_j^{1/(1-\alpha)}} \tag{1.1}$$

$$\frac{Y_{i,-1}}{L_{i,-1}} = \frac{Y_{j,-1}}{L_{j,-1}} = \frac{Y_{T,-1}}{L_{T,-1}} = c \Rightarrow Y_{T,-1} = \left(\sum z_i^{1/(1-\alpha)} \right)^{1-\alpha} \cdot L_{T,-1}^{\alpha} \tag{1.2}$$

where i, j index firm i and firm j ($i \neq j$); $Y_{T,-1}$ and $L_{T,-1}$ represent the total output and employment in period –1, respectively, and c is a constant. The aggregate production function belongs to the same class as the firm-level production function, with the same degree of decreasing returns to scale.[11] In the case of two firms, suppose the economy

[8] The model is equivalent to one with two inputs, labor and capital, while the price (interest rate) of capital is a constant across areas and periods. I discuss a version of the model with both labor and capital as inputs in Appendix B, showing that the analytical solution is basically the same as that in this simplified version.

[9] The shock is indistinguishable from firm-specific demand shock, as we cannot observe the price. In the following, I will assume it is a shock to the productivity.

[10] An extreme example of the shock in the downturn could be that productivity becomes 0, once hit by the shock, and then firms shut down.

[11] Although the main focus of this chapter is on the change of employment instead of output, I also derive the formula for the change of output. Equation (2) is similar to that used in Hopenhayn (2014). The only difference is that employment is fixed in Hopenhayn (2014), while the total employment in this

is in equilibrium and we can observe the employment ratio of these two firms (firm B is the big one): $\Phi = \frac{L_{B,-1}}{L_{C,-1}} = \frac{z_B^{1/(1-\alpha)}}{z_C^{1/(1-\alpha)}} \geq 1$, which is proportional to the productivity draws. Then, we can compute the Herfindahl-Hirschman Index as follows:

$$HHI = (\frac{L_{B,-1}}{L_{B,-1} + L_{C,-1}})^2 + (\frac{L_{C,-1}}{L_{B,-1} + L_{C,-1}})^2 = \frac{\Phi^2 + 1}{(\Phi + 1)^2} > \frac{1}{2}.$$

To close the model, we turn to the labor supply side. Suppose the labor supply is represented by

$$W = \psi(L^s)^\epsilon, \quad (0 < \epsilon < \infty) \tag{1.3}$$

where L^s indexes the labor supply, and $1/\epsilon$ is the labor supply elasticity. Assume the labor supply has the same function form across areas and periods.[12]

In equilibrium, labor supply is equal labor demand in each area. Combining labor supply and demand functions, we can derive the formula for total employment in the equilibrium in period –1:

$$Ln(L_{T,-1}) = G * Ln[z_B^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}] + H,$$

where $G = \frac{1-\alpha}{1-\alpha+\epsilon}$, and $H = \frac{1}{1-\alpha+\epsilon}Ln(\frac{\alpha}{\psi})$. Employing Equation 1.2, I can derive the total output as: $Ln(Y_{T,-1}) = \frac{(1-\alpha)(1+\epsilon)}{1-\alpha+\epsilon}Ln[z_B^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}] + \alpha H$, and wage level as: $Ln(W_{-1}) = \frac{\epsilon(1-\alpha)}{(1-\alpha+\epsilon)}Ln[z_B^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}] + Ln(\psi) + \epsilon H$.

Now, let us move to period 0. At the beginning of period 0, each firm faces a stochastic idiosyncratic productivity shock, which generates three scenarios: (1) neither firm is hit, the probability is $(1-s)^2$; (2) both firms are hit, $p = s^2$; and (3) only one firm is hit by the shock, $p = 2 * s(1-s)$. It is easy to see that size distribution does not matter in the first case, so we focus on the last two cases. We start with the case that only one

chapter is determined by equating labor supply to demand, and it will change after the idiosyncratic shock.

[12]There are two different ways to look at this reduced-form labor supply function. First, it could be considered as the outcome of the trade-off between consumption and leisure in a closed economy, similar to Carvalho and Grassi (2019). If the instantaneous utility function is $U(C, L) = C - \psi L^{1+\epsilon}/(1+\epsilon)$, where C represents the consumption bundle, then we can derive the labor supply function as Equation (8). Second, this supply function could be considered as the outcome of spatial equilibrium with worker mobility and specific preferences for labor markets, similar to the Rosen-Roback model. Suppose the indirect utility function is $U_{ji} = \epsilon_{ji}X_{ji}^{1-\beta}(1-L_{ji})^\beta Z_i$, subject to: $X_{ji} + W_i(1-L_{ji}) = W_i$, where X indexes consumption bundle with price equal to 1, L indexes labor supply, Z indexes amenity, W is the wage/income, and j, i indexes worker j in city i. I assume away the housing market to make it simple. Similar to Equation (10) in Hsieh and Moretti (2019), I can derive that $W_i = \psi_i L_i^\epsilon$, where $\psi_i = V/Z_i$, and V denotes the average utility in all local labor markets.

firm is hit by the shock.

Suppose that only firm B is hit by the shock at the beginning of period 0; then its productivity becomes $z'_B = \mu z_B$. Based on the new productivity level, firm B chooses labor given the new wage level. During the downturn ($0 \leq \mu < 1$), firm B will fire workers, which pushes down the wage, while firm C will add workers as a response to the lower wage level. Following the same process described in period –1, the total employment in the new equilibrium in period 0 is as follows:

$$Ln(L_{0,B\_hit}) = G * Ln[z_B'^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}] + H,$$

where T and G have the same formulas as those in period –1. The only difference between employment in period 0 and period –1 is the productivity of firm B becomes z'_B instead of z_B, which is the only change in this scenario. We can then compute the growth rate of employment compared with period –1 in the scenario that only firm B is hit by the shock:

$$g_{0,B\_hit} \simeq Ln(L_{0,B\_hit}) - Ln(L_{T,-1}) = G \cdot Ln\left[\frac{z_B'^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}}{z_B^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}}\right] = G \cdot Ln[1 + (\nu - 1)\omega_B]$$

$$\simeq G \cdot \left[(v-1)\omega_B - \frac{(v-1)^2}{2}\omega_B^2\right]$$

where $\quad \nu = \mu^{1/(1-\alpha)}, \quad \omega_B = \dfrac{L_{B,-1}}{L_{B,-1} + L_{C,-1}} = \dfrac{z_B^{1/(1-\alpha)}}{z_B^{1/(1-\alpha)} + z_C^{1/(1-\alpha)}}, \quad$ and $\quad G = \dfrac{1-\alpha}{1-\alpha+\epsilon};$

Only if the exact growth rate $(\frac{L_{B,0} - L_{-1}}{L_{-1}})$ or $(\frac{L_{B,0} - L_{-1}}{(L_{B,0} + L_{-1})/2})$ is very small could $Ln(L_{0,B\_hit}) - Ln(L_{-1})$ be used to approximate the growth rate; otherwise, it is not precise.[13] Similarly, I derive employment growth rate if only firm C is hit by the shock: $g_{0,C\_hit} \simeq Ln(L_{0,C\_hit}) - Ln(L_{T,-1}) = G \cdot Ln(\frac{\Phi+\nu}{\Phi+1}) = G \cdot Ln[1 + (\nu - 1)\omega_C] \simeq G \cdot [(v-1)\omega_C - \frac{(v-1)^2}{2}\omega_C^2]$, so the expected growth rate conditional on only one firm being shocked should

[13] If we use the exact formula – $(\frac{L_{B,0} - L_{-1}}{L_{-1}})$, then $g_{0,B\_hit} = (\frac{\nu\Phi+1}{\Phi+1})^G - 1$, and the expected growth rate conditional on only one firm hit by the shock is $\frac{1}{2}g_{0,B\_hit} + \frac{1}{2}g_{0,C\_hit} = \frac{1}{2}(\frac{\nu\Phi+1}{\Phi+1})^G + \frac{1}{2}(\frac{\Phi+\nu}{\Phi+1})^G - 1 = \frac{1}{2}(\nu + \frac{1-\nu}{\Phi+1})^G + \frac{1}{2}(1 + \frac{\nu-1}{\Phi+1})^G - 1$. Take the first-order derivative with respect to Φ, and derive: $0.5G(1-\nu)(\Phi+1)^2[(1 + \frac{\nu-1}{\Phi+1})^{(G-1)} - (\nu + \frac{1-\nu}{\Phi+1})^{(G-1)}]$, which is a decreasing function of Φ no matter whether $0 \leq \mu < 1$ or $\mu > 1$, because $\Phi \geq 1$, $G \leq 1$ and $1 + \frac{\nu-1}{\Phi+1} \geq \nu + \frac{1-\nu}{\Phi+1}$ when $0 \leq a < 1$ $(1 + \frac{\nu-1}{\Phi+1} \leq \nu + \frac{1-\nu}{\Phi+1}$ when $\nu \geq 1)$. It is also easy to see that HHI is an increase function of Φ. Putting these two relations together, the employment growth rate is still a decreasing function of HHI, even when the log difference could not approximate the employment growth rate.

be:

$$\frac{1}{2} * g_{0,B\_hit} + \frac{1}{2} * g_{0,C\_hit} \simeq \frac{G}{2} \cdot Ln\{[1+(\nu-1)\omega_B][1+(\nu-1)\omega_C]\} =$$
$$\frac{G}{2} \cdot Ln[\nu + \frac{(\nu-1)^2}{2}(1-HHI)] \simeq \frac{G}{2} \cdot \left[(\nu-1)(\omega_B+\omega_C) - \frac{(v-1)^2}{2}(\omega_B^2+\omega_C^2)\right]$$
$$= \frac{G}{2} \cdot [\nu - 1 - \frac{(\nu-1)^2}{2} \cdot HHI] \quad (1.4)$$

where $0 < HHI < 1$, $\nu = \mu^{1/(1-\alpha)}$, $0 \leq \nu < 1$ during the downturn, and $1 < \nu \leq 2$ (or $1 < \mu \leq 2^{(1-\alpha)}$) during the recovery.[14]

This conditional expected growth rate is an increasing function of ν during the downturn ($0 \leq \nu < 1$), and equals 0 when ν is 1 – there is no negative shock. Most importantly, this conditional expected growth rate is a decreasing function of the concentration level (HHI) in the first period regardless of the magnitude of the shock ν; that is, when the employment distribution is really skewed in period –1 (high HHI), the conditional expected growth rate will be lower whether it is a negative ($0 \leq \mu < 1$) or positive shock ($1 < \mu \leq 2^{(1-\alpha)}$).

Now, consider the case that both firms are hit by the shock. Following the same process, I derive the employment growth rate conditional on two firms being hit by the shock is $G \cdot Ln(\nu)$(or $\frac{G}{(1-\alpha)}Ln(\mu)$). This rate is independent of the concentration level, and it is negative when $0 \leq \mu < 1$ (negative productivity shock), and positive when $1 < \mu \leq 2^{(1-\alpha)}$ (positive productivity shock).

Adding these three cases up, the unconditional expected employment growth rate is:[15]

$$(1-s)^2 * 0 + 2s(1-s) * \frac{G}{2} \cdot [\nu - 1 - \frac{(\nu-1)^2}{2} \cdot HHI] + s^2 * G \cdot Ln(\nu)$$

$$\simeq G \cdot s(\nu-1) - G \cdot s^2 \frac{(\nu-1)^2}{2} - G \cdot s(1-s)\frac{(\nu-1)^2}{2} HHI; \quad \text{where} \quad G = \frac{1-\alpha}{1-\alpha+\epsilon}. \quad (1.5)$$

Thus, $\triangle g$ (difference in employment growth rates) $\propto -G \cdot s(1-s) \cdot \frac{(\nu-1)^2}{2} * \triangle HHI$ – that is, the areas with high HHIs in the first period would have experienced a larger decline in employment. Similarly, I can also derive the change rate of wage level and

[14] I need to put the restriction $\nu \leq 2$ here to guarantee that $(\nu-1)\omega_i$ is below 1, so that the second-order Taylor expansion is a good approximation. This condition is equivalent to $\mu \leq 2^{(1-\alpha)}$.

[15] I use $(v-1) - \frac{(v-1)^2}{2}$ to approximate $Ln(v)$ in the last step to make the last formula looks like that in the case of N firms.

total output: $g_{wage} \simeq G_1 \cdot s(\nu-1) - G_1 \cdot s^2 \frac{(\nu-1)^2}{2} - G_1 \cdot s(1-s)\frac{(\nu-1)^2}{2} HHI$, and $g_Y \simeq G_2 \cdot s(\nu-1) - G_2 \cdot s^2 \frac{(\nu-1)^2}{2} - G_2 \cdot s(1-s)\frac{(\nu-1)^2}{2} HHI$, where $G_1 = \frac{\epsilon(1-\alpha)}{1-\alpha+\epsilon}$, and $G_2 = \frac{(1-\alpha)(1+\epsilon)}{1-\alpha+\epsilon}$.

1.2.2 Discussion

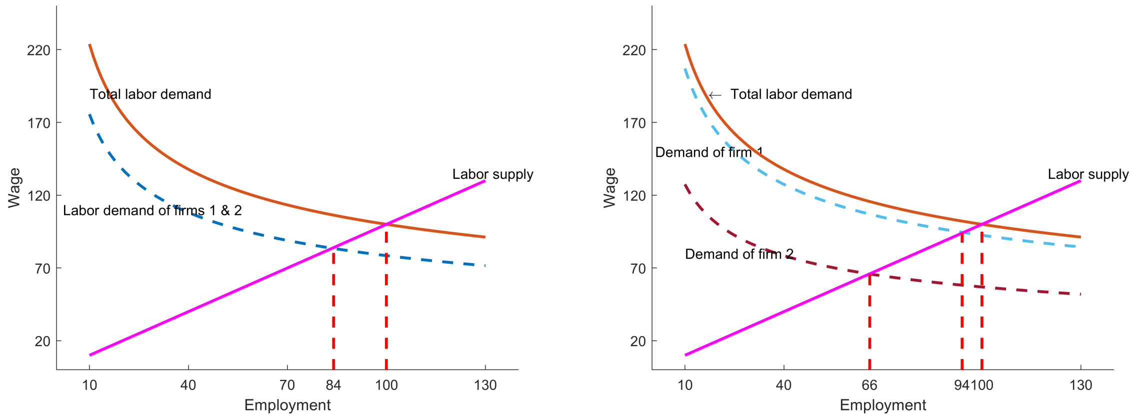
In this part, I first show the intuition using an extreme case, and then discuss how the impact of HHI depends on the values of parameters. Figure 1.2 shows the changes of employment facing extreme firm-level shocks: shutdown shocks, with just two firms and a simple labor supply as W=L, that is, $\psi = \epsilon = 1$ in the labor supply function. Subfigure (a) represents the case with two equal-size firms (low HHI), while subfigure (b) corresponds to one large firm and one small firm (high HHI). Adding up each firm's labor demand horizontally leads to the aggregate demand curve in each market. Initially, these two areas have the same total labor supply and demand curves, leading to the same level of employment in the first period (employment=100).

What makes a difference is the second period after the firm-idiosyncratic shock. In subfigure (a), when either firm is hit by the shock, the total labor demand curve shifts down to the dashed line, and the intersection of the dashed line and the labor supply curve determines the new employment, about 84 workers.[16] The same process also applies to the case with two unequal-size firms (firm 1's initial size is 90, while firm 2's is 10), except that the aggregate demand could be represented by the lower dashed line when firm 1 is hit by the shock, or the upper dashed line when firm 2 is hit by the shock. The expected employment conditional on only one firm being hit is in subfigure (b), that is 80, less than that in subfigure (a). Given that the employment changes are independent of size distributions in the other two scenarios, neither firm and both firms are hit, hence the expected employment is lower in the case shown in subfigure (b), which is the area with a high initial HHI.

The main reason for this difference is that the labor demand curve shifts inward disproportionately more when firm 1 (the relatively large firm) is hit by the shock, leading to a bigger decline in employment. This disproportionate decline could not be compensated by the smaller decline in employment when firm 2 is hit by the shock; hence, on average employment declines more in Panel B.[17]

[16] Here, I employ the production function $Y_i = z_i L_i^{\alpha}$ with $\alpha = 0.65$, and W=L as the labor supply curve to gauge the change of employment; otherwise, it is difficult to see directly that the employment declines more in subfigure (b).

[17] If both total labor supply and demand are straight lines, then pre-crisis HHI does not affect the



(a) Two firms of equal sizes **(b) Two firms of unequal sizes**

Figure 1.2: The impact of idiosyncratic firm shocks on the total employment.

This figure shows the changes of employment facing the extreme firm-level shocks, shutdown shocks with just two firms and a simple labor supply, as W=L. Subfigure (a) represents the case with two equal-size firms. Subfigure (b) corresponds to the case with unequal-size firms. These two areas have the same employment in the first period (100 workers), but they have different expected employment in the second period facing the idiosyncratic shocks.

Next, let us discuss how the impact of HHI relies on the values of those parameters and the intuitions. I first examine the role of labor supply elasticity. Let us start from two extreme cases: infinitely elastic ($\epsilon = 0$) and inelastic ($\epsilon = \infty$) local labor markets. The case of $\epsilon = 0$ is special in the sense that second-order expansion is not a good approximation in this case, because when ϵ approaches 0, G reaches its minimum value 1, and we know $\frac{L_{0,B\_hit}-L_{T,-1}}{L_{T,-1}} = (\nu-1)\omega_B$ in this case; hence, using $(\nu-1)\omega_B - \frac{(\nu-1)^2\omega_B^2}{2}$ to approximate $\frac{L_{0,B\_hit}-L_{T,-1}}{L_{T,-1}}$ is problematic. Instead, I can plug $\epsilon = 0$ into the original formulas of g_{0,B_hit} and g_{0,C_hit} (i.e., $(\frac{L_{i,0}-L_{-1}}{L_{-1}})$), and derive the unconditional growth rate $(1-s)^2 * 0 + 2s(1-s) * \frac{\nu-1}{2} + s^2 * Ln(\nu)$, which is independent of firm size distribution. Without considering the role of labor market adjustment (equivalent to the case that wage is a constant), the idiosyncratic shock will not lead to various declines in employment across different size distributions. When the local labor market is inelastic, wages will always fully adjust to achieve the same employment level $\bar{L}^s$, which is also independent of HHI.

When the labor supply elasticity takes on a value between 0 and ∞, the second-order approximation works fine. The results show that a high labor supply elasticity (low ϵ)

employment growth rate. However, as long as the production function has decreasing returns to scale, α is below 1, the labor demand curve will have this shape and the effect of HHI stands out.

leads to a larger impact of concentration levels (HHI) on employment changes, and a smaller impact on wage changes. When labor supply elasticity is low, most workers are likely to hang in there instead of moving to a different industry when large firms are hit by adverse shocks, pushing wage levels down, allowing other nearby firms to absorb more displaced workers. I will test this prediction in the empirical section.

When the value of the marginal returns to labor (α) is large and close to 1, that is, the production function has almost constant returns to scale in labor, the firm with relatively high productivity will absorb almost all the displaced workers, which makes the effect of HHI negligible.

Importantly, the effect of HHI is always negative, whether it is during the recession ($0 \leq \mu < 1$) or recovery ($1 < \mu \leq 2^{(1-\alpha)}$). The intuition behind the negative effect of HHI during the recovery when faced with positive productivity shocks, is that when big firm is hit by the positive shock, it will not add that many new workers because of its decreasing returns to scale and an upward-sloping labor supply curve. Hence, on average, the highly concentrated areas will grow slower during the recovery. Moreover, if the magnitude of the shock once hit is bigger (ν is close to 0 during the recession, or close to 2 during the recovery), the effect of an increase of HHI on the employment growth rate becomes larger. Take recession as an example. When the magnitude of the shock is greater, the employment growth rate is much smaller when big firms are hit by the shock comparing to areas of equal-size firms, and then highly concentrated areas on average have a larger drop in employment.

The impact of the probability of the shock (s) is not monotonic: having all firms (s=1) or no firms (s=0) hit by the shock leads to no difference in employment growth rate across areas with different HHIs. As I show above, when all firms are hit (s=1; it is considered an aggregate shock in this case), the employment growth rate is $G \cdot Ln(\nu)$, which is independent of the initial size distribution.

1.2.3 N Firms Case

In the above case of two firms, there is negative effect of the Herfindahl-Hirschman Index (HHI) on the employment growth rate. However, the case of two firms might be too special, because HHI is a sufficient statistic for the size distribution. In the following, I show that the same relation (Equation 1.5) still holds when we have N firms.

The basic setting is analogous to the case of two firms. Each firm maximizes its profit by choosing labor given productivity draw z_i and wage level. The employment ratio is proportional to the productivity ratio $\frac{L_{i,-1}}{L_{j,-1}} = \frac{z_i^{1/(1-\alpha)}}{z_j^{1/(1-\alpha)}}$. I define the employment share of firm i as

$$\omega_i = \frac{L_{i,-1}}{L_{1,-1} + L_{2,-1} + \cdots + L_{N,-1}} = \frac{z_i^{1/(1-\alpha)}}{z_1^{1/(1-\alpha)} + z_2^{1/(1-\alpha)} + \cdots + z_N^{1/(1-\alpha)}} = \frac{B_i}{\sum_{i=1}^N B_i}$$

and $HHI = \sum_{i=1}^N \omega_i^2$. Similarly, I can derive the total employment in period −1 by equating the total labor demand to the supply:

$$Ln(L_{T,-1}) = G * Ln\left(\sum_{i=1}^{N} z_i^{1/(1-\alpha)}\right) + H = G * Ln\left(\sum_{i=1}^{N} B_i\right) + H, \tag{1.6}$$

where $G = \frac{1-\alpha}{1-\alpha+\epsilon}$, $B_i = z_i^{1/(1-\alpha)}$, and $H = \frac{1}{1-\alpha+\epsilon} Ln(\frac{\alpha}{\psi})$. Employing Equation (2), I derive the total output as $Ln(Y_{T,-1}) = \frac{(1-\alpha)(1+\epsilon)}{1-\alpha+\epsilon} Ln\left(\sum_{i=1}^N z_i^{1/(1-\alpha)}\right) + \alpha H$, and wage level as: $Ln(W_{-1}) = \frac{\epsilon(1-\alpha)}{(1-\alpha+\epsilon)} Ln\left(\sum_{i=1}^N z_i^{1/(1-\alpha)}\right) + Ln(\psi) + \epsilon H$.

Now, let us move to period 0. Since we have N firms, we have the following scenarios: (1) no firms are hit by the shock, $p = C_N^0 \cdot s^0(1-s)^N$; (2) only one firm is hit, $p = C_N^1 \cdot s^1(1-s)^{(N-1)}$; (3) only two firms are hit, $p = C_N^2 \cdot s^2(1-s)^{(N-2)}$; ... ; and (N+1) all of the firms are hit: $p = C_N^N \cdot S^N(1-S)^0$. In the first and last scenarios, the employment growth rate is independent of size distributions, so we can ignore them. Let us start with the second case. I first consider the conditional employment growth rate, then the unconditional growth rate.

Suppose firm j is hit by the shock at the beginning of period 0; then, its productivity becomes $z_j' = \mu z_j$. Combining the new demand curve of firm j and all other firms' demand, and equating it to the labor supply, I can derive the new total employment in the equilibrium in period 0 in this scenario:

$$Ln(L_{0,j\_hit}) = G * Ln(\sum_{i \neq j}^{N} B_i + \nu B_j) + H \tag{1.7}$$

$$\text{where} \quad B_i = z_i^{1/(1-\alpha)}, \quad \nu = \mu^{1/(1-\alpha)}, \quad \text{and} \quad G = \frac{1-\alpha}{1-\alpha+\epsilon}.$$

Then, the employment growth rate when only firm j is hit conditional on only one firm being hit by the shock is

$$g_{0,j\_hit} \simeq \frac{Ln(L_{0,j\_hit}) - Ln(L_{-1})}{C_N^1} = \frac{G \cdot Ln[(\sum_{i \neq j}^N B_i + \nu B_j)/\sum_{i=1}^N B_i]}{C_N^1}$$
$$= \frac{G \cdot Ln[1 + (\nu - 1)\omega_j]}{C_N^1} \quad (1.8)$$

where $1/C_N^1$ represents the probability that firm j is hit conditional on only one firm being hit.

With this formula in hand, we can derive the expected employment growth rate conditional on only one firm being hit:

$$\sum_{j=1}^N g_{0,j\_hit} = \frac{G \cdot Ln[1 + (\nu - 1)\omega_1] + ... + Ln[1 + (\nu - 1)\omega_N]}{\binom{N}{1}} \simeq$$
$$\frac{G}{\binom{N}{1}}[(\nu-1)\omega_1 - \frac{1}{2}(\nu-1)^2\omega_1^2 + ... + (\nu-1)\omega_N - \frac{1}{2}(\nu-1)^2\omega_N^2] = \frac{G}{\binom{N}{1}}[(\nu-1) - \frac{1}{2}(\nu-1)^2 \cdot HHI];$$

while, the second to the last step uses a second-order Taylor series expansion of $log(1+x)$, HHI represents the concentration level in the first (pre-crisis) period.

The same process could apply to the cases in which more than one firm is hit. Suppose the number of i firms are hit by the shock, I can derive the conditional expected employment growth rate[18]

$$\frac{G}{\binom{N}{i}} * \left[\binom{N-1}{i-1}(\nu-1) - \binom{N-2}{i-2}\frac{(\nu-1)^2}{2} - \binom{N-2}{i-1}\frac{(\nu-1)^2}{2}HHI\right], (i \geq 2). \quad (1.9)$$

Using the sum of these conditional growth rates, I can derive the unconditional employment growth rate:[19]

$$g_{emp} \simeq G \cdot s(\nu - 1) - G \cdot s^2 \frac{(\nu - 1)^2}{2} - G \cdot s(1 - s)\frac{(\nu - 1)^2}{2}HHI \quad (1.10)$$

This formula is exactly the same as that in the case of two firms, represented by Equation 1.5. Similarly, we have $\triangle g_{emp} \propto -G \cdot s(1-s)\frac{(\nu-1)^2}{2} * \triangle HHI$, that is, the difference in employment growth rates is proportional to the HHI across areas, where $G = \frac{1-\alpha}{1-\alpha+\epsilon}$. Similarly, I derive the formula for the expected changes of wage level and

[18]See Appendix A.1 for the detailed derivation.
[19]See Appendix A.1 for the detailed derivation.

output.

1.2.4 Simulation

The previous section provides an analytic relation between the initial HHI and the employment growth rate using a second-order approximation. In this section, I provide simulation results without using approximation, showing that the results are very similar to the analytical relation. The simulation results also show that the concentration level measured by HHI (second-order approximation) conveys the most important information about the effect of the size distribution on employment changes under the model setting.

There are two ways to think about the observed firm size distributions: (1) they come from the same productivity-generating process, but represent different realizations; or (2) they come from different productivity distributions. Because I do not know which one is true, I combine these two to conduct the simulation. Specifically, I use the power distribution with three different values of β: 0.2, 0.6, and 1, in the power law distribution: $Prob(S > x) = x^{-\beta}, (x \geq 1)$.[20,21] Lower β represents a more dispersed distribution, and, on average, higher HHI.

For each parameter value, I generate 1,000 random samples, and within each sample, I randomly create N firms (N=20) in period −1 with sizes following the power distribution with one specific parameter value.[22] I directly draw the firm size instead of productivity, because the firm size and productivity have a one-to-one mapping, as shown in Equation 1.1, and the employment growth rate depends only on the initial size based on the derivation of the model.

Table 1.1 summarizes the calibration of parameter values. The values of these two parameters ((μ and s) are set to match the data pattern observed in the LBD. On average, about 46% of establishments are hit by the negative shock, and once they are hit by the shock, their employment declined by 67%.[23]

[20]Many previous papers find that power distribution with β close to 1 could well approximate the real size distribution of the whole country (e.g., Axtell 2001; Gabaix 2009), however, to the best of my knowledge, no paper focuses on size distribution in the local labor market. Hence, I try different values of parameter β, and I find that what matters is the realization of size distribution instead of data-generating process (different values of β).

[21]I choose $x_{min} = 1$ for different values of β, and use the code provided by Clauset, Shalizi, and Newman (2009) to generate the random sample following power law distribution.

[22]I choose 20 firms instead of a larger number because when N is above 20, there are too many combinations. For example, there are about $1.38 * 10^{11}$ combinations if 20 out of 40 firms are hit, then it takes too much memory and time to conduct this simulation.

[23]The probability of being hit by a negative shock is calculated using the employment-weighted

Table 1.1: **Parameter Values Used in the Simulation.**

Symbol	Description	Value	Source
α	Marginal returns to labor	0.65	Hsieh and Moretti (2019)
ϵ	Inverse of labor supply elasticity	0.5	Hornbeck and Moretti (2019) and Serrato and Zidar (2016)
μ	Magnitude of productivity shock	0.68	LBD, 2006-2010
s	Probability of being hit	0.46	LBD, 2006-2010
β	Power distribution parameter	{0.2, 0.6, 1}	Axtell (2001); Gabaix (2009)

The values of productivity shock (μ) and probability of shocks (s) are chosen to make the decline of employment close to the mean level of employment declines during the Great Recession.

The value of ϵ (the inverse of labor supply elasticity) is based on Hornbeck and Moretti (2019) and Serrato and Zidar (2016). Hornbeck and Moretti (2019) estimate a long-run inverse elasticity of 0.35, less than the estimate in Serrato and Zidar (2016), which is slightly greater than 1 in most specifications, that is, the elasticity is slightly below 1. I choose a baseline of $\epsilon = 0.5$, but I also present robust checks with $\epsilon = 1$ and 2 in the Appendix.

With these parameter values in hand, I generate the conditional growth rate of employment for cases where 0, 1, 2,..., N firms are hit by the shock using the original formula for the growth rate ($\frac{L_{T,0}}{L_{T,-1}} - 1$). I sum these conditional expected employment growth rates multiplied by the probability of each scenario to get the unconditional expected employment growth rate.[24]

Figure 1.3 shows the relationship between HHI and the employment growth rate using the simulation results. There are four subplots in total. The upper left, upper right, and lower left graphs employ different parameters in generating firm size distributions. The lower value of β corresponds to a more dispersed distribution, and usually high HHI. That is why it is more dense among high HHI in the upper left graph, and relatively sparse in the lower left graph. Each of these three graphs includes 1,000 random samples, each sample has 20 firms. The lower right graph packs these three graphs together, and also plots the analytical solution with a solid red line.[25]

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probability of reducing employment by more than 20% at the establishment level from 2006 to 2010. Similarly, the magnitude of the shock is the employment-weighted employment growth rate conditional on being hit by this shock, which is about -67%. Hence, we can infer that the value of μ is about $0.68(\mu^{(\frac{1}{1-\alpha})} = \nu = 1 - 0.67)$.

[24]See Appendix A for the general formula for the growth rate when i firms are hit by the shock.

[25]I check the simulation process through setting $\epsilon = 0$, and find that the employment growth rate is a constant, which is consistent with the discussion in Subsection II.B.

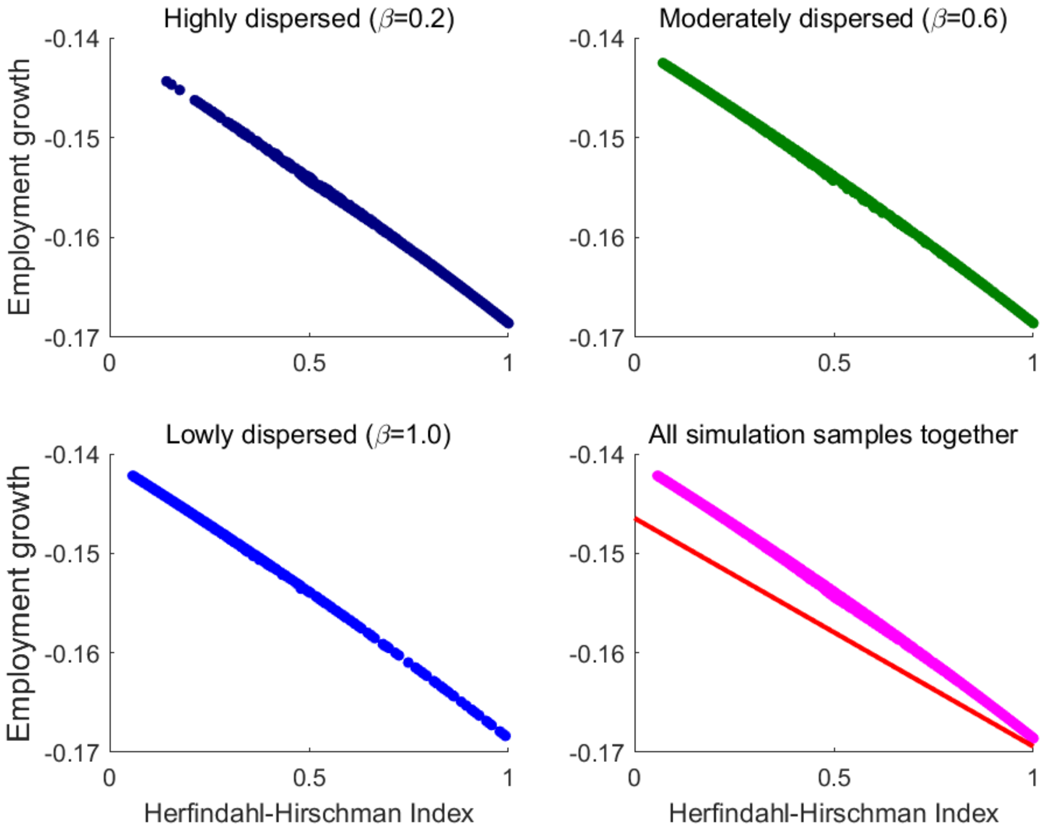


Figure 1.3: Simulation results: The impact of pre-crisis Herfindahl-Hirschman Index on employment growth rate.

The inverse of labor supply elasticity takes on the same value $\epsilon = 0.5$ in these subplots. The upper left, upper right and lower left graphs employ different parameters in generating firm size distributions. The lower value of β corresponds to a more dispersed distribution, and usually high HHI, so it is more dense among high HHI in the upper left graph, and relatively sparse in the bottom left graph. Each of these three includes 1,000 random samples, each has 20 firms. The bottom right graph packs these three graphs together and also shows the analytical solution with the red solid line.

We get three important pieces of information from this simulation result. First, we see the negative effect of HHI on employment growth rates from this graph. The result is also close to the analytical result (shown as the solid red line in the bottom right graph of Figure 1.3) from the previous subsections. Using the parameter values shown in Table 1.1, the analytical relation in Equation 1.10 suggests an additional 0.92% ($0.4 * 0.023$) decline in the growth rate when HHI increases by 0.4 (the difference between 25th and 75th percentiles of HHI; see Table 1.2 for details). This number is slightly lower than that from the simulation result shown in the above graph, which is 1.12%

$(0.4 * 0.028)$.[26]

Second, the patterns in the four subplots are basically the same, meaning that what matters is the realization of firm size distribution instead of the distribution parameters (data-generating process). While the small value of β corresponds to high HHI on average, there still exists a relatively large variation of HHI given a value of β, due to different realizations.[27] Finally, there is no variation of employment growth rate given an HHI level, that is, HHI (second-order approximation) contains almost all the information about the size distribution that could affect the employment growth rate under the model setting.[28] Thus, in the empirical analysis that follows, we can focus on this key piece of information about firm size distribution: HHI.

1.3 Data Source, Measurement, and Summary Statistics

I mainly use the establishment level data from the Longitudinal Business Database (LBD) of the U.S. Census Bureau. The LBD covers the universe of nonfarm, taxpaying establishments and firms in the United States that employ at least one worker. It includes annual observations from 1976 through 2014, and it contains information on industry, location, employment, and parent firm affiliation (Jarmin and Miranda 2002).

The LBD provides employment, total payroll, and location (county) for each establishment, so I cluster the counties into 722 commuting zones (CZs) developed by Tolbert and Sizer (1996). Commuting zones are based on journey-to-work data and are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. This definition of local labor market could better represent the areas where people could look for new jobs.[29] These 722 CZs cover the mainland United States, including metropolitan and rural areas.

For the industry code, I employ NAICS 2012 classifications. This code was developed by Fort and Klimek (2018). Designed to improve the accuracy of the industry codes, it

[26]I regress the expected employment growth rate on the HHI using these 3,000 simulated samples and get an estimate of 0.028.

[27]For example, when $\beta = 0.6$ and N=1,000 (1,000 firms in each sample), the 25th and 75th percentiles of HHI from 1,000 random samples are 0.18 and 0.62, respectively.

[28]When I regress employment growth rate on HHI using the simulation results from the random samples, R^2 is as high as 99.97%.

[29]Similar analyses at the county level yield very robust and consistent results.

provides a continuous industry code for the entire sample. I drop the industries that have three-digit NAICS code below 200 or above 900.[30] I define local labor market as the CZ by industry cell, which implies that it is costly to move across industries and CZs. With this definition of local labor market and employment information for establishments in each market, I calculate the concentration level. Based on the prediction of the theoretical model (Equation 1.10), the Herfindahl-Hirschman Index (HHI) is a good measure of firm size distribution in a local labor market. It is constructed as follows:

$$HHI_{ci} = \sum_{j=1}^{n} s_{j,ci}^2 \tag{1.11}$$

where n indexes the total number of establishments, and $s_{j,ci}$ represents the employment share of establishment j in commuting zone c and industry i:

$$s_{j,ci} = \frac{Emp_{j,ci}}{\sum_{j=1}^{n} Emp_{j,ci}}$$

To address the concern of workers moving across industries within a CZ, I also employ two concentration measures at the CZ level. One is the weighted HHI at the CZ level: $HHI_c^1 = emp\_share_i * HHI_{ci}$, where emp_share_i indexes the employment share of industry i in CZ c, and HHI_{ci} is the concentration level in CZ c and industry i, defined in Equation 1.11. The other index is analogous to Equation 1.11, but is defined directly at the CZ level: $HHI_c^2 = \sum_{j=1}^{n} s_{j,c}^2$, where $s_{j,c}$ represents the employment share of firm j in commuting zone c.

For the employment growth rate in each CZ-industry cell, I follow Davis, Haltiwanger, and Schuh (1996), defining the growth of employment at commuting zone c, industry i, between 2006 and 2010 using the symmetric growth rate:

$$\Delta Emp_{(06-10),ci} = \frac{(Emp_{2010} - Emp_{2006})}{0.5 * (Emp_{2010} + Emp_{2006})}. \tag{1.12}$$

The growth rate definition in Equation 1.12 is bounded in the range $[-2, 2]$, and it can accommodate both entry and exit: the value of growth is 2, if there is an establishment entry in a new industry, and it is –2, if all establishments in one existing industry shut down.

[30] Including these industries does not affect the results, but agriculture (NAICS code below 200) and the public sector (NAICS above 900) are unique industries, so are excluded from the analyses.

To test one alternative hypothesis related to firms' leverage, I employ the information of financial indices of these publicly listed firms from Compustat. I use two measures of firms' leverage ratios following Giroud and Mueller (2017) and Serfling (2016). One measure is the book leverage, defined as the ratio of the sum of debt in current liabilities (dlc) and long-term debt (dltt) to book value of assets (at). The other measure is market leverage, which is the ratio of debt in current liabilities (dlc) plus long-term debt (dltt) divided by the market value of debt and equity (long-term debt (dltt) plus debt in current liability (dlc) plus the market value of equity (prcc_f*csho)).[31] Following the literature, I winsorize both ratios at the 99% percentile.

I merge the Compustat data with the LBD data at the firm level using the Compustat-SSEL Bridge (CSB), so that I know the exact location and industry of each establishment of these publicly-listed firms. I impute the same leverage ratios to each establishment as those of their firms to calculate the weighted average (book and market) leverage ratios at the CZ by industry cell.

In addition to finding that the effect of a negative shock on employment depends on the HHI, the model also predicts negative effects of HHI on changes of wage and total output. To investigate the impact on the changes in output, measured by sales, I employ the information from the Census of Manufacturing (CMF), as LBD does not include the information about sales. The CMF is conducted every five years. I use the total value of shipments and the total value added for each establishment in the two most recent years for which data is available: 2007 and 2012.

I also use information from the American Community Survey (ACS), obtained from the Integrated Public Use Micro Samples (IPUMS, Ruggles et al. 2015). One limitation of LBD is that we do not know the number of unemployed workers in each CZ by industry cell. For this information I use the three-year ACS in 2007 and 2010, which covers information for the periods 2005-2007 and 2008-2010, respectively. The sample in each year is 3% of the total population. This data set has information on people's industries, working history, and location (information prior to job loss for the unemployed or people out of the labor force), which is used to compute the number of non-employed workers (unemployment and people out of the labor force) in each CZ by industry cell. This information is matched to the concentration levels in each cell calculated using the

[31] I also use another definition of market leverage ratio as the ratio of debt in current liabilities (dlc) plus long-term debt (dltt) to the total assets minus the book value of equity plus the market value of equity. The results are robust.

County Business Pattern (CBP) data set.[32]

The combined data set is used to explore how the concentration level affects the likelihood and duration of being unemployed. For most individuals (about 60%), ACS does not provide the county information because of confidentiality issues, but it provides information on Public Use Microdata Areas (PUMAs), the lowest level of geography identified. Each PUMA contains at least 100,000 people to satisfy the disclosure rule. PUMAs do not overlap, and they are contained within a single state. For the ACS before the year 2011, the 2000 version of PUMAs is used, and there are 2,101 PUMAs in total. I followed the crosswalk between PUMA and CZ provided by Autor, Dorn, and Hanson (2013) to get the CZ information for each individual. For the industry code, ACS provides the NAICS code of the industry that a person is working in if he or she is currently employed, and the NAICS code of the industry a person previously worked in if they are not currently employed.

To test how labor supply elasticity shapes the impact of firm concentrations on changes in employment and wage, I employ the monthly Current Population Survey (CPS) data. In this data set, each individual receives one interview per month for four consecutive months, and then there is a gap of eight months. After that, the same person receives one interview per month for an additional four months. Making use of this short panel, I compute the transition rate for each sector and month by comparing the industry an individual is in during the current survey to the industry he or she is in after 12 months. See section 1.6 for the details.

Table 1.2 shows the summary statistics of variables using the LBD data set. One observation in this sample is a local labor market defined as a CZ by industry cell. There are in total about 51,500 CZ-industry cells. The mean level of HHI is 0.298, and the difference between the 25th and 75th percentiles is 0.387. The mean level of employment growth rate between 2006 and 2010 is −13%. There is also a significant variation in the employment declines in this period, as the 25th and 75th percentiles are −28.9% and 8.8%, respectively. The wage growth rate from 2006 to 2010 without adjusting for inflation is 9.5%, on average. In comparison, the inflation rate from 2006 to 2010 is about 8.16%, according to the Bureau of Labor Statistics consumer price index.

[32] I follow Autor, Dorn, and Hanson (2013) to impute the missing values in employment. The HHI index calculated using CBP data is very similar to that using the LBD data set, although it is not as precise as that in the LBD. I do not merge the ACS to the LBD, because the ACS data set is quite large and it is difficult to bring ACS into the Research Data Center.

Table 1.2: **Summary Statistics.**

	N	mean	sd	p25	p75
Herfindahl-Hirschman Index (HHI) in 2005	51,500	0.298	0.309	0.058	0.445
Employment change from 2006 to 2010	51,500	-0.130	0.565	-0.289	0.088
Log (the number of establishments in 2005)	51,500	2.930	1.855	1.488	4.196
Log (the total employment in 2005)	51,500	5.450	2.333	3.881	7.078
Employment share of establishments with:					
51-100 workers	51,500	0.102	0.177	0.000	0.146
101-250 workers	51,500	0.107	0.199	0.002	0.147
More than 250 workers	51,500	0.111	0.242	0.000	0.000
Employment change from 2002 to 2005	51,500	0.069	0.483	-0.104	0.174
Employment changes caused by new entries	51,500	0.139	0.231	0.003	0.172
Wage change from 2006 to 2010	49,500	0.095	0.299	-0.004	0.205
Wage change from 2002 to 2005	49,500	0.085	0.284	-0.004	0.182
HHI in 2010	51,500	0.301	0.311	0.058	0.451
Employment change from 2011 to 2014	51,500	-0.006	0.487	-0.109	0.148
Wage change from 2011 to 2014	49,500	0.076	0.271	-0.008	0.163
Weighted mean of firms' book leverages	24,000	0.257	0.163	0.14	0.344
Weighted mean of firms' market leverages	24,000	0.275	0.214	0.116	0.397

This table uses LBD dataset. The sample has one observation per commuting zone-industry cell. Observations rounded to nearest five hundred and numbers rounded to 4 significant digits according to Census disclosure rules.

1.4 The Impact of Concentration Level on Employment Growth

Figure 1.1 shows a negative relation between pre-crisis HHI and employment growth rate, and this section digs deeper into this relation. I first take the pre-crisis HHI as exogenous coming from the random productivity draws, and then I deal with an important concern that employment declines more in highly concentrated areas not because these areas have a high pre-crisis concentration level, but rather because of other reasons unrelated to HHI. Although I could not rule out this possibility in general, I address specific alternative stories in this section. I also show that not all displaced workers find new jobs by moving to other markets; that is, the employment decline implies a waste of human capital.

1.4.1 The Effect of Pre-crisis Concentration on Employment Changes

Table 1.3 presents the estimates of the effect of concentration levels of local labor market and changes of employment. Using the full sample of 51,500 CZ-industry cells, I fit models of the following form:

$$\Delta Emp_{(06-10),ci} = \beta_1 HHI_{2005,ci} + X'_{ci}\beta_2 + \gamma_c + \alpha_i + e_{ci} \tag{1.13}$$

where $\Delta Emp_{(06-10),ci}$ is the employment growth rate between 2006 and 2010 in commuting zone c and industry i using the formula shown in Equation 1.12, $HHI_{2005,ci}$ is the Herfindahl-Hirschman Index (HHI) in year 2005 defined in Equation 1.11, and the vector X_{ci} contains a set of controls that might independently affect employment growth. Finally, γ_c and α_i represent CZ and industry fixed effects, respectively. Standard errors are clustered at the commuting zone level to account for the correlations of different industries in the same CZ.

Table 1.3: The Effect of Concentration Level on Employment Change.

	Dependent variable: Employment change from 2006 to 2010			
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	-0.217***	-0.259***	-0.130***	-0.141***
	(0.013)	(0.014)	(0.015)	(0.018)
Observations	51,500	51,500	51,500	51,500
Adjusted R^2	0.014	0.025	0.078	0.086
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

This sample consists of about 51,500 observations. Each observation represents a commuting zone by industry cell. The estimate in column (4) implies that going from the 25th to the 75th percentile of HHI leads to a 5.46% (0.387*-0.141) higher decline. As a comparison, the growth rate difference between the 75th and the 25th percentiles is 37.7%. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The first column does not include any fixed effects or controls. The results are similar to Figure 1.1 results: Highly concentrated areas have a larger employment drop during the Great Recession.

One concern with this raw regression is that some CZs were hit harder, and industries in these CZs, accidentally, had a high HHI. Mian and Sufi (2014) show that some counties experienced a larger decline in housing net worth leading to a larger drop in employment, so an alternative explanation could be that the counties/CZs hit the hardest (experienced the largest declines of housing wealth) during the Great Recession, coincidentally had higher concentration levels. If this is true, then it is not the concentration but the demand shocks to specific areas that drive this relation. The second column adds the CZs' fixed effects and the absolute value of the coefficient becomes a little larger, suggesting that the demand shock is actually more severe in less concentrated cells and is not the driver of the result.

The third column deals with the concern that some industries, such as those producing durable goods, were hit harder during the Great Recession, and these industries might also have higher local concentration levels, on average. To test this alternative hypothesis, column (3) adds the industry fixed effects to rule out any alternative stories related to specific industry shocks. The estimates indeed become smaller in both Panels A and B, indicating that some industries that have higher concentration levels experienced a larger drop in employment; however, the coefficient of HHI is still significant.

The fourth column adds both the industry and CZs' fixed effects, and the results are close to those in column (3). The coefficient -0.141 in column (4) indicates that when HHI increases from the 25th to the 75th percentile, employment falls by about 5.46% more. As a comparison, the difference between the 25th and 75th percentiles of employment growth is 37.7%.

1.4.2 Alternative Hypothesis: The Labor Market Thickness

Next, I examine whether the impact of the local labor market concentration on employment growth rates can be explained by labor market thickness. The canonical argument, as described by Moretti (2010), is that thick labor markets reduce the probability that a worker remains unemployed following an idiosyncratic negative shock to her firm, so the presence of a large number of other firms implies a lower probability of not finding a new job. Meanwhile, thick labor markets also make it easy for firms to fill vacancies. Since thick labor markets are usually associated with low HHI (see Table A.3 for the relation between HHI and labor market thickness), the competing hypothesis is that it is the thickness of the market rather than the concentration level that drives the results.

To test this hypothesis, I add two variables controlling for the local market thickness. The first index is the total employment in each CZ by industry cell. The other is the total number of establishments. Table 1.4 presents the estimates using the same specifications as those in Table 1.3. All the estimates of the coefficient of HHI are significantly negative, consistent with results in Table 1.3, which means it is not the

Table 1.4: Control for Market Thickness.

	Dependent variable: Employment change from 2006 to 2010			
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	-0.276***	-0.261***	-0.202***	-0.227***
	(0.018)	(0.019)	(0.019)	(0.019)
Log (total employment in 2005)	-0.028***	-0.023***	-0.054***	-0.055***
	(0.003)	(0.003)	(0.005)	(0.005)
Log (the number of establishments in 2005)	0.016***	0.020***	0.046***	-0.003
	(0.003)	(0.003)	(0.007)	(0.008)
Observations	51,500	51,500	51,500	51,500
Adjusted R^2	0.019	0.027	0.086	0.097
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

This sample consists of about 51,500 observations. Each observation represents a commuting zone by industry cell. The estimate in column (4) implies that going from the 25th to the 75th percentile of HHI leads to a 8.78% (0.387*-0.227) higher decline. In comparison, the growth rate difference between the 25th and the 75th percentiles is 37.7%. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

market thickness that drives the relation between HHI and employment growth rate we observe.

When I control for both the log of the total employment and the number of establishments, I implicitly control for the average firm size in each industry by CZ cell. Hence, the results in Table 1.4 also help to tease out the possibility that large firms suffered bigger employment losses during the Great Recession (shown in Figure A.5), and they also occupy higher employment shares in highly concentrated cells, together resulting in the larger employment declines. To address this concern further, Table A.5 controls for the employment shares of different-sized groups (having 50-100, 100-250, or more than 250 workers) instead of controlling only for the average firm size. All of these results show that the effect of HHI still stands out.

The (absolute value of) coefficients of HHI after controlling for the labor market thickness become a little larger, especially in the last two columns, compared with corresponding coefficients in Table 1.3. The correlation between HHI and these two control variables are both negative, and the role of *Log (total employment in 2005)* dominates, so there exists an upward bias in the corresponding coefficients in Table 1.3. That is, the absolute values of coefficients in Table 1.3 are lower than the true value.[33]

[33] If the model controlling for market thickness is the true model, then the bias in Table 1.3 is

Moreover, the coefficients of *Log (total employment in 2005)* are negative. Perhaps an increase in total employment while holding HHI and the number of establishments constant increases each establishment size (employment) proportionally, and the large establishments have had a bigger drop in employment (shown in Figure A.5). The coefficient of *Log (the number of establishments in 2005)* is positive in the first three columns, while it becomes insignificant in column (4). The positive effect of *Log (total employment in 2005)* is caused mainly by industries or CZs with more establishments getting hit less hard.

1.4.3 Alternative Hypothesis: Firm Leverage

One explanation for the decline in employment during the Great Recession is that financially constrained firms are more likely to reduce employment (Giroud and Mueller 2017). The literature provides two channels through which the labor market concentration level affects corporate financing decisions. First, the firm's leverage decision is partly affected by the unemployment cost borne by workers (Agrawal and Matsa 2013). Workers require a premium for a high distress risk, so firms choose leverage ratios to mitigate the risk, and then reduce the compensation required by workers. In the highly concentrated cells, firms with more bargaining power over workers can choose a relatively high leverage level without paying a large amount of compensation.

The second channel shows that firms use financial leverage as a strategic tool to strengthen their bargaining power and then capture a larger proportion of future cash flow (Matsa 2010; Woods, Tan, and Faff 2019). Thus, in cells with lower concentration levels, firms lacking bargaining power may resort to high leverage ratios, that is, lower leverage ratios in highly concentrated cells. However, this channel usually applies in the context of unionization.

If the first channel dominates – when we observe a positive correlation between labor market concentration levels and firm leverage ratios – then having larger employment declines in highly concentrated areas might be caused by having higher firm leverage ratios on average, and then being hit harder during the Great Recession.

$\frac{\beta_2 * Cov(HHI, log(total\ employment))}{Var(HHI)}$, where β_2 represents the coefficient of *Log (total employment in 2005)* in Table 1.4, and $\frac{Cov(HHI, log(total\ employment))}{Var(HHI)}$ is the coefficient of regressing *Log (total employment in 2005)* on HHI. The latter term is larger for *Log (total employment in 2005)* compared with that of *Log (total number of establishments)*, so the term *Log (total employment in 2005)* determines the direction of bias.

Table 1.5: **The Alternative Hypothesis: Leverage ratios.**

	Dependent variable: employment change from 2006 to 2010							
	Control for weighted book leverage				Control for weighted market leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Herfindahl-Hirschman Index in 2005	-0.243***	-0.228***	-0.257***	-0.235***	-0.244***	-0.228***	-0.259***	-0.236***
	(0.035)	(0.036)	(0.037)	(0.039)	(0.035)	(0.036)	(0.037)	(0.039)
Weighted mean of the book leverage in 2005	0.050***	0.054***	-0.032	-0.033*				
	(0.015)	(0.015)	(0.020)	(0.020)				
Weighted mean of the market leverage in 2005					0.033**	0.043***	-0.062***	-0.053***
					(0.013)	(0.013)	(0.019)	(0.019)
Log (total employment in 2005)	-0.024***	-0.018***	-0.030***	-0.035***	-0.023***	-0.017***	-0.030***	-0.035***
	(0.004)	(0.005)	(0.008)	(0.009)	(0.004)	(0.005)	(0.008)	(0.009)
Log (the number of establishments in 2005)	0.015***	0.017***	0.025**	0.024*	0.015***	0.016***	0.024**	0.023*
	(0.005)	(0.005)	(0.010)	(0.012)	(0.005)	(0.005)	(0.010)	(0.012)
Observations	24,000	24,000	24,000	24,000	24,000	24,000	24,000	24,000
Adjusted R^2	0.020	0.043	0.133	0.155	0.020	0.043	0.134	0.155
CZ FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

The first four columns add the book leverage ratio in each cell as the control variable, while the last four columns control for the market leverage ratio. The book leverage is defined as the ratio of the sum of debt in current liabilities (dlc) and long-term debt (dltt) to book value of assets (at), while the market leverage is the ratio of debt in current liabilities (dlc) plus long-term debt (dltt) divided by the market value of debt and equity (long-term debt (dltt) plus debt in current liability (dlc) plus the market value of equity (prcc_f*csho)). I also use another definition of market leverage ratio as the ratio of debt in current liabilities (dlc) plus long-term debt (dltt) to the total assets minus the book value of equity plus the market value of equity. The results using this definition of market leverage are very similar to those using the first one, so I do not report them. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

To test this alternative story, I employ Compustat to get the financial indices of those publicly-listed big firms. Following Serfling (2016), I calculate book and market leverages for each publicly-listed firm.[34] Then, I merge this firm-level information to the LBD data set using the Compustat–SSEL Bridge (CSB), and calculate the employment weighted mean of leverage ratios in each CZ by industry cell. Because not all cells have establishments belonging to public firms, we now have 24,000 CZ by industry cells in total.

Table 1.5 presents the results after controlling for the average leverage ratio. Columns (1) to (4) control for the weighted book leverage, while the last four columns add the weighted market leverage as the new control variable. Since firms in different industries have substantially different leverage ratios, and shocks to industries are various,

[34]The book leverage is the book value of long-term debt (dltt) plus debt in current liabilities (dlc) divided by book value of assets (at), and the market leverage is the book value of long-term debt (dltt) plus debt in current liabilities (dlc) divided by market value of debt and equity (long-term debt (dltt) plus debt in current liabilities (dlc) plus market value of equity (prcc f*csho)).

controlling for the industry fixed effect is necessary to deal with this confounding issue. Columns (3)-(4) and (7)-(8) show that after controlling for industry fixed effects or both fixed effects, CZ by industry cells of higher weighted leverage ratios exhibit significantly large declines in employment during the Great Recession. This is consistent with the finding in Giroud and Mueller (2017), although their focus is not on the role of leverage ratios but on how firms with various leverage ratios respond differently to the local demand shock during the Great Recession.

The coefficient of HHI is very robust and significantly negative no matter what fixed effects are included and which leverage ratio is controlled for. These results help rule out the alternative story, which means that the pattern between HHI and declines in employment are not driven by higher leverage ratios in highly concentrated areas. For the debate over whether high HHI is related to high leverage ratios, the results in Table A.4 show the opposite direction, which supports the second channel mentioned above. Although I cannot argue this is the causal effect of HHI on the firms' leverage ratios, it provides information about the relation between these two variables.

1.4.4 Addressing Concern about Prior Trends

One important concern about the results in Table 1.4 is that the economic fluctuation might be larger in those highly concentrated areas: They grow faster during the expansion period and decline more in the recession. Or, these highly concentrated cells are just shrinking for some other reason.

To address this concern, Table 1.6 controls for the pre-trend: employment changes from 2001 to 2005. Still, the concentration level in 2005 has a negative effect on the employment growth rate from 2006 to 2010, although the magnitude becomes a little smaller compared with that in Table 1.4. Moreover, cells that have higher employment growth rates before the crisis tend to decline more during the Great Recession.

1.4.5 Moving across Industries

Even though employment declined more in highly concentrated areas, it does not necessarily mean that more human capital became idle in these markets; people who lost jobs in one industry may have switched to another industry. This section provides indirect empirical evidence at the commuting zone level, showing that workers switching

Table 1.6: Control for Pre-trend of Employment.

	Dependent variable: employment change from 2006 to 2010			
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	-0.253***	-0.235***	-0.178***	-0.200***
	(0.019)	(0.019)	(0.020)	(0.020)
Employment change from 2002 to 2005	-0.071***	-0.074***	-0.089***	-0.085***
	(0.010)	(0.010)	(0.010)	(0.010)
Log (total employment in 2005)	-0.029***	-0.023***	-0.052***	-0.053***
	(0.002)	(0.003)	(0.005)	(0.005)
Log (the number of establishments in 2005)	0.019***	0.023***	0.046***	0.002
	(0.003)	(0.003)	(0.006)	(0.008)
Adjusted R^2	0.022	0.031	0.091	0.101
Observations	51,500	51,500	51,500	51,500
CZ FE	NO	YES	NO	YES
IND FE	NO	NO	YES	YES

All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

industries or CZs could not fully explain the larger declines, as well as direct evidence exploring the effect of HHI on the change in non-employment.

First, I conduct analyses at the commuting zone level using the weighted HHI. I generate an index aggregating the HHI in each CZ by industry cell to the CZ level using the employment share of each cell as the weight (see section 1.3 for the details of constructing this index). This measure represents the average concentration level that a worker in a CZ is facing. If we think workers moving across industries is likely to happen, then the change in total employment in a CZ should not be affected by this weighted HHI because people losing jobs in a highly concentrated industry could switch to another industry within the same CZ.

The first four columns of Table 1.7 present the results using this weighted HHI at the CZ level. Columns (1)-(2) do not add any fixed effects, while columns (3)-(4) control for state fixed effects. Columns (2) and (4) add the aggregate industry shock using *Bartik predicted employment growth rate* (Bartik 1991). This index is defined as the employment growth rate that would obtain in a CZ if employment in each local industry grew at exactly the same rate as employment in that industry in the rest of the country, similar to that used in Chodorow-Reich and Wieland (2016). The detailed formula for this control variable is as follows: $\sum_{i=1}^{I} s_{c,i} g_{-a,i}$, where $s_{c,i}$ indexes the employment

Table 1.7: The Effect of Pre-crisis HHI on Declines of Employment at the CZ Level.

	Dependent variable: Employment change from 2006 to 2010							
	Weighted HHI of each industry within a CZ				HHI at the CZ level in 2005			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Herfindahl-Hirschman Index	-0.217*	-0.280**	-0.232**	-0.258***				
	(0.115)	(0.118)	(0.098)	(0.098)				
HHI at the CZ level in 2005					-0.567	-1.458**	-0.787*	-1.241***
					(0.593)	(0.613)	(0.459)	(0.460)
Log (employment in 2005)	-0.062***	-0.031	-0.017	-0.015	-0.060***	-0.005	-0.009	0.007
	(0.022)	(0.023)	(0.022)	(0.021)	(0.019)	(0.018)	(0.022)	(0.021)
Log (the number of establishments in 2005)	0.046*	0.011	0.006	0.004	0.057***	-0.005	0.009	-0.009
	(0.024)	(0.023)	(0.027)	(0.025)	(0.022)	(0.020)	(0.025)	(0.024)
Bartik predicted employment growth rate		1.160***		0.798***		1.420***		1.007***
		(0.188)		(0.193)		(0.148)		(0.162)
Observations	700	700	700	700	700	700	700	700
Adjusted R^2	0.069	0.192	0.297	0.339	0.057	0.218	0.292	0.354
State FE	NO	NO	YES	YES	NO	NO	YES	YES

This sample has one observation for each commuting zone. Columns (1)-(4) use weighted HHI as the main measure of concentration level. The weighted HHI is constructed by using the HHI of each CZ by industry cell multiplied by the employment share of each industry in that CZ, and then summing up to the CZ level. The coefficient in column (4) implies that the total employment in a CZ at the 75th percentile of HHI fell by 4.36 $(-0.258 * (0.277 - 0.108))$ percentage points more than in a CZ at the 25th percentile. In comparison, the difference between the 25th and 75th percentiles of employment declines is -8.7%. Columns (5)-(8) employ the HHI at the CZ level, calculated using the sum of the squares of each establishment's employment share within a CZ. The coefficient in column (8) implies that going from the 25th to the 75th percentile of CZ-level concentration leads to an additional decline in employment of 1.37 $(-1.241 * (0.015 - 0.004))$ percentage points. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

share of the three-digit industry i in CZ c, and $g_{-c,i}$ is the national growth rate of industry i from 2006 to 2010 excluding CZ c. The weighted HHI has a significantly negative impact on employment changes from 2006 to 2010 in all four columns, meaning that CZs with high weighted HHI have experienced larger declines in employment. The coefficient in column (4) implies that total employment in a CZ at the 75th percentile of HHI fell by 4.36 $(-0.258 * (0.277 - 0.108))$ percentage points more than in a CZ at the 25th percentile. In comparison, the difference between 25th and 75th percentiles of employment declines is -8.7%.

Columns (5)-(8) add an HHI index using the employment share within a CZ instead of at the CZ by industry level.[35] Here, it considers all industries within a CZ as a local market, assuming workers can change industries. The results still show that highly concentrated CZs experienced a larger decline in employment even controlling for the

[35] The formula for this index is as follows: $HHI^2_c = \sum_{j=1}^{n} s^2_{j,c}$, where $s_{j,c}$ represents the employment share of firm j in CZ c.

Bartik predicted employment growth rate. The coefficient in column (8) implies that going from the 25th to the 75th percentile of CZ level concentration level leads to an additional decline in employment of 1.37 ($-1.241 * (0.015 - 0.004)$) percentage points. These two sets of results together provide indirect evidence that workers moving across industries could not totally explain the effects of HHI on the employment growth rate. One implied assumption of the above analyses is that laid-off workers did not move across CZs. This assumption is supported by Foote, Grosz, and Stevens (2019) and Saks and Wozniak (2011), who find that during recessions, out-migration plays a less important role in the local labor market adjustment than in a non-recessionary period because of fewer opportunities.

Second, I directly investigate the effect of pre-crisis concentration on the changes of total non-employment (unemployment plus the number of people who are out of the labor market) in each industry by CZ cell. This analysis addresses the concern about moving across industries and also deals with the potential movement across CZs. I collect information about non-employment from the three-year American Community Survey (ACS) in 2007 and 2010 and match it to the concentration levels in each CZ by industry cell from the County Business Pattern (CBP). If unemployed people are able to switch to another industry easily, we should not observe any impact of HHI on the changes in non-employment.

Table 1.8 presents the results.[36] The four specifications are the same as before. The results show a strong and robust positive effect of HHI on the change in the non-employment figure; the number of non-employed people increased more in highly concentrated cells during the Great Recession. This accords with the results of larger declines in employment in these cells. Combining these results on the changes in non-employment with those on employment shows that people who lost their jobs remained unemployed or dropped out of the labor force, consistent with the finding by Yagan (2017) that exposure to a higher local shock during the Great Recession led people to be less likely to be employed in 2015.

[36] The number of observations in this table is smaller than those tables using LBD dataset, because I drop the CZ by industry cells that have less than 30 interviewees. Dropping cells with a small number of interviewees makes the count of the total number of non-employment more precise due to its small proportion in the whole population.

Table 1.8: The Effect of Pre-crisis HHI on Changes of Non-Employment.

Dependent variable: Changes of the non-employment (i.e., unemployment + out of labor force)				
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	0.386***	0.416***	0.186***	0.264***
	(0.028)	(0.027)	(0.028)	(0.029)
Log (total employment in 2005)	-0.049***	-0.100***	-0.046***	-0.076***
	(0.003)	(0.005)	(0.005)	(0.006)
Log (the number of establishments in 2005)	0.036***	0.037***	0.048***	0.014***
	(0.002)	(0.001)	(0.006)	(0.005)
Observations	28,311	28,311	28,311	28,311
Adjusted R^2	0.034	0.066	0.214	0.232
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

The sample is at the CZ by industry level. The dependent variable is equal to: 2*(the number of non-employment in 2010 − the number of non-employment in 2007)/(the number of non-employment in 2010 + the number of non-employment in 2007). Non-employment information is drawn from the three-year ACS in year 2007 (covering 2005-2007) and 2010 (covering 2008-2010). Each year consists of 3% of the total population. I drop the CZ by industry cells if the number of interviewees in 2007 is below 30 because the information about non-employment might be imprecise if the number of interviewees is too small. The concentration level comes from the CBP data set. I follow Autor, Dorn, and Hanson (2013) to impute the missing values in employment. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

1.5 The Impact of HHI on the Changes in Wage Levels and Output

The previous section focused on the changes of employment; however, the model also predicts a similar effect of HHI on changes of wage levels and total output. This section provides evidence on these two important aspects.

1.5.1 Effects on the Changes in Wage Level

I first look at the effect on the changes in wage level. I measure the average wage per employee as the ratio of total annual payroll to the total number of employees in each CZ by industry cell, then compute the changes using $2*(wage_{2010} - wage_{2006})/(wage_{2010} + wage_{2006})$. The specifications are analogous to those in Table 1.4, controlling for the labor market thickness.

Table 1.9: The Effects of Pre-crisis Concentration Levels on the Changes in Wage Levels.

Dependent variable: Wage-level changes from 2006 to 2010				
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	-0.045***	-0.033***	-0.044***	-0.040***
	(0.011)	(0.011)	(0.011)	(0.012)
Log (total employment in 2005)	0.009***	0.013***	0.012***	0.013***
	(0.001)	(0.002)	(0.003)	(0.003)
Log (the number of establishments in 2005)	-0.014***	-0.010***	-0.024***	-0.012***
	(0.002)	(0.002)	(0.004)	(0.005)
Adjusted R^2	0.001	0.010	0.015	0.021
Observations	49,500	49,500	49,500	49,500
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

One observation in this table represents a Community Zone by industry cell. Wage is calculated by using total payroll divided by the total employment. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 1.9 presents the result. The coefficients of HHI are all significantly negative; the average wage level dropped more in highly concentrated areas during the Great Recession, consistent with the model's prediction. The magnitude implied by the coefficients also suggests an important role of HHI: moving from the 25th to the 75th percentile of HHI level implies a 1.55% larger drop in wage level; in comparison, the difference between the 25th and the 75th percentile of wage growth rate is -20.9%.

Moreover, the coefficients of the variable *log (total employment in 2005)* are all significantly positive. Why is that? From the literature, we know that workers receive higher wages in larger firms (Brown and Medoff 1989), and a recent paper by Grigsby, Hurst, and Yildirmaz (2019) shows that workers in larger firms have a higher frequency of nominal wage upward adjustment using administrative payroll data from the largest U.S. payroll processing company. One possible explanation for the positive effect of total employment is that an increase in total employment while holding HHI and the number of establishments constant is likely to increase all firms' sizes proportionally, subsequently leading to more large firms. Since large firms more frequently increase the wage base (Grigsby, Hurst, and Yildirmaz 2019), a local market with more large firms will have a larger increase in wage level. Similarly, an increase of the total number of establishments holding the total employment constant results in more small firms, which leads to slower wage growth.

1.5.2 The Effects on the Changes in Output

Another important outcome of a negative shock is the change in total output. According to the analytical solution from the model, we have: $g_Y \simeq G_2 \cdot s(\nu-1) - G_2 \cdot s^2 \frac{(\nu-1)^2}{2} - G_2 \cdot s(1-s)\frac{(\nu-1)^2}{2} HHI$, where $G_2 = \frac{(1-\alpha)(1+\epsilon)}{1-\alpha+\epsilon}$. To test this prediction, I employ the information about firms' sales from the CMF data. Since the CMF is conducted once every five years during years ending in 2 and 7, I change the horizon in the main tables to the growth rate of the output from 2007 to 2012 to accommodate this difference. For the output indices, I use two measures: total value of shipments and total value added. I aggregate these two measures from the establishment level to the CZ by industry (CMF only includes manufacturing industries) level, and then compute the change rates from 2007 to 2012 following the same formula as in Equation 1.12. Table 1.10 presents the results. For each measure of output, I use the four specifications as in Table 1.4. All the coefficients of HHI are significantly negative, showing that the total output declined more in highly concentrated areas.

Furthermore, all the coefficients in this table are larger than those in the main table using the change in employment as the dependent variable. This result is consistent with the prediction of the model, as $G_2 \cdot s(1-s)\frac{(\nu-1)^2}{2} > G \cdot s(1-s)\frac{(\nu-1)^2}{2}$ in the analytical solution. The reason is that the declines in output come from two sources: the drops in productivity and induced decreases in employment, as the aggregate output function in Equation 1.2 shows. Combining these two effects leads to a larger change in output facing a negative shock.[37]

[37]Based on Equation 1.2, $Y_T = \left(\sum z_i^{1/(1-\alpha)}\right)^{1-\alpha} \cdot L_T^{\alpha} \Rightarrow Ln(Y_T) = (1-\alpha)Ln[\sum z_i^{1/(1-\alpha)}] + \alpha Ln(L_T) = \frac{(1-\alpha)(1+\epsilon)}{1-\alpha+\epsilon} Ln[\sum z_i^{1/(1-\alpha)}] + \alpha H$, while $Ln(L_T) = \frac{(1-\alpha)}{1-\alpha+\epsilon} Ln[\sum z_i^{1/(1-\alpha)}] + H$. Hence, productivity shock has a larger effect on output than that on employment.

Table 1.10: The Effects of Pre-crisis Concentration Levels on the Changes in Output.

Dependent variable:	Change in total value of shipments from 2007 to 2012				Change in total value added from 2007 to 2012			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Herfindahl-Hirschman Index in 2006	-0.364***	-0.349***	-0.271***	-0.241***	-0.711**	-0.578**	-0.607*	-0.352**
	(0.058)	(0.062)	(0.058)	(0.063)	(0.318)	(0.247)	(0.326)	(0.163)
Log (employment in 2006)	0.045***	0.045***	0.004	-0.003	-0.008	-0.015	-0.069	-0.108
	(0.009)	(0.010)	(0.012)	(0.013)	(0.039)	(0.054)	(0.051)	(0.089)
Log (the number of establishments in 2006)	-0.050***	-0.036**	0.005	0.012	-0.039*	-0.006	0.045	0.161
	(0.012)	(0.015)	(0.015)	(0.025)	(0.022)	(0.030)	(0.035)	(0.154)
Observation	7,300	7,300	7,300	7,300	7,300	7,300	7,300	7,300
Adjusted R^2	0.019	0.037	0.111	0.127	0.002	0.063	0.003	0.066
CZ FE	NO	YES	NO	YES	NO	YES	NO	YES
IND FE	NO	NO	YES	YES	NO	NO	YES	YES

This table uses CMF data set. It only includes manufacturing industries (NAICS codes: 31-33). All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

1.6 Heterogeneous Effects across Sectors

In Section II.B, my model predicts that when the labor supply elasticity is lower, the impact of concentration levels (HHI) on employment changes should be smaller, while the effect on changes of wage level should be larger. To empirically test this prediction, I calculate the transition rate from the years 2003 to 2010 (CPS industry code was changed in 2003) for each three-digit NAICS code using the Current Population Survey (CPS). Specifically, I compare the industry each interviewee is in to the industry that the same person is in after 12 months, and assign a value of “1” if the (three-digit NAICS) industry is different. I aggregate this variable to the industry level calculating the transition rate for each month and industry. After that, I compute the “transition ratio” using the mean value of transition rate from 2003 to 2010, and categorize industries whose transition rates are below the 25th and above the 75th percentiles as sectors with low and high labor supply elasticity, respectively. For those industries with low (high) transition rates, workers are likely to have more industry-specific human capital, and more (less) likely to stay in the same sector even when wages go down.

Table 1.11 presents the results for these two sectors. Panel A examines the effect of concentration on employment changes. Columns (1)-(4) focusing on the low-elasticity sector and columns (5)-(8) focus on the high-elasticity sector. All specifications are similar to those used in the main table and control for the market thickness. The

Table 1.11: Heterogeneity across Sectors with Low vs. High Labor Supply Elasticity.

Panel A: Dependent variable – employment change from 2006 to 2010								
	Sector with low labor supply elasticity				Sector with high labor supply elasticity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Herfindahl-Hirschman Index in 2005	-0.292***	-0.269***	-0.166***	-0.162***	-0.315***	-0.336***	-0.277***	-0.315***
	(0.036)	(0.036)	(0.039)	(0.038)	(0.045)	(0.048)	(0.046)	(0.048)
Adjusted R^2	0.014	0.031	0.082	0.105	0.018	0.024	0.057	0.067
Observations	14,000	14,000	14,000	14,000	10,500	10,500	10,500	10,500
Panel B: Dependent variable – wage change from 2006 to 2010								
Herfindahl-Hirschman Index in 2005	-0.072***	-0.056***	-0.059***	-0.062***	-0.008	-0.004	-0.003	0.002
	(0.018)	(0.018)	(0.020)	(0.020)	(0.027)	(0.029)	(0.028)	(0.029)
Control for market thickness	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.014	0.031	0.082	0.105	0.018	0.024	0.057	0.067
Observations	13,500	13,500	13,500	13,500	9,500	9,500	9,500	9,500
CZ FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

Using the Current Population Survey (CPS) from 2003 to 2010 (CPS industry code was changed in 2003), I categorize industries into sectors with low and high labor supply elasticity, respectively. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

absolute value of the coefficient of HHI in the high-elasticity sector is about one-half of that in the other sector using the tightest specification. The results on wage changes presented in Panel B differ substantially. The effect of firm concentrations on wage changes is significantly different from 0 in the sector with low labor supply elasticity, while it is almost 0 in the other sector.

These two sets of results are consistent with the prediction of my model discussed in Section II.B. When the labor supply elasticity is low (i.e., low transition rate), most workers are likely to stay rather than move to a different industry when large firms are hit by adverse shocks. A large number of displaced workers will push down the wage level and, hence, allow other nearby firms to absorb more displaced workers. Thus, wage declines more, while employment drops less, in sectors with low supply elasticity.

1.7 Effects of HHI during the Recovery

The main focus of this chapter is on the employment decline during the Great Recession; the model, however, also sheds light on the recovery period. Although employment marched back to the pre-crisis level in 2014, the recovery from the Great Recession has been slow and uneven. Table 1.2 shows that the 25th and 75th percentiles of employment growth rate across CZ by industry cells from 2010 to 2014 are −10.9% and 14.8%, respectively.

Table 1.12: The Effect of Concentration Level during the Recovery.

Panel A: Dependent variable – employment change from 2011 to 2014

	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2010	-0.137***	-0.150***	-0.117***	-0.142***
	(0.017)	(0.017)	(0.018)	(0.018)
Log (total employment in 2010)	-0.005**	-0.004*	-0.025***	-0.023***
	(0.002)	(0.003)	(0.004)	(0.005)
Log (the number of establishments in 2010)	0.007**	0.003	0.033***	0.006
	(0.003)	(0.003)	(0.006)	(0.007)
Employment change from 2006 to 2010	-0.087***	-0.091***	-0.095***	-0.095***
	(0.007)	(0.007)	(0.007)	(0.008)
Adjusted R^2	0.022	0.029	0.038	0.046
Observations	51,500	51,500	51,500	51,500

Panel B: Dependent variable – wage change from 2011 to 2014

	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2010	-0.032***	-0.031***	-0.038***	-0.042***
	(0.009)	(0.010)	(0.010)	(0.010)
Log (total employment in 2010)	-0.004***	-0.002	0.003	0.004
	(0.001)	(0.001)	(0.002)	(0.003)
Log (the number of establishments in 2010)	-0.001	-0.000	-0.012***	-0.011***
	(0.002)	(0.002)	(0.003)	(0.004)
Wage change from 2006 to 2010	-0.102***	-0.105***	-0.101***	-0.104***
	(0.008)	(0.008)	(0.008)	(0.008)
Adjusted R^2	0.013	0.018	0.026	0.032
Observations	49,500	49,500	49,500	49,500
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

This sample in Panel A consists of about 51,500 observations. Each observation represents a commuting zone by industry cell. Because of missing wage levels, we have about 49,500 cells in Panel B. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Part of the recovery process involves a positive firm-idiosyncratic shock ($\mu > 1$). Section II.C shows that the analytical relation: $g_{emp} \simeq T \cdot s(\nu - 1) - T \cdot s^2 \frac{(\nu-1)^2}{2} - T \cdot s(1-s)\frac{(\nu-1)^2}{2} HHI$ still holds, as long as $0 \leq |\nu - 1| \leq 1$, where $\nu = \mu^{1/(1-\alpha)}$, and μ

represents the productivity shock.[38] Thus, the model predicts the same effect of HHI during the recovery as during the Great Recession. When large firms are hit by positive shocks and need to hire more workers, they cannot add that many workers because it would push the wage level to a very high level, so, on average, highly concentrated areas will have a slower recovery pace.

To test this hypothesis, I use the HHI in 2010 as the measure for the initial concentration level, and calculate the employment/wage growth rate from the years 2011 to 2014. Table 1.12 presents the results. Columns (1)-(4) represent four different specifications analogous to those in Table 1.4. I also added the employment/wage change from 2006 to 2010 to control for pre-trends in all specifications. Panel A uses the employment change from 2011 to 2014 as the dependent variable. The coefficients of HHI are all significantly negative, consistent with the prediction of the model. The magnitude is also substantial. Take the coefficient in the most restrictive specification as an example: If the HHI moves from the 25th to the 75th percentile, the recovery pace will be 5.58% lower (-0.142*(0.451-0.058)), while the difference between the 25th and 75th percentiles of employment growth rate is 25.7%. Panel B shows the same pattern for the wage change: Wages recover more slowly in highly concentrated cells. All these results are consist with the predictions of my model.

1.8 Conclusion

This chapter documents an important new fact that total employment declined more in highly concentrated local labor markets during the Great Recession. By building a model with heterogeneous firms that are subject to stochastic firm shocks, I provide an explanation for this pattern. In highly concentrated areas, when relatively large firms are hit by idiosyncratic shocks, the total employment declines disproportionately more than in less concentrated markets. The reason is that relatively small firms are unable to absorb many displaced workers, driven by decreasing returns to scale and an upward-sloping labor supply curve. Because of the disproportionately large drop in employment in this scenario, on average, employment declines more in highly concentrated areas, even though the shock is symmetric.

The analytical solution shows the negative relation between the initial HHI and the employment growth rate after the shock, and also how this relation is affected by param-

[38] When $|\nu - 1| \geq 1$, the second order Taylor expansion might not be a good approximation, and the analytical relation might not hold.

eters, such as labor supply elasticity, the probability of the stochastic shock occurring, and the magnitude of the shock. Moreover, the simulation result based on the model setting is close to the analytical relation that uses an approximation, and shows that HHI is a nearly sufficient statistic to describe the size distribution—that is, we only need to know HHI from the size distribution to predict the employment growth rate after the shock under the model setting.

Empirically, I show that the correlation between pre-crisis concentration and employment decline is economically and statistically significant. An industry-CZ labor market in the 75th percentile of HHI has a 5.46% larger decline in employment, relative to a labor market in the 25th percentile of HHI during the Great Recession. I address important concerns that highly concentrated areas might be different from other areas in other aspects, and the pattern we observe might be caused by other reasons rather than concentration level. Although I could not rule out this possibility, I address specific hypotheses. Through adding industry, CZ, or both fixed effects, I show that this pattern is not driven by hardest hit industries/CZs having high concentration levels by coincidence. I also show that the pattern is not driven by highly concentrated markets having a smaller market size, higher firm leverage ratios, more large firms, or higher volatility.

I provide evidence suggesting that the decline in employment represents a waste of human capital, as displaced workers were not able to find new jobs in different markets. In addition, the empirical results show that wages and output declined more in highly concentrated industry-CZ cells during the Great Recession. However, in sectors with low labor supply elasticity, employment dropped less, while wage levels declined more, compared to sectors with high elasticity. These empirical findings are consistent with my model's predictions. Interestingly, the empirical and analytical results also show that highly concentrated markets recovered more slowly after the Great Recession. When large firms were hit by the positive shocks and needed to hire more workers, they could not add many due to decreasing returns to scale and an upward-sloping supply curve, so, on average, highly concentrated areas had a slower pace of recovery.

The results of this chapter provide insights for local governments to build healthy and resilient ecosystems to weather future negative shocks. Going back to the example of Janesville, can we do better next time in dealing with negative shocks in similar areas? Within any industry of an area, when most jobs are concentrated in one or a few firms, workers in that industry are likely to suffer more when facing an idiosyncratic shock.

Since diversification of firms within the same industry is important for building a healthy and resilient economy, local government should take this into consideration when giving tax incentives to attract more firms. Moreover, if a recession were to happen, federal and local governments can predict which groups of people and which areas will suffer more based on this chapter's findings, then conduct policies to bail out people who need the help most.

On the firms' side, because they are less incentivized to take the characteristics of local labor markets into consideration when choosing which plants to shut down or conduct mass layoffs at, they usually do not internalize the relatively high cost borne by workers living in highly concentrated places, potentially leading to a socially non-optimal choice.

Chapter II

Social Insurance and Entrepreneurship: The Effect of Unemployment Benefits on New-Business Formation

2.1 Introduction

Startups play a crucial role in fostering competition, pushing innovation, and generating job creation (Schumpeter 1939; Audretsch, Keilbach, and Lehmann 2006). Indeed, an abundance of new firms is critical for a healthy labor market because of the span-of-control problem (Beaudry, Green, and Sand 2018). And, even though most new businesses exit in their first ten years, young businesses account for 70 percent of gross job creation (Decker et al. 2014).

While entrepreneurship has been studied broadly, few studies have examined startup businesses founded by unemployed workers. During the years 2009–2011, the unemployment rate was as high as 9–10%, and the human capital of such a large group of people is idle during recessions. Many of the unemployed spend a long time searching for new jobs, but the effectiveness of job searching is limited by the rationing of jobs during recessions (Toohey 2014). While losing a job is a challenge and a harsh reality for most people, it can also provide new opportunities. A recent paper by Hacamo and Kleiner (2016) finds that individuals displaced by corporate bankruptcy are more likely to engage in self-employment. The effects of social insurance on the propensity of unemployed individuals to form new businesses, however, remains under-explored.

This chapter studies how the Unemployment Insurance (UI) system affects an unemployed person's decision to build a business, with a primary focus on the impact of the generosity of unemployment benefits. I employ the product of the maximum weekly benefit and the maximum duration as a measure of the generosity of each state's UI, following Hsu, Matsa, and Melzer (2018), and exploit the variation in the generosity of benefits across states and over time. To filter out the effect of other policies, macroeconomic shocks, or shocks to some specific states, I utilize unemployed people who are ineligible for the UI benefits as the control group, because the changes of the UI benefit generosity should not affect these people' decision of starting a firm. The key identifying assumption is that absent the changes of benefit generosity, people who are eligible and ineligible for the UI benefits would have had similar pattern in entrepreneurial activity.

The empirical results show that higher UI benefits discourage unemployed people from starting a firm—a one-standard-deviation increase in state maximum UI benefits (about $\$2,385$ or 32% of the mean level) reduces the likelihood of starting a business among the unemployed by 0.28 percentage points—that is, 11.00% of the average switching rate. All of the estimates control for individual demographics, household-level income, and state economic conditions to ensure that the results are not driven by the differences of individuals, households, or economic situations.

I surveyed states to understand how starting a new business would affect UI eligibility. Among those who responded to the questionnaire, 88 percent allow unemployed people to start a business while receiving UI benefits, but any profit (gross earning in some states) from business is deducted from their unemployment benefits. All of the states require people to satisfy the job search requirements and be available to accept a full-time job to keep receiving benefits. These deductions, search requirements and being available for a new job might discourage an unemployed person from starting a business.

Being aware of this disincentive effect and trying to boost entrepreneurship, eight states have adopted the Self-Employment Assistance (SEA) program. This program allows the unemployed who are involved in starting new businesses to receive the same amount of benefits as any unemployed person, and it waives the job search requirements to allow them to focus on their businesses (see Kugler 2015 and Messenger, Peterson-Vaccaro, and Vroman 2002). The federal Middle Class Tax Relief and Job Creation Act of 2012 provides grants to each state to encourage them to adopt the SEA program (SEC. 2182 and 2183). Ideally, introducing this program should stimulate the entrepreneurship among the unemployed, and high benefits in states having the SEA program should have a smaller negative impact on entrepreneurship among the unemployed, because it mitigates the financial constraints on them, which have been shown to inhibit the creation of new firms (Evans and Jovanovic 1989; Kerr and Nanda 2009; Adelino, Schoar, and Severino 2015; Schmalz, Sraer, and Thesmar 2017). Focusing on states that offer the SEA program, I find the negative effect of high unemployment benefits on starting a firm is indeed much smaller, compared to states that do not have this SEA program.

To fully understand the effect of the deduction of business income from unemployment benefits, I distinguish two types of business, unincorporated and incorporated, and explore the heterogeneity of these two types. A major difference between these two is that an incorporated business has a legal identity separate from the owners and provides limited liability, while an unincorporated business does not have a separate legal identity. According to a study by Levine and Rubinstein (2017), median hourly earnings in incorporated businesses are about 80% greater than those of unincorporated businesses using the March Annual Supplement of Current Population Survey data. Theoretically, if a business is expected to make a profit far beyond the total UI benefits, the deduction should not matter much, while for some small businesses, the deduction causes the margin income of starting a business to be 0, and thus prevents/delays the creation of a firm by the unemployed. Indeed, I find that switching to an unincorporated business is more sensitive to changes in UI benefits, while starting an incorporated business is not significantly affected by variation in UI benefits. In addition, higher benefits make the unemployed wait longer if they do start an unincorporated business, while having no effect on the waiting period before creating an incorporated business. In this sense, the deduction might mainly deter businesses that are not that profitable.

Several papers have studied the relation between UI systems and self-employment. Hombert et al. (2014) study a large-scale French reform that provided generous downside insurance for unemployed individuals who start a business. Their finding shows that monthly firm creation increased by 25% after the risk of losing UI benefits are reduced due to the reform. This result is consistent with the finding of this chapter, while the angle is different: this chapter exploits variation in the generosity of UI benefits across states and years rather than the eligibility to receive benefits in the context of U.S., where the risk of losing UI benefits once starting a firm is high in most states. This chapter also explores the interaction of UI benefits and other important factors, such as the SEA program and job search requirements. The SEA program plays a similar role as the French reform studied by Hombert et al. (2014) in the sense that both of them allow unemployed people to receive UI benefits, but the amount of UI benefits will not be affected by the business income for participants in the SEA program, while unemployment benefits in France is computed to complement the business income up to 70% of the pre-unemployment income level after the reform. Moreover, the SEA program is still a small-scale program adopted in a few states, while the French reform is a nationwide policy. Another key difference is that the duration of receiving UI benefits is mostly up to 26 weeks in the US, but up to three years after the French reform. These policy differences could explain why this chapter does not find a significantly positive effect of SEA as the finding of Hombert et al. (2014).

Using data from OECD countries, Koellinger and Minniti (2009) find that higher unemployment benefits crowd out nascent entrepreneurial activity, but this finding is for the general population rather than the unemployed, so the mechanism causing the phenomenon is uncertain. Røed and Skogstrøm (2014) find that the transition from unemployment to entrepreneurship is more sensitive to UI incentives than the transition from unemployment to regular employment.

There are many papers studying the effect of the UI system with a primary focus on finding a new job instead of on becoming an entrepreneur. As Feldstein (2005) points out, social insurance programs generally involve a trade-off of protection and distortion, and indeed, many previous papers find a spike in the exit rate from unemployment around the expiration of jobless benefits (see e.g., Moffitt 1985; Katz and Meyer 1990). This sharp rise is widely interpreted as an example of the distortionary effects of UI. Recent studies also find the positive effects of UI extension on unemployment exits, duration, and the overall unemployment rate, although the evidence is mixed regarding the magnitude of effects. Rothstein (2011), Farber and Valletta (2015), and Farber, Rothstein, and Valletta (2015) find limited effects of UI extensions on job finding due to the tight labor market, while Johnston and Mas (2018) provide evidence of very large effects of UI duration cuts on compensated UI and unemployment spells, and Hagedorn, Manovskii, and Mitman (2015) also find a substantial effect of UI cuts on employment.

This chapter is also in line with a growing literature that studies the policy determinants of entrepreneurial outcomes. For example, Autor, Kerr, and Kugler (2007) find that wrongful discharge protections reduce entry of new establishments. Curtis and Decker (2016) study the effects of three state-level policies: corporate income taxes, minimum wages, and personal income taxes. They find significant negative effects of corporate tax increases, moderate effects of minimum wages, and no statistically significant impacts of personal tax rates. This chapter focuses on the UI system and employs plausibly exogenous benefit changes to study entrepreneurial activities.

The rest of this chapter proceeds as follows. Section 2.2 introduces the Unemployment Insurance system in the United States, while Section 2.3 proposes the economic framework in which to study the effects of UI benefits. Section 2.4 describes the data and empirical strategy. Section 2.5 discusses the main results. Section 2.6 concludes with a discussion of the main results.

2.2 Unemployment Insurance System

The current UI system in the United States is designed to provide income to unemployed workers for a limited period, given they satisfy certain requirements. Basically, there are four requirements. First, claimants must have had sufficiently long working history and earned a sufficient amount of money in the previous year or five quarters. Second, claimants must have lost their job through no fault of their own. A person who quits is typically not eligible for UI benefits, although some states have exceptions—for example, if the departure is caused by sexual assault, domestic violence, or a spouse's job relocation, he or she may qualify for partial or full unemployment benefits. However, a worker who becomes unemployed after closing his or her own business is not eligible for UI benefits. The third requirement relates to job search effort. Unemployed people are required to make contacts with employers, keeping a record of these contacts for each week. The final requirement is that claimants must be available for full-time work.

While the requirements for UI eligibility are clear, it is unclear how starting a business while collecting UI benefits is treated in this system: is this behavior treated as finding a new job, a part-time job, a side business, or a separate category? How does the decision to start a new firm jeopardize a person's eligibility for and the amount of UI benefits? I searched states' labor department websites and UI claimant handbooks, but unfortunately, the answers to these questions are not clear in most states.[39] To understand these policy details in practice, I made a simple questionnaire with six questions and sent it to the labor department of each state through email or online form (see Table B.3 for the questionnaire). Out of 17 states that replied, all but 2 indicated that they allow unemployed people to start a business while receiving benefits. All 17 states, however, require people to satisfy the job search requirements and be available to accept a full-time job in order to keep receiving benefits, and any profit (gross earnings in some states) from business is deducted from their UI benefits using different rules. For example, South Dakota requires that "seventy-five percent of [a person's] earnings over $25 will be deducted from their weekly benefit amount"; while in West Virginia,

[39] I found relevant information in the labor department websites of five states (Maryland, Minnesota, Nevada, Ohio, Virginia).

"a person would have to report his or her gross earnings minus any expenses for the business. A person can earn up to $60 per week without any deducting earnings from his or her weekly benefit amount. After that, we would deduct dollar for dollar from the weekly benefit amount." If earnings are above some threshold, then the unemployed person cannot receive any benefits.

In the process of contacting each state's labor department, I learned about the Self-Employment Assistance (SEA) program, which aims to remove barriers for the unemployed who plan to start a firm. This program targets unemployed people who wish to start their own business by allowing them to receive UI benefits and waiving their job search requirements. As of 2016, eight states had this program in 2016 (based on information in Kugler 2015 and Messenger, Peterson-Vaccaro, and Vroman 2002). Two states (Pennsylvania and Maryland) that had this program discontinued it in 2009 (they conducted this program in 1997 and 2000, respectively) due to a lack of funding. Maine, New York, and Rhode Island have had this program since 1995; Delaware and Oregon have had it since 1996; and New Jersey has had this program since 1998. Mississippi and New Hampshire recently launched this program (in 2012 and 2013, respectively) after former President Barack Obama signed the Middle Class Tax Relief and Job Creation Act of 2012, which provides grants to each state to promote implementing Self-Employment Assistance (SEA). This program, however, is so far a small one due to participation restrictions, with only about 2,000 participants each year (see the Green Book 2016 published by the Congressional Research Service).

To understand the potential effect of the UI system on entrepreneurship among the unemployed, we need to know how large the benefits would usually be. The total amount of benefits depends on both the number of weeks that a claimant could collect benefits and the weekly amount. To determine the weekly amount, the unemployment agency in each state applies a benefit schedule that is increasing in the individual's prior wage, but is capped at the state's maximum weekly benefit (the replacement rate did not vary much below the earning cap). State benefit caps bind for about half of UI recipients (Hsu, Matsa, and Melzer 2018). The duration of receiving benefits is also capped by the maximum duration. I use the product of the maximum weekly benefit and the maximum duration to measure the generosity of each state's UI benefits annually between 1995 and 2016, following Agrawal and Matsa (2013) and Hsu, Matsa, and Melzer (2018).

Many factors lead to variations in UI benefits across states and over time periods. First, economic conditions, like local unemployment rates and average wage levels, usually relate to changes in benefits. There are, however, noneconomic reasons that also influence the changes of UI benefits: governors may increase UI benefits to win reelection, and political parties may have different preferences for the UI system. For example, in California, the UI maximum benefit was kept at \$230 for more than a decade, until it increased to \$330 in 2002, allegedly to bolster political support for the governor's reelection (Kiplinger Washington Editors 2001; Agrawal and Matsa 2013). As Hsu, Matsa, and Melzer (2018) show that the changes in the benefit generosity appear to be uncorrelated with state macroeconomic variable, changes in other government benefits, etc., conditional on state and year fixed effects, the variation in benefit generosity could be considered as plausibly exogenous.

Moreover, according to my questionnaire results (question 4), once a claimant starts to receive benefits, the amount will not change even after he or she receives the maximum benefits, and there is an increase in the maximum benefit during the periods that he or she is receiving it. This policy means there is no variation in UI benefits for each unemployment episode of an unemployed person. In the empirical section, I use the maximum benefits in the month that people lost their job to measure the generosity of benefits and fixed the amount over that unemployment period.

2.3 Economic Framework

After understanding the policy details, how should UI benefits affect an unemployed person's decision to start a business? The traditional job search model suggests that UI benefits distort the relative price of leisure and consumption, reducing the marginal incentive to search for a job (Pissarides 1985; Mortensen and Pissarides 1994). The same logic can apply to becoming self-employed as well: consider starting a business and getting a new job as two options other than staying unemployed. More generous UI benefits will increase the reservation profits or reservation wages, and thus increase the probability of staying unemployed. This has also been interpreted as the substitution effect. Chetty (2008) proposes another channel through which UI benefits affect search intensity, called the "liquidity effect." The idea is that many unemployed individuals have limited liquidity and exhibit excess sensitivity of consumption to cash on hand, while UI benefits can increase cash on hand and then relieve the pressure to find a new job quickly. Both of these two effects will lead the unemployed more likely to stay unemployed, which means they are less likely to start a business. There are, however, some other channels through which UI benefits may influence the decision of starting a business.

As starting a business involves a lot of uncertainty, how to cover living expenses in the case of failure is an important question facing most unemployed individuals who are considering starting businesses. Most of them do not have significant savings, so UI benefits would be useful to cover the basic costs of living in the case of failure—thereby reducing tail risk. Furthermore, UI benefits can mitigate the borrowing constraints to some degree. In this sense, UI insurance helps to reduce risk and soothe the borrowing constraint, so more generous benefits could prompt more unemployed individuals to start businesses.

In the current UI system, nevertheless, in states that have not adopted the SEA program, profits or revenues need to be deducted from UI benefits, and all job search efforts still need to be satisfied. This deduction will generate disincentive effects. Imagine an unemployed person living in a state where she could collect \$7,500 benefits in total (the mean level in the sample). Suppose she starts a business and makes a profit. The profit from the business will basically not affect her aggregate net income unless the profit is more than \$7,500, yet she has to spend many hours on that business in addition to satisfying the requirements of searching for a new job and being available to accept a full-time job. The marginal profit of starting a business is zero for small businesses, whose profits are below the UI benefits, while the marginal cost is above zero, so more generous benefits will crowd out more small businesses. However, for businesses that are expected to make a lot of profits, like incorporated businesses (Levine and Rubinstein 2016), the disincentive effect should be smaller, because once the level of profit is above the level of benefits, the marginal profit becomes positive, and the total income could increase beyond the total UI benefits.

One important requirement to be eligible for UI benefits is putting effort toward searching for a new job, whether one is starting a business or not. Different states have different requirements regarding job search intensity. Theoretically, high search-intensity requirements make the option of staying unemployed less attractive, thus leading to more exits out of unemployment—that is, more people will find jobs or switch to self-employment, thereby counteracting the negative effect of generous UI benefits on starting a business. Thus, the negative effects of UI benefits in states with high search requirements might be smaller.

The other possible response to the job search requirement is to both satisfy the search requirement and spend time setting up a business. Then, one can open the business on the day benefits end. In this case, UI benefits essentially delay the starting of a business—that is, extend the unemployment duration. Higher UI benefits would make this strategy more attractive and lead to a longer waiting period, especially for businesses that do not make large profits, like unincorporated businesses, and should not have a large effect on the waiting period to start incorporated businesses. In the empirical part, I test this hypothesis as well.

To summarize, the effects of UI benefits on starting businesses are uncertain. There are a few channels through which it could have positive effects, while there are many channels through which it could exert a negative influence. In the following, I study the overall effects and tease out the possible channels empirically.

2.4 Data and Empirical Strategy

2.4.1 Data Description

I use four sources of data. Information on each state's benefit schedule is obtained from the U.S. Department of Labor's publication "Significant Provisions of State UI Laws," which provides information on maximum duration and maximum weekly benefit amounts for each state and each year from 1995 to 2016.[40] I use the product of these two maximums to measure the generosity of UI benefits (max benefits) for each state in each year. To isolate the real changes of UI benefits, I use monthly CPI provided by the U.S. Department of Labor Bureau of Labor Statistics to adjust the max benefits. I take the price level in January 1995 as the baseline.

The information of individuals' labor market status comes from Current Population Survey (CPS) monthly data. In this data set, each individual receives an interview per month for four consecutive months, and then there is a gap of eight months. After that, the same person receives an interview per month for an additional four months. Surely, some interviewees do not finish all eight interviews. Each month, interviewees are asked their labor market status: whether they are unemployed or not. Those who are not unemployed are asked whether they have a paid job or are self-employed. Those who report having started a business need to state whether the business is incorporated or unincorporated. Information on reasons for unemployment is also available, which is sorted into five different categories: (1) Job loser/On layoff; (2) Other job loser; (3)

[40] For each state and year, it provides the maximum duration and weekly benefit in January and July. I combine this information and adjust it using monthly inflation rate.

Temporary job ended; (4) Job leaver; (5) Re-entrant. I grouped the first two categories into the “laid-off” group and the last three reasons into the “quit” group. In the “laid-off” group, people are eligible to receive UI benefits if they satisfy certain requirements, while those in the “quit” group are not eligible for UI benefits. I obtained the data set from the IPUMS-CPS website (Ruggles et al. 2015).

As I focus on the decisions of unemployed people and see how their job status changed after being unemployed, I include only people who were unemployed in at least one period of the sample, and not self-employed before losing a job, to ensure those in the sample would be eligible for UI benefits. The age restriction is between 20 and 70. I also set a restriction that unemployed people who do not switch to self-employment have to stay in the sample for at least three months after losing jobs. This ensured that I would have reasonably long periods to observe their choices (results are robust without this restriction, but a little smaller in magnitude). I keep one observation for each individual, because according to the survey results I collected, UI benefits will not change once unemployed people start to receive UI, which means there is no variation in UI benefit for each unemployment period.

Although the CPS dataset contains a rich set of individual level variables, like: gender, age, education, family income, marital status, etc., it does have a few limitations. First, it does not have detailed information about the business performances, like: sales, profits or size/employment, which restricts the comparison with businesses started by other people. Second, the eight months gap during the interview might create measurement errors, because I assume an unemployed person transits from unemployment to self-employment if he or she is unemployed in the last month of the first four consecutive interviews, and self-employed in the first month of the second four consecutive interviews. Third, since in the CPS dataset, I could not distinguish people who are receiving benefits and people whose benefits are capped by the maximum from others, I use all the unemployed and consider unemployed people who are laid off as people who are eligible for the UI benefits. The measurement error in determining the eligibility and the fact that changes in the benefit cap only affects half of unemployed people are likely to attenuate estimated magnitude.

Finally, I follow Toohey (2014) to get the search requirements in each state across periods. Through searching UI claimant handbooks or “frequently asked questions” brochures and web pages, he grouped job search policies by the number of required weekly employer contacts. Using his measure, I group state-periods that require 0–

Table 2.1: Summary Statistics.

	Observations	Mean	SD	p25	Median	p75
A. Labor Market Status						
Different outcomes for the unemployed (%)						
Switch to unincorporated self-employment	252,791	2.30	14.98	0.00	0.00	0.00
Switch to incorporated self-employment	252,791	0.25	5.01	0.00	0.00	0.00
Find a new job	252,791	41.73	49.31	0.00	0.00	100.00
Drop out of labor force	252,791	40.07	49.00	0.00	0.00	100.00
Stay unemployed	252,791	15.79	36.47	0.00	0.00	0.00
Dummy: Layoff	252,791	0.46	0.50	0.00	0.00	1.00
Having SEA program	252,791	0.15	0.36	0.00	0.00	0.00
Unemployment rate in the current month (%)	252,791	4.86	2.15	3.30	4.40	6.13
Unemployment rate in the past 3 months (%)	252,791	4.79	2.11	3.27	4.29	6.02
Nonspecific work-search requirements	156,613	0.60	0.49	0.00	1.00	1.00
Low work-search requirements	156,613	0.25	0.44	0.00	0.00	1.00
High work-search requirements	156,613	0.15	0.36	0.00	0.00	0.00
B. Unemployment Insurance Benefits						
Max UI benefit (adjusted for inflation)	252,791	7,535	2,385	6,045	7,321	8,769
Log (max benefit)	252,791	8.88	0.30	8.71	8.90	9.08
Dummy – max UI benefits increase by more than 20%	252,791	0.23	0.42	0.00	0.00	0.00
Dummy – max UI benefits decrease by more than 20%	252,791	0.03	0.17	0.00	0.00	0.00
C. Demographics						
Age	252,791	37.33	13.07	26.00	35.00	47.00
Female	252,791	0.49	0.50	0.00	0.00	1.00
Have College Degree or Above	252,791	0.25	0.43	0.00	0.00	1.00
Married, Spouse Present	252,791	0.39	0.49	0.00	0.00	1.00
Spouse has a job	252,791	0.32	0.47	0.00	0.00	1.00
Annual family income below $20,000	252,791	0.30	0.46	0.00	0.00	1.00
Annual family income between $20,000 and $50,000	252,791	0.33	0.47	0.00	0.00	1.00
Annual family income between $50,000 and $75,000	252,791	0.13	0.34	0.00	0.00	0.00
Annual family income above $75,000	252,791	0.14	0.35	0.00	0.00	0.00
Annual family income is missing	252,791	0.10	0.30	0.00	0.00	0.00

The main sample comes from 1995 to 2016 Current Population Survey (CPS) monthly data. The sample includes only people who were unemployed during at least one period of the sample, and not self-employed before losing a job, so that they would be eligible for UI benefits. The age restriction is between 20 and 70. I also set a restriction that unemployed people who do not switch to self-employment have to stay in the sample for at least three months after losing a job, to ensure reasonably long periods to observe their choice (results are robust without this restriction, but a little smaller in magnitude). I keep one observation for each individual, because UI benefits will not change once unemployed people start to receive them. All UI benefits are those of months when the unemployed lost their jobs. I use a dummy variable for a switch to self-employment equal to 1 if an unemployed person makes a transition out of unemployment to self-employment in the sample period. In CPS, respondents are interviewed for four consecutive months, left alone for eight months, and then re-interviewed for another four months, so I assume an unemployed person transits from unemployment to self-employment if he or she is unemployed in the last month of the first four consecutive interviews, and self-employed in the first month of the second four consecutive interviews. Layoff is a dummy variable indicating the unemployed person falls into the categories “Job loser/On layoff” or “Other job loser,” instead of “Temporary job ended,” “Job leaver,” “Re-entrant,” or “New entrant,” so Layoff likely represents the group of people who are eligible for UI benefits and thus might be affected by changes in UI benefits. Job search requirement information comes from Toohey (2015), and it covers only the period from 2001 to 2013. That is why the numbers of observations are smaller for these three dummy variables related to search requirements. Finally, family incomes and other demographic variables represent the values before losing the job.

2 contacts in the "low search requirement" group, state-periods that need more than (including) 3 contacts in the "high search requirement" group, and state-periods that do not indicate an exact number of employer contacts in the "non-specific".

Table 2.1 shows the summary statistics of all variables used in this chapter. There are 252,791 observations in our main sample. While in the sample period, about 2.55% of unemployed people choose to start a business after losing a job, 2.30% of them choose to start an unincorporated business, and only 0.25% decide to start an incorporated business. The average maximum benefit, adjusted for monthly inflation, is % 7,535 (about % 289 per week). The average log max benefit is 8.88. The average unemployment rate from 1995 to 2016 is 4.86% . Based on our definition, 46% of unemployed people are laid off, so they are likely to be eligible for UI benefits. About 15% of state-periods have the SEA program. Of the state-periods, 60% do not indicate an exact number of employer contacts to be eligible for the UI benefits, 25% require 0–2 contacts per week, and 15% need 3 or more contacts per week. The average person in the sample is 37 years old, 49% of them are female, 39% are married with spouse present, 25% have a college degree or above, and 32% have a spouse who had a job when the respondent became unemployed. CPS also provides categories of family income. In our sample, 30% have a family income below $20,000; 33% have a family income between $20,000 and $50,000; 13% have a family income between $50,000 and $75,000; and only 14% have a family income above $75,000.

2.4.2 Empirical Strategy

I mainly rely on the linear probability model to analyze the effects of UI benefits and other factors at the individual level. The main specification is as follows:

$$y_{ist} = \beta_1 \times log(Max\ benefit)_{st} + \beta_2 \times log(Max\ benefit)_{st}) \times Layoff_{ist}$$

$$+\beta_3 \times Layoff_{ist} + \beta_4 \times X_{ist} + \gamma_t + \alpha_s + \epsilon_{ist}$$

where i indexes individual, s indexes state, and t indexes year-month. The dependent variable is a dummy variable: 1 indicates this unemployed person has switched from unemployment to self-employment, and 0 means this person has switched from unemployment to other options, such as finding a new job, staying unemployed, or being out of the labor market. Max benefit is the product of maximum weekly benefit and maximum duration. I follow Hsu, Matsa, and Melzer (2018) in interacting Layoff with

$log(Max\ benefit)_{st}$, so that I utilize unemployed people who are ineligible for the UI benefits as the control group, because the changes of the UI benefit generosity should not affect these people' decision of starting a firm. The key identifying assumption is that absent the changes of benefit generosity, people who are eligible and ineligible for the UI benefits would have had similar pattern in entrepreneurial activity. $log(Max\ benefit)_{st}$ is demeaned (with respect to the mean for the entire sample) before it is interacted with Layoff, so the coefficient of Layoff represents the change in the probability of switching to self-employment associated with being laid off in a state with average UI generosity. X refers to state unemployment rate and demographic variables, including age, education, marital status, spouse's job status, and family income. I also add state (α_s), year by month fixed effects (γ_t). All standard errors are clustered at the state level, except three columns in Table 2.5, where standard errors are clustered by state and year, because of too few states in that sub-sample.

2.5 Empirical Results

2.5.1 Overall Effects of UI Benefits on Switching to Self-Employment

Table 2.2 shows the effects of UI benefits on starting a business. Column (1) uses max benefit as the key explanatory variable, and adds year and state fixed effects. As I mentioned before, changes in UI benefits are correlated with local economic conditions, and these economic conditions in turn affect unemployed people's decisions to start a business. I add the unemployment rate in the current month and in the past 3 months as proxies for local economic conditions. The second column adds a few control variables at the individual level. After controlling for age, education, and family income, the coefficient of Layoff become significantly negative, meaning that laid off workers have a 0.239 percentage points less probability of starting a firm comparing to unemployed people who quit their job at the mean level of UI benefits. The third column includes the month fixed effects. The coefficients of maximum benefit in these three columns are negative but not statistically significant. This average effect, nevertheless, might disguise the effect on the relevant sub-population.

Both columns (4) and (5) add the interaction of $log(Max\ benefit)$ and *Layoff* to allow the different coefficients of $log(Max\ benefit)$ by layoff status, while they use the different fixed effects. As I mentioned in the Section 2.2, people who quit their jobs are not eligible for the UI benefits, and then the change of UI benefits should not affect their decision about whether starting a firm or not, thus this group of people could be used as the control group. For the fixed effects, column (4) adds the month fixed effects besides the state and year fixed effects to control for the potentially different patterns of entrepreneurial activity across months, and the relation between benefits and month.

One concern is that a small part of the UI benefits variation within a state comes from the inflation/CPI adjust, although most variations come from the policy changes, the column (5) adds year by month fixed effects so that I only focus on the benefit variation caused by the policy changes. This specification is used for all the following tables except Table 2.4, although estimates are very similar with these two specifications.[41] The results in both column (4) and (5), show that the increases in $log(Max\ benefit)$ significantly lower the probability of becoming self-employed. The coefficient of the interaction in column (5) is –0.876, indicating that, for a 20% increase in the maximum UI benefit, the probability of switching from unemployment to self-employment decline by 0.175 (0.876*20/100, because the dependent variable is scaled by 100) percentage points more among laid-off workers than other unemployed workers. This magnitude is relatively smaller than what I get in column (2) of Table B.1, where I use a dummy variable to indicate big changes in the UI benefit (increase or decrease by more than 20%). The coefficient there shows that a 20% increase in maximum UI benefit reduces the probability of self-employment by 0.317 percentage points, and a 20% decrease in maximum UI benefit has an even bigger positive effect, about 0.791 percentage points. The coefficient in Column (5) of Table 2.2 implies that a one-standard-deviation increase in $log(Max\ UIbenefit)$ (0.30) reduces the probability by 0.263 percentage points, or about 10.31% compared with the mean level (2.55%).

The coefficients of demographic variables are also of interest. Unemployed people with a spouse who has a job are about 0.185 percentage points higher, or about 7.26% higher compared with the mean level, in the probability of switching to self-employment. The age pattern of switching from unemployment to self-employment is an inverted U-shape, with a peak around age 45. Generally, people who are male, married, or have a college degree are more likely to switch to self-employment after losing a job. Unemployed people at the highest family income level (above $75,000) are more likely to start a business.

[41] Table 2.4 uses two specification: 1. With no fixed effects; 2. With state, year and month fixed effects. The reason that I do not use state and year by month fixed effects is that the model does not converge with too many dummy variables.

Table 2.2: Effects of UI Benefits on Self-Employment (Linear Probability Model).

	Switch from unemployment to self-employment				
	(1)	(2)	(3)	(4)	(5)
log (max UI benefit)	-0.458	-0.426	-0.455	-0.080	-0.011
	(0.364)	(0.368)	(0.371)	(0.396)	(0.415)
log (max UI benefit) × Layoff				-0.886***	-0.876***
				(0.226)	(0.227)
Layoff	0.329***	-0.239***	-0.237***	-0.234***	-0.233***
	(0.091)	(0.089)	(0.088)	(0.083)	(0.084)
Current unemployment rate	0.009	-0.001	-0.018	-0.018	-0.005
	(0.043)	(0.044)	(0.045)	(0.045)	(0.051)
Unemployment rate in the past 3 months	0.132**	0.138**	0.143**	0.143**	0.124**
	(0.054)	(0.056)	(0.056)	(0.056)	(0.059)
Female		-1.877***	-1.874***	-1.874***	-1.872***
		(0.106)	(0.105)	(0.105)	(0.105)
Age		0.307***	0.307***	0.307***	0.307***
		(0.022)	(0.022)	(0.022)	(0.021)
Age2/100		-0.339***	-0.339***	-0.339***	-0.339***
		(0.025)	(0.025)	(0.025)	(0.024)
Having College Degree		0.837***	0.842***	0.842***	0.844***
		(0.071)	(0.071)	(0.071)	(0.071)
Married		0.225**	0.226**	0.226**	0.229**
		(0.089)	(0.089)	(0.089)	(0.090)
Spouse has a job		0.186**	0.185**	0.187**	0.185**
		(0.090)	(0.090)	(0.090)	(0.089)
Annual family income below $20,000		-0.002	-0.002	-0.003	-0.003
		(0.105)	(0.105)	(0.105)	(0.105)
Annual family income between $20,000 and $50,000		-0.311**	-0.312**	-0.313**	-0.310**
		(0.125)	(0.125)	(0.125)	(0.125)
Annual family income between $50,000 and $75,000		-0.412***	-0.415***	-0.413***	-0.416***
		(0.128)	(0.127)	(0.127)	(0.128)
State fixed effects	Yes	Yes	Yes	Yes	YES
Year fixed effects	Yes	Yes	Yes	Yes	NA
Month fixed effects	No	No	Yes	Yes	NA
Year by Month fixed effects	No	No	No	No	Yes
Number of observations	252,791	252,791	252,791	252,791	252,791
Adjusted R2	0.001	0.007	0.007	0.007	0.009

This table uses CPS monthly data from 1995 to 2016. The sample includes only people who were unemployed in at least one period of the sample, and not self-employed before losing a job, so that they would be eligible to the UI benefits during the unemployment period. The age restriction is between 20 and 70. I also set a restriction that unemployed people who do not switch to self-employment have to stay in the sample for at least three months after losing a job, to ensure reasonably long periods to observe their choice (results are robust without this restriction, but a little smaller in magnitude). I keep one observation for each individual, because according to the survey results I collected, UI benefits will not change once unemployed people start to receive them, which means there is no variation in UI benefit for each unemployment period. The dependent variable is equal to 100 (scaled by 100 to see the coefficients more clearly) if the unemployed person switches from unemployment to self-employment, and equal to 0 if he or she switches from unemployment to another option except self-employment in the sample period. Layoff is a dummy variable indicating the unemployed person falls into the categories "Job loser/On layoff" or "Other job loser," instead of "Temporary job ended," "Job leaver," "Re-entrant," or "New entrant," so Layoff likely represents the group of people who are eligible for UI benefits who might be affected by changes in UI benefits. *Log(Max benefit)* is demeaned (with respect to the mean for the entire sample) before it is interacted with Layoff, so the coefficient of Layoff in column (4) measures the change in the probability of switching to self-employment associated with being laid off in a state with average UI generosity. The base group of family income is those whose annual family income is above $75,000. I do not report the coefficient of the group whose family income is missing. All coefficients are from the linear probability model. All benefits are in 1995 dollars. All standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

One possible response to the requirements and deduction in the UI system is that unemployed people could just delay their decision to start a firm, waiting until after they collect all of the benefits. To test this possibility, I focus on individuals who achieved a successful transition from unemployment to self-employment to observe how UI benefits affect the waiting period. Table B.2 shows that high benefits indeed lead to a longer waiting period.

2.5.2 Heterogeneous Effects on Two Types of Businesses

In Table 2.3, I distinguish two types of businesses: unincorporated and incorporated. Why do we expect the effects differ across these two types of businesses? One possible reason is that starting an incorporated business is usually associated with a large and risky investment, so it is less sensitive to UI benefits. For example, when Michael Bloomberg was laid off from an investment bank, he started his own company. He said, "Nobody offered me a job; I was probably too proud to go look for one." Bloomberg is an example of a person who is very sure of what they want to do and does not care much about UI benefits. However, unincorporated business are usually small businesses, not that profitable, and therefore more sensitive to the changes of UI benefits, as discussed in Section 2.3. What if those profitable incorporated businesses come from unincorporated businesses—that is, the business's legal form is based on ex post performance? If this is true, then I cannot say that incorporated businesses are more profitable than unincorporated businesses during the early stage, and the above explanation may not be a good one. However, Levine and Rubinstein (2017) find that unincorporated businesses rarely incorporate, and incorporated ones rarely become unincorporated sole partnerships. Their results suggest that the choice of legal form is largely based on the ex ante nature of business, rather than ex post performance. Thus, an unemployed individual who decides to start an incorporated business is likely to have profitable projects and plans to undertake large and risky investments, and thus is less likely to be affected by UI benefits.

In the first two columns of Table 2.3, starting unincorporated businesses is the dependent variable—that is, it is equal to 100 if an unemployed person has switched from unemployment to starting an unincorporated business; otherwise it equals 0. In the last two columns, starting an incorporated business is the dependent variable. I first exclude the interaction to observe the average effect of *Max UI benefit* and then explore the heterogeneous effects on the sub-sample by adding the interaction of *Benefit* and *Layoff*.

Table 2.3: Effects of UI Benefits on Different Types of Businesses (Linear Probability Model).

	Unincorporated self-employment		Incorporated self-employment	
	(1)	(2)	(3)	(4)
log (max UI benefit)	-0.277	0.067	-0.104	-0.078
	(0.396)	(0.408)	(0.092)	(0.097)
log (max UI benefit) × Layoff		-0.815***		-0.061
		(0.194)		(0.083)
Layoff	-0.261***	-0.259***	0.026	0.026
	(0.077)	(0.073)	(0.029)	(0.029)
Married	0.063	0.063	0.166***	0.166***
	(0.082)	(0.082)	(0.030)	(0.030)
Spouse has a job	0.185**	0.187**	-0.002	-0.002
	(0.078)	(0.078)	(0.035)	(0.035)
Annual family income below $20,000	0.220**	0.219**	-0.222***	-0.222***
	(0.106)	(0.106)	(0.038)	(0.038)
Annual family income between $20,000 and $50,000	-0.111	-0.112	-0.198***	-0.198***
	(0.111)	(0.111)	(0.038)	(0.038)
Annual family income between $50,000 and $75,000	-0.284**	-0.283**	-0.133***	-0.133***
	(0.113)	(0.113)	(0.047)	(0.046)
Control for unemployment rates and demographic characteristics	YES	YES	YES	YES
State fixed effects	YES	YES	YES	YES
Year by Month fixed effects	YES	YES	YES	YES
Number of observations	252,791	252,791	252,791	252,791
Adjusted R2	0.008	0.008	0.002	0.002

This table distinguishes two types of businesses: unincorporated and incorporated. Incorporated business owners face additional fees and regulations, but take limited liability, and the company is a separate legal identity, while unincorporated businesses are not legal identities. Unincorporated businesses rarely incorporate, and incorporated ones rarely become unincorporated (Levine and Rubinstein 2016). In the first two columns, the dependent variable is equal to 100 if the unemployed person has switched from unemployment to unincorporated self-employment, and equal to 0 if the person switches from unemployment to another option, except unincorporated self-employment, in the sample period. In the last two columns, incorporated self-employment is the dependent variable. The definition is similar to that for unincorporated business. All benefits are in 1990 dollars. The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2.2. I do not report these coefficients to save the space. All standard errors are clustered at state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The coefficient of Maximum benefit is negative but statistically insignificant in column (1), but the interaction of UI benefit and Layoff has a significantly negative coefficient in column (2). The coefficient implies that a one-standard-deviation increase in *Log(Max benefit)* (0.30) reduces the likelihood of starting an unincorporated business by 0.245 percentage points, or 10.63 percent compared with the mean (2.30%). The coefficients of *Log(Max benefit)* and the interaction are negative but not statistically significant in the last two columns, implying that generous UI benefits do not crowd out incorporated businesses, even among the sub-population who were laid off and thus eligible for the UI benefits. Table B.2 shows a similar pattern for the effects on the duration of the waiting period: the impact on the duration is mainly significant among those switching to unincorporated businesses, and not significant among those switching to incorporated businesses.

For the covariates, I also see very interesting comparisons. Risk sharing within the family (spouse has a job) has a significantly positive effect on starting an unincorporated business, but almost zero effect on incorporated businesses. The unemployment rate in the past three months has a significant positive effect on the decision of switching to unincorporated self-employment, but no significant effects on incorporated self-employment. This could be because during bad periods, it is difficult to find a job, so a bad economic situation could push a person to start an unincorporated business. Getting married has a significantly positive effect on switching to incorporated self-employment, but not on unincorporated self-employment. The family income effect is also quite different. For unincorporated businesses, families with the lowest and highest incomes have the highest likelihood (a U-shape), while for incorporated businesses, only the highest-income families have the highest likelihood.

The effects of gender, age pattern, and education are similar for these two different types of businesses. Unemployed people who are male, middle aged, and have a college degree are more likely to switch to both unincorporated and incorporated businesses.

To see the effects of UI benefit on different choices more clearly, I exploit a multinomial logit model in Table 2.4. The dependent variable takes a value from 1 to 5. It equals 1 if an unemployed person has made a transition to unincorporated self-employment, 2 if he or she switches to incorporated self-employment, 3 if he or she finds a new job, 4 if he or she reports an exit out of the labor force, and 5 if he or she remains unemployed during the whole sample period. The final group is used as the base group. The figures shown in this table are coefficients, not the marginal effects.

Table 2.4: Effects of UI Benefits on Different Choices Using Multinomial Logit Regression.

	Different choices after being unemployed							
	Unincorporated	Incorporated	Finding a new job	Out of labor market	Unincorporated	Incorporated	Finding a new job	Out of labor market
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (max UI benefit)	-0.097	0.021	0.019	0.031	0.073	-0.172	0.079	0.061
	(0.122)	(0.207)	(0.068)	(0.059)	(0.216)	(0.415)	(0.097)	(0.081)
log (max UI benefit) × Layoff	-0.486***	-0.374	-0.144***	-0.198***	-0.466***	-0.352	-0.125**	-0.184***
	(0.092)	(0.283)	(0.055)	(0.049)	(0.090)	(0.259)	(0.052)	(0.043)
Layoff	-0.303***	-0.071	0.121***	-0.636***	-0.260***	-0.056	0.149***	-0.616***
	(0.033)	(0.110)	(0.019)	(0.014)	(0.033)	(0.112)	(0.017)	(0.013)
Married	0.298***	0.785***	0.307***	0.231***	0.265***	0.797***	0.287***	0.220***
	(0.040)	(0.108)	(0.018)	(0.020)	(0.039)	(0.109)	(0.019)	(0.020)
Spouse has a job	0.123***	0.017	0.037*	0.050**	0.128***	0.004	0.035*	0.062***
	(0.040)	(0.117)	(0.021)	(0.019)	(0.038)	(0.122)	(0.021)	(0.019)
Annual family income below $20,000	-0.124**	-1.086***	-0.482***	-0.019	-0.181***	-1.058***	-0.527***	-0.032
	(0.059)	(0.157)	(0.034)	(0.023)	(0.059)	(0.163)	(0.036)	(0.023)
Annual family income between $20,000 and $50,000	-0.139**	-0.630***	-0.187***	-0.032	-0.177***	-0.619***	-0.220***	-0.040*
	(0.057)	(0.115)	(0.024)	(0.021)	(0.053)	(0.118)	(0.025)	(0.021)
Annual family income between $50,000 and $75,000	-0.141**	-0.297**	-0.034	0.010	-0.159**	-0.297**	-0.054*	0.008
	(0.062)	(0.121)	(0.027)	(0.026)	(0.062)	(0.125)	(0.028)	(0.027)
Control for unemployment rates and demographic characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	No	No	No	No	YES	YES	YES	YES
State fixed effects	No	No	No	No	YES	YES	YES	YES
Month fixed effects	No	No	No	No	YES	YES	YES	YES
Number of observations	252,791	252,791	252,791	252,791	252,791	252,791	252,791	252,791

This table uses CPS monthly data from 1995 to 2016. The dependent variable takes on a value from 1 to 5. It equals 1 if an unemployed person has made a transition to unincorporated self-employment; 2 if the person switches to incorporated self-employment; 3 if the person finds a new job; 4 if the person reports an exit out of the labor force; and 5 if the person remains unemployed during the whole sample period. The last group is the base group. I follow the same sample selection criterion as before. The sample includes only people who were unemployed in at least one period of the sample, and not self-employed before losing a job, so that they would be eligible for UI benefits during the unemployment period. The age restriction is between 20 and 70. I also set a restriction that unemployed people who do not switch to self-employment have to stay in the sample for at least three months after losing a job, to ensure reasonably long periods to observe their choice (results are robust without this restriction, but a little smaller in magnitude). I keep one observation for each individual, because according to the survey results I collected, UI benefits will not change once unemployed people start to receive them, which means there is no variation in UI benefit for each unemployment period. Log(max UI benefit) is demeaned (with respect to the mean for the entire sample). The figures in this table are just coefficients, not the marginal effects. All benefits are in 1995 dollars. The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2.2. I do not report these coefficients to save the space. All standard errors are clustered at state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The main information this table conveys is that when UI benefits are high, unemployed people tend to stay unemployed and are less likely to exit to other options, like starting an unincorporated business, finding a new job, or leaving the labor market. Compared with staying unemployed, the effect of UI benefits on starting an incorporated business is not statistically significant. This is consistent with what I asserted earlier: people who have a profitable project will choose to start an incorporated business, and they are not sensitive to deductions of business profits from UI benefits. These results are robust with or without fixed effects.

The coefficients of the interaction in columns (5)-(8) indicate that a one-standard-deviation increase in $long(Max\ benefit)$ reduces the probabilities of starting an unincorporated business, incorporated business, and dropping out of the labor force by 0.22, 0.02, and 0.53 percentage points (9.57%, 8.00%, and 1.32% compared to the mean), respectively, and increases the probabilities of staying unemployed and finding a new job by 0.63 and 0.14 percentage points (3.99% and 0.34% compared to the mean), respectively. Hence, the disincentive effect on the choice of switching to self-employment compared to the mean level is larger, relative to other choices.

2.5.3 Effects of UI Benefits in States With or Without the SEA Program

As mentioned in Section 2.2, a few states have the SEA program, which allows the unemployed to keep receiving the same amount of UI benefits even if they start a new business. In states with this program, I expect that the negative effect of UI benefits on self-employment should be weak. In Table 2.5, I show the effects on self-employment, and then follow the same rule as in Table 2.3: I look at the effects on unincorporated and incorporated businesses separately. For each dependent variable, I first use the whole sample to see the general effect of the SEA program and then use the subsample—state-periods that have the SEA program versus state-periods that do not have it—to explore the heterogeneous effects of UI benefits in these two subgroups.

Table 2.5: Heterogeneous Effects across States having SEA Program or not (Linear Probability Model).

	Self-employment			Unincorporated self-employment			Incorporated self-employment		
	Whole	Non-SEA	SEA	Whole	Non-SEA	SEA	Whole	Non-SEA	SEA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log (max UI benefit)	-0.001	0.031	-1.130	0.071	0.127	-1.350	-0.072	-0.097	0.220
	(0.415)	(0.426)	(0.898)	(0.410)	(0.418)	(0.831)	(0.095)	(0.107)	(0.371)
log (max UI benefit) × Layoff	-0.877***	-0.842***	-0.117	-0.815***	-0.757***	-0.409	-0.062	-0.085	0.292
	(0.227)	(0.251)	(0.706)	(0.194)	(0.211)	(0.600)	(0.083)	(0.089)	(0.274)
Having SEA program	0.155			0.065			0.090		
	(0.370)			(0.346)			(0.082)		
Layoff	-0.233***	-0.163*	-0.674***	-0.259***	-0.205***	-0.566***	0.026	0.041	-0.107
	(0.083)	(0.083)	(0.194)	(0.072)	(0.073)	(0.174)	(0.029)	(0.033)	(0.071)
Married	0.229**	0.262***	0.044	0.063	0.113	-0.222	0.166***	0.149***	0.265***
	(0.090)	(0.091)	(0.216)	(0.082)	(0.084)	(0.203)	(0.030)	(0.031)	(0.073)
Spouse has a job	0.185**	0.167*	0.301	0.187**	0.159*	0.359*	-0.002	0.009	-0.058
	(0.089)	(0.093)	(0.219)	(0.078)	(0.081)	(0.206)	(0.035)	(0.039)	(0.080)
Annual family income below $20,000	-0.003	-0.006	0.010	0.219**	0.213*	0.240	-0.222***	-0.219***	-0.231***
	(0.105)	(0.110)	(0.254)	(0.106)	(0.115)	(0.235)	(0.038)	(0.041)	(0.085)
Annual family income between $20,000 and $50,000	-0.310**	-0.333**	-0.196	-0.112	-0.125	-0.050	-0.198***	-0.208***	-0.146
	(0.126)	(0.135)	(0.225)	(0.111)	(0.123)	(0.201)	(0.038)	(0.038)	(0.092)
Annual family income between $50,000 and $75,000	-0.416***	-0.445***	-0.261	-0.283**	-0.320***	-0.100	-0.133***	-0.125**	-0.161*
	(0.128)	(0.126)	(0.264)	(0.113)	(0.111)	(0.243)	(0.047)	(0.053)	(0.094)
Control for unemployment rates and demographic characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
State fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year by Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	252,791	210,877	41,913	252,791	210,877	41,913	252,791	210,877	41,913
Adjusted R2	0.009	0.009	0.008	0.008	0.008	0.006	0.002	0.002	0.002

This table explores the impacts of the Self-Employment Assistance (SEA) program, and whether the program mitigates the negative effects of UI benefits. SEA allows unemployed people to receive UI benefits while starting a business, and it waives the search requirements. Eight states reported having this program in 2016 (based on the information provided by Kugler 2015 and Messenger et al. 2002). The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2.2. I do not report these coefficients to save the space. All standard errors are clustered at state level except columns (3), (6), and (9), which cluster the standard errors by state and year, because there would only be too few clusters, otherwise. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

I find that the SEA program has a positive but not statistically significant coefficient in column (1) of Table 2.5, meaning that the adoption of SEA program increases the probability of starting a firm among the unemployed although the increase is not significantly from 0. This might be caused by the small size and selection criterion of the SEA program. For example, between January 2013 and June 2015, only 0.3% of UI recipients in New York and 1.0% of those in Oregon applied for the SEA program (Weigensberg et al. 2017). Also, the target group of the SEA program is only a portion of UI recipients who are identified as likely to exhaust their benefits and interested in becoming self-employed.

Although the SEA program does not statistically increase the likelihood of starting a business directly, it does mitigate the negative effects of UI benefits in state-periods where such a program is available. In column (2), which focuses on states and periods that SEA is not available, the coefficient of the interaction of UI benefit and Layoff is significantly negative, while in column (3), which focuses on places where SEA is available, the coefficient of the interaction is negative but much smaller and not significant. While I cannot reject the hypothesis that the effect of UI benefits on the probability of starting a business is zero in states with SEA, I cannot reject the hypothesis that the effect is equal in the two groups of states, either.

I find a similar pattern when focusing on unincorporated self-employment: the negative effect of UI benefits become much smaller in states and periods that SEA program is available, while for incorporated self-employment, the coefficients of the interaction are not significant no matter whether the SEA program is available or not.

2.5.4 Heterogeneous Effects Across States Having Different Search Requirements

Another important characteristic of the unemployment insurance system is the job search requirement. Unemployed people need to satisfy job search requirements to receive UI benefits. I group state-periods into three groups: (1) Not indicating an exact number of employer contacts; (2) Low search requirements (0–2 contacts per week); and (3) High search requirements (3 or more contacts per week). I drop six states that provide search requirements that are individualized for claimants, following Toohey (2015). Table 2.6 presents the results for self-employment (columns (1)–(3)), unincorporated self-employment (columns (4)–(6)), and incorporated self-employment (columns (7)–(9)) in each subgroup.

Table 2.6: Heterogeneous Effects across Different Search Requirements (Linear Probability Model).

	Self-employment			Unincorporated self-employment			Incorporated self-employment		
Search requirement:	Non-specific	Low	High	Non-specific	Low	High	Non-specific	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log (max UI benefit)	-0.404	-2.508***	2.404	-0.273	-2.523***	2.593	-0.131	0.015	-0.189
	(0.832)	(0.836)	(1.475)	(0.549)	(0.807)	(1.545)	(0.399)	(0.349)	(1.011)
log (max UI benefit) × Layoff	-1.322***	-0.629	-0.454	-1.318***	-0.334	-0.595	-0.003	-0.296	0.142
	(0.434)	(0.787)	(0.730)	(0.303)	(0.700)	(0.570)	(0.169)	(0.203)	(0.223)
Layoff	-0.353**	0.164	-0.555**	-0.403***	0.170	-0.544**	0.049	-0.005	-0.011
	(0.143)	(0.158)	(0.251)	(0.117)	(0.142)	(0.198)	(0.054)	(0.048)	(0.128)
Married	0.128	0.242	0.642	-0.109	0.108	0.163	0.237***	0.134*	0.479***
	(0.145)	(0.199)	(0.445)	(0.129)	(0.219)	(0.393)	(0.057)	(0.076)	(0.149)
Spouse has a job	0.075	0.326**	-0.008	0.154	0.289*	0.279	-0.079	0.037	-0.287**
	(0.173)	(0.137)	(0.408)	(0.150)	(0.146)	(0.336)	(0.059)	(0.046)	(0.124)
Annual family income below $20,000	0.153	-0.068	-0.326	0.334	0.068	-0.091	-0.181***	-0.136*	-0.235
	(0.219)	(0.282)	(0.403)	(0.239)	(0.274)	(0.329)	(0.058)	(0.071)	(0.142)
Annual family income between $20,000 and $50,000	-0.347**	-0.219	0.073	-0.164	-0.092	0.193	-0.182**	-0.127*	-0.121
	(0.159)	(0.264)	(0.333)	(0.138)	(0.246)	(0.248)	(0.070)	(0.072)	(0.157)
Annual family income between $50,000 and $75,000	-0.375*	-0.461**	-0.139	-0.260	-0.442**	-0.057	-0.115	-0.019	-0.083
	(0.200)	(0.212)	(0.446)	(0.179)	(0.195)	(0.398)	(0.084)	(0.087)	(0.163)
Control for unemployment rates and demographic characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
State fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year by Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	83,236	49,304	24,073	83,236	49,304	24,073	83,236	49,304	24,073
Adjusted R2	0.007	0.007	0.008	0.006	0.006	0.007	0.002	0.001	0.002

Following the information on the number of required weekly employer contacts provided by Toohey (2015), I group state-periods into three groups: not indicating an exact number of employer contacts, low search requirements (0–2 contacts per week), and high search requirements (3 or more contacts per week). I drop six states that provide job search requirements that are in some way individualized for claimants, following the suggestions by Toohey (2015). Columns (1)–(3), 4–6, and 7–9 focus on switching to self-employment, unincorporated self-employment, and incorporated self-employment, respectively. For each dependent variable, there are three columns, representing the results of using three subgroups: state-periods that have non-specific search requirements, 0–2 contacts per week, and 3 or more contacts per week, respectively. The sample selection and definitions of dependent variables are the same as before. The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2.2. I do not report these coefficients to save the space. All standard errors are clustered at state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results indicate that the coefficient of the interaction of *log(Max benefit)* and *Layoff* is significant only in the subgroup that does not indicate an exact number of employer contacts. For the subgroup with the highest search requirement, the coefficient is smallest (column (3)) compared with another two groups, although it is not statistically significant. If we consider the subgroup that does not indicate the search requirement as having no requirement, one possible explanation for this differential effect could be that high UI benefits usually make unemployed people more likely to stay unemployed (less likely to start businesses), but high search requirements make the option of staying unemployed less attractive. Non-specific search requirements in turn make this option of staying unemployed more attractive, so there is a lower probability of transition out of unemployment, which might decrease the probability of starting a business in states with non-specific search requirements.

So far, we have found a negative effect of an increase in UI benefits on switching from unemployment to self-employment. Is this negative effect the same in the recession period, when it is most needed, and the non-recession period? Next I explore the heterogeneous effects of UI benefits on starting a business over recent business cycles.

2.5.5 Heterogeneous Effects of UI Benefits over Recent Business Cycles

Table 2.7 shows the results in of an increase in UI benefits in two different periods: recession and non-recession periods. Based on the NBER definition, I define March–November 2001 and December 2007–June 2009 as recession periods, and all other periods as non-recession periods. The first three columns present the results for the recession periods, and last three columns show results for the non-recession periods.

I do find that the negative effect of the interaction of *log(Max benefit)* and *Layoff* is larger during recession periods (column (1)); however, even during normal periods, the negative effect of UI benefits is still statistically significant and important in the magnitude. Take the coefficients of the interaction in columns (1) and (4) as an example. The coefficient in column (1) implies that during the recession periods, a one-standard-deviation increase in *log(Max benefit)* (0.26 during the recession) reduces the likelihood of starting businesses by 0.57 percentage points more among laid-off workers than other workers, or 22.86% compared with the mean level (2.49 percent during the recession).

Table 2.7: Effects of UI Benefits on Different Types of Businesses in Recession and Non-recession Periods.

	Recession Periods			Non-recession Periods		
	Self-employment	Unincorporated	Incorporated	Self-employment	Unincorporated	Incorporated
	(1)	(2)	(3)	(4)	(5)	(6)
log (max UI benefit)	1.343	1.092*	0.251	-0.109	0.032	-0.141
	(0.819)	(0.588)	(0.296)	(0.458)	(0.434)	(0.101)
log (max UI benefit) × Layoff	-2.195***	-2.085***	-0.110	-0.668***	-0.619***	-0.049
	(0.689)	(0.541)	(0.235)	(0.203)	(0.181)	(0.074)
Layoff	-0.117	-0.160	0.043	-0.249***	-0.270***	0.021
	(0.164)	(0.141)	(0.065)	(0.091)	(0.080)	(0.029)
Married	0.378*	0.128	0.250***	0.200**	0.051	0.149***
	(0.202)	(0.191)	(0.066)	(0.095)	(0.090)	(0.031)
Spouse has a job	0.062	0.081	-0.019	0.209**	0.207**	0.002
	(0.233)	(0.215)	(0.086)	(0.096)	(0.085)	(0.037)
Annual family income below $20,000	0.263	0.398	-0.134	-0.052	0.188*	-0.239***
	(0.297)	(0.260)	(0.103)	(0.105)	(0.107)	(0.045)
Annual family income between $20,000 and $50,000	-0.192	-0.049	-0.143	-0.335**	-0.126	-0.209***
	(0.254)	(0.239)	(0.100)	(0.142)	(0.122)	(0.043)
Annual family income between $50,000 and $75,000	-0.597**	-0.671***	0.073	-0.378***	-0.205	-0.173***
	(0.266)	(0.239)	(0.138)	(0.134)	(0.123)	(0.047)
Control for unemployment rates and demographic characteristics	YES	YES	YES	YES	YES	YES
State fixed effects	YES	YES	YES	YES	YES	YES
Year by Month fixed effects	YES	YES	YES	YES	YES	YES
Number of observations	39,514	39,514	39,514	213,277	213,277	213,277
Adjusted R2	0.007	0.006	0.003	0.009	0.009	0.002

This table distinguishes between two types of economic conditions: recession and non-recession periods. Based on the NBER definition, I define March–November 2001 and December 2007–June 2009 as recession periods. The sample selection and definitions of dependent variables are the same as before. The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2.2. I do not report these coefficients to save the space. All standard errors are clustered at state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

During non-recession periods, the magnitude is smaller, about 0.19 percentage points, or about a 7.2% decrease compared with the mean level. The effects on unincorporated and incorporated businesses during both periods are similar to what is evident in Table 2.3: most negative effects of UI benefits are on unincorporated businesses, and not statistically significant on incorporated businesses. In sum, the negative effects of UI benefits on entrepreneurship are more severe when the economy is in a downturn.

2.6 Conclusion

This chapter explores the effect of generosity of UI benefits on the decision of an unemployed person to start a business. In an attempt to understand the policy in practice, I distributed a short survey to the labor departments of each state via email. I found that most states deduct business profits from UI benefits, except for a few states that have adopted the SEA program. My empirical results show that high UI benefits deter laid-off workers from starting a business, meaning that overall, the negative effect dominates. Through distinguishing two types of businesses, incorporated and unincorporated, I find that most negative effects happen with respect to the unincorporated businesses—that is, high UI benefits mainly crowd out unincorporated businesses. The different impacts on these two types of businesses are consistent with the disincentive effects of the deduction of business income from benefits: the negative effect of benefits should be larger for businesses with small profits (unincorporated ones) and smaller on highly profitable businesses (incorporated ones). I also find that for individuals who have switched to self-employment, there is a longer period before the transition when the UI benefit is higher, and the impact on the duration of the wait period is mainly significant among those switching to unincorporated businesses.

For states that offer the SEA program, which allows unemployed people to receive full UI benefits without deduction, I find that the effect of UI benefits on switching to self-employment becomes positive, although insignificant. This is consistent with the hypothesis that UI benefits could provide assistance to reduce risk and soothe the borrowing constraint for unemployed people looking to start a business, which could offset the substitution and liquidity effects (both lead to lower exit rates out of unemployment). Interestingly, the negative effect of UI benefits on starting a business is also smaller in states with high job search requirements, which could be caused by the fact that high job search requirements make the option of staying unemployed less attractive or help people find a new job, leading to more exits out of unemployment (some of them might choose to start a business), counteracting the negative effect of generous UI benefits. The negative effect is more severe during recession periods, when the aggregate demand is weak.

Chapter III

Caveat Emptor: The Impact of Product Line Exceptions on Firm Acquisitions and Performance

3.1 Introduction

Frictions in the process of resource reallocation within and across firms are important to many aspects of markets and firm strategy. At the economy level, the ease of allocating resources across firms influences aggregate total factor productivity (Hsieh and Klenow 2009), while at the industry level it is associated with industry competition (Balasubramanian and Sivadasan 2009). Within strategic management, market frictions in general and those related to resource reallocation in particular such as information asymmetry, uncertainty and asset specificity have been extensively studied, including as sources of competitive advantage for firms (e.g., Mahoney 2001; Mahoney and Qian 2013; Yao 1988). However, most analyses of such frictions have largely focused on their impact on firm scope such as how such frictions may confer advantages to diversified firms relative to undiversified firms (e.g., Belenzon and Tsolmon 2016) or how such frictions may influence the ownership and governance of assets (e.g., Silverman 1999). In contrast, we know little about how frictions related to resource reallocation may affect the creation, growth and survival of firms.

In this chapter, we contribute to addressing this gap in the literature by studying the adoption in six U.S. states of product line exceptions (PLE) to the successor non-liability doctrine, a plausibly exogenous mechanism that introduced new product liability-related transaction cost for acquisitions (especially those of manufacturing firms).

Acquisitions and sell-offs are important ways to allocate resources within and across firms (e.g., Capron and Mitchell 2012; David 2017; Jovanovic and Rousseau 2002). For instance, acquisitions allow a firm to obtain access to assets and capabilities that it may not be able to develop in a timely manner with its current resources, including those needed for growth (Lee and Lieberman 2010). Similarly, the sale of business assets facilitates the redeployment of resources within a firm and provide an avenue for poorly performing firms to re-focus or exit the market (Chang and Singh 1999; Lieberman, Lee, and Folta 2017). For entrants, acquisitions not only offer a possible mode of entry, but more importantly, potential gains from selling their business in the future can be an important motivator for entry (David 2017; Hollenbeck 2019).

For states which have adopted PLE, there is a friction in the market for acquisitions in the form of an additional transaction cost, because potential liabilities accumulated by the seller becomes the responsibility of the buyer. While our formal model (discussed below) treats the potential liability as a known/certain transaction cost, in reality an additional friction arises from the fact that these liabilities are uncertain and subject to asymmetric information, as sellers are likely to have more information about potential liability claims than potential buyer. This additional friction can be expected to act as a further deterrent to acquisitions (Akerlof 1970).[42]

Two recent cases offer anecdotal evidence on the salience of product liability related frictions in corporate transactions. The 2009 bankruptcy reorganization of General Motors (GM) was structured as a sale of assets from the "old GM" to a "new GM" entity that took on only certain specified assets and liabilities. Related to this transaction, GM fought a court case all the way to the US Supreme Court, requesting for protection from product liability lawsuits related to cars made by the "old GM", arguing that this was vital for the reorganization to be viable (Fisher 2017). As a second example, the steep decline in value of Bayer (by 46.6% one year after the acquisition of Monsanto in 2018) following victories by plaintiffs in lawsuits related to the Roundup herbicide produced by Monsanto, have prompted the labeling of this acquisition as one of the worst in corporate history (Bender 2019). This example also highlights the significant uncertainty associated with target's product liabilities, with analysts' estimates of total costs from Roundup-related litigation varying from \$5.5 billion to \$27.5 billion (Bender 2019).[43]

[42]Throughout, we use the taxonomy of market frictions developed in Mahoney and Qian 2013, who identify transaction costs and information asymmetry as two key sources of frictions that lead to deviations from the first welfare theorem.

[43]More generally, product liability lawsuits have become increasingly important in the United States. For instance, the number of product-liability related legal cases has grown significantly, from just 1,579

However, such product-line related liabilities are usually not problematic because under traditional corporate law principles governing asset sale transactions (adopted by most state courts), the buyer does not have to bear liabilities associated with the sale of products manufactured by the seller before the acquisition unless it explicitly assumes them. Matheson (2011) quotes the Supreme Court as declaring 120 years ago that "The general rule, which is well settled, is that where one company sells or otherwise transfers all its assets to another company, the latter is not liable for the debts and liabilities of the transferor" [Fogg v. Blair, 133 U.S. 534, 538 (1890)]. However, under the PLE, the buying firm continuing to market a product line previously sold by the selling firm would be liable for tort-based product defect claims arising from products and services sold by the seller before closing. The six courts that adopted the PLE doctrine cite the need to balance the public policy interest of providing necessary remedies for injured parties. Because courts in twenty three states (and the District of Columbia) have explicitly rejected this doctrine (per footnote 20, Kuney 2013), the adoption by the courts in the six states could be considered to be unexpected.[44]

We begin our analysis by developing a simple three-period model of the frictional impact of adopting PLE, where potential sellers face three options in each of the first two periods: continue to the next period, sell to a buyer, or exit. We posit two key features: (a) liabilities associated with the products manufactured prior to the transaction add an additional cost for buyers in states where PLE is adopted; (b) these liabilities accumulate over time, so there are lower potential liabilities for younger firms. The model yields a straightforward baseline prediction: for older firms, imposing the seller's product liabilities on the buyer reduces the buyers' willingness to pay and leads to a reduction in the extent of resource reallocation as measured by the number of acquisitions in the market. More interestingly, this also leads to an increase in firm exit as poorly performing sellers that would otherwise have found a buyer in the absence of the friction do not find it optimal to continue. Furthermore, because potential product liabilities accumulate over time (as more products are sold) and hence, their expected costs increase with age, our framework predicts that younger sellers will be affected differently compared with older ones. In particular, we show that a reduction in ability to exit profitably (by discarding

cases in federal courts in 1974 (Skoppek 1989) to 15,200 in 2000 (Zekoll 2002), and to 39,200 in 2018 (Galasso and Luo 2018).

[44] Section 2 provides more details on the debate relating to PLE adoption. Importantly, because product defect claims may surface long after the assets have been acquired, it is hard to structure the transaction in a way as to separate those liabilities from the underlying assets, or obtain sufficient product liability insurance (Beyer 2012, Thune 2018).

liabilities) leads to an increase in both firm sales and closures for young sellers, as well as a reduction in the entry rate of new firms.

We use comprehensive U.S. Census Bureau data on about 150 million establishment-year observations from 1976 to 2014 to test our model predictions regarding the impact of adopting PLE on firms over their lifecycle. We use a difference-in-differences approach with state fixed effects to control for omitted state-level variables that may be correlated with the adoption of PLE. In particular, we compare the changes in outcomes in six states (CA, CT, NJ, NM, PA, and WA) that adopted PLE (as a consequence of the State Supreme or Superior courts adopting the doctrine) with the corresponding changes in the other states. These six states are economically important and accounted for one-fifth of the total employment in the United States in 2000. Further, the richness of our data allows us to include establishment-level fixed effects, in specifications examining establishment-level outcomes, which also addresses potential heterogeneity across establishments located in the affected states and those in unaffected states. In addition, we exploit the fact that PLE is salient mainly for manufacturing firms (as it relates to liability from products manufactured by the target firm), by comparing the effects for manufacturing firms with firms in other sectors serving as controls. This serves to rule out temporal variations in any state-level factors that may affect firm outcomes of interest to us (acquisitions, closures and growth) in all sectors similarly.

In line with our baseline prediction, we find that the probability of a manufacturing establishment being acquired decreases after the adoption of PLE relative to the acquisition probability of non-manufacturing establishments. Beyond confirming this baseline prediction, we find that the relative probability of manufacturing establishment closure increases, suggesting increased resource reallocation frictions leads to increased exit. Furthermore, in line with our model predictions, we find a stark difference between the effects for young and old establishments. As predicted, the probability of acquisition as well as the probability of closure increases for young manufacturing establishments after PLE is adopted. In contrast, the effect for older establishments are more in line with the overall effects, albeit statistically insignificant. At the firm level, we find that the introduction of PLE has a negative effect on manufacturing firms relative to non-manufacturing firms: growth and entry of manufacturing firms declines while their rate of exit increases.

Together, our results show that resource reallocation frictions have important and varied implications for the entry, growth and survival of firms. To our knowledge, this is the first study to highlight these implications, and our work contributes to a number of related literatures. Beyond documenting novel and important economic effects of product liability-related frictions, our findings also suggest a novel channel for a negative effect of age on organizational fitness, parallel to the liability of obsolescence (from loss of alignment with the environment over time; see Barron, West, and Hannan 1994, Hannan 1998) or liability of senescence (from accumulation of internal frictions; Hannan 1998). Unlike for other sources of senescence, the successor non-liability doctrine provides a method for getting rid of accumulated product liabilities; PLE eliminates that ability to shed accumulated liabilities, with important implications for corporate decisions over the lifecycle of the firm.

Because the PLE affects only one mechanism for firm growth, viz. acquisitions, and not organic growth, our study also sheds light on some broader aspects of acquisitions and firm growth. Our results suggest that organic growth does not completely substitute for growth from acquisitions. Though organic growth and growth from acquisitions have been compared before (e.g., Moatti et al. 2015), empirical evidence is lacking on whether firms can offset frictions in the acquisitions process by growing organically. In theory, if these two modes of growth were perfectly substitutable, PLE should not have any effect on overall firm growth as firms would be able to offset any declines in growth from acquisitions with organic growth. However, we find that overall firm growth declines after PLE, suggesting that such an offset did not happen. Our model and results also suggest that the corporate transaction markets could in fact be a complement to organic growth. In particular, in our model continuation decisions by young firms are negatively impacted by a reduction in probably of selling the firm in the future; in an augmented model with endogenous investment, the same mechanism could discourage investments and hence organic growth of young firms, consistent with the empirical results we find.

Another novel contribution of our study is the simultaneous consideration of acquisitions (i.e., sell-offs) and firm closures. In particular, though acquisitions and sell-offs have been extensively studied, the vast majority of studies focus on acquirer performance and returns (e.g., Haleblian et al. 2009; Singh and Montgomery 1987; Capron and Pistre 2002; Siegel and Simons 2010; Schoar 2002). By explicitly modeling sell-offs as an alternative to firm closures, our study is able to generate new insights into how frictions in the acquisitions and sell-off process have differential impacts over the firm lifecycle. Furthermore, by extending the analysis to entry, our findings emphasize a role for resource reallocation frictions as a potential deterrent for entry.

Relatedly, our results highlight a possible condition under which younger firms and establishments may be more attractive acquisition targets. Shen and Reuer (2005) suggest that younger targets suffer from poorer information quality and availability, and find that young target firms are more likely to be public firms (which have more mandated transparency). Ransbotham and Mitra (2010) find that younger targets may be attractive in the face of uncertainty, as they provide flexible growth options and are available at lower prices (due to valuation uncertainty). Our study suggests aging is concomitant with the accumulation of liabilities, thus forcing the buyers and sellers to trade-off the information benefits of waiting against the costs from the potential increase in liabilities. This is evidenced in the increased acquisitions among young establishments after PLE is introduced.

A key novelty of this study in terms of empirical findings is that frictions in corporate transaction markets deter entry, survival and growth of young firms. As discussed above, the incentive effects provided by the possibility of future sale for entry and sustenance of young firms highlighted in our model is similar to that in recent models by David (2017) and Hollenbeck (2019). At a more fundamental level, the channel in these models is same as that in real options theory: continuation (or entry) provides an opportunity or option to match with and obtain (an uncertain) value from a (random) acquirer in the future (Dixit and Pindyck 1994, Trigeorgis 1996, Li et al. 2007). Thus our findings indirectly provide empirical support for real options theory.

Finally, our study complements existing studies of the impact of product liability on innovation (e.g., Galasso and Luo 2018; Shepherd 2013; Viscusi 1991; Viscusi and Moore 1993). Generally, these studies find that product liability can have important consequences for innovation. Unlike these studies that examine direct effects of variation in product liability laws on innovation, we focus on analyzing how a legal doctrine change related to transmission of potential product liabilities from a buyer to seller in corporate M&A transactions affects corporate entry, exit and acquisition/sale decisions.

The rest of the chapter is organized as follows. Section 3.2 provides a discussion of the product line exemption and arguments used by courts for and against upholding this exemption to the doctrine of successor (non)liability. Section 3.3 discusses our model and predictions. We discuss our data sources and empirical methodology in Section 3.4. We present results from our empirical analysis in Section 3.5, and Section 3.6 provides discussion of conclusions and limitations.

3.2 Product Line Exception to Successor Liability as A Resource Reallocation Friction

Traditional corporate law principles hold that the purchaser of business assets is not liable for injuries caused by defective products manufactured by the seller. With respect to this non-liability, the Supreme Court declared over 120 years ago, "this doctrine is so familiar that it is surprising that any other can be supposed to exist."[45] The rationale behind this general rule is that 'successors' (purchasers) do not produce, market, or sell the goods and hence, should not be responsible for the damages or injuries caused by the products. To this general rule, there are four widely-accepted exceptions.[46] Since the late 1970s, the courts in several states have expanded these four traditional exceptions by adopting the PLE. Under the PLE, *the successor continuing to market a product line previously sold by the predecessor* would be liable for tort-based product defect claims (for instance, personal injury) arising from products and services sold by the seller before closing. California was the first state that adopted this new exception in 1977, and was joined later by five more states: Mississippi (2001), New Jersey (1981), New Mexico (1997), Pennsylvania (1981), and Washington (1984) (See Appendix Table C.2).

While adopting courts stated the purpose of the PLE was to provide an incentive for firms to produce safer products and to provide recourse to victims of defective products, PLE has been strongly opposed by other courts and experts, related to concern for the effects of this new exception on business activities. For example, the Florida Supreme Court rejected the expansion of traditional exception as it predicted that this could lead to the "economic annihilation [of] small businesses," which would be forced to liquidate rather than transfer ownership. Epstein (2002) voiced a similar concern that firms may be forced towards bit-by-bit liquidation, saying "one possible way to defeat all products liability claims against successors is through a piecemeal disposition of the company. Astute corporate owners could decide to sell off bits and pieces of the assets to different buyers, engage in partial liquidations or dividends to current shareholders, and then finally liquidate the rest."

[45]See 15 William Meade Fletcher et al., Fletcher Cyclopedia of the Law of Corporations § 7122 (perm. ed., rev. vol. 2008) and Matheson (2011).

[46]These are (1) the transaction is a fraudulent effort to avoid liabilities of the predecessor, (2) the successor expressly or impliedly assumes the obligations of the predecessor, (3) the transaction is a de facto merger, or (4) the successor is a mere continuation of the predecessor (see Matheson (2011) and Zager, Jeffrey; Johnson (2005)). Table C.3 provides more details and relevant case citations, based on information in Kuney 2013.

Because under the PLE, the successor is responsible for liabilities such as personal injury claims caused by the predecessor's products, the adoption of PLE increases the uncertainty associated with the purchased assets. Some of the uncertainty is hard to hedge against through insurance, because insurance is not always a realistic option in cases of unknowable claims and even when available, has many restrictions (Thune 2018). This implies that even if insurance is available, it might not fully cover the loss. One recent example of this is Pacific Gas and Electric (PG&E). Because this utility's equipment was a possible cause of the deadly "Camp Fire", its potential liability could reach \$15 billion, while the insurance company could only cover \$1.4 billion. So PG&E chose to file for bankruptcy.[47] Courts have been concerned specifically about the unavailability or infeasibility of insurance; e.g., Beyer (2012) cites the Wisconsin Supreme Court decision that rejected PLE exemption as noting [in Fish v. Amsted Indus., Inc., 376 N.W.2d 820, 827–828 (Wis. 1985)] that "*[s]mall manufacturers have a difficult problem obtaining products liability insurance and find it impossible to cover the risks by raising prices because they have to compete with larger manufacturers who can keep the price down. Additionally, it is one thing to assume that a manufacturer can acquire insurance against potential liability for its own products and another to assume it can acquire such insurance for the products made by a different manufacturer.*"

More broadly, these arguments suggest that PLE could inhibit acquisitions and other related economic activities. Product liability lawsuits are pervasive in the United States, and have increased in frequency over the years. For instance, during the twelve-month period ending September 30, 2000, about 15,300 products liability cases were filed in federal courts and accounted for 5.6% of all civil cases, 39.4% of tort actions and 44.2% of all personal injury cases (Zekoll 2002). By 2016, the number of product liability lawsuits increased significantly to 39,200, accounting for roughly 70 percent of the personal injury civil cases filed in US district courts (Galasso and Luo 2018), while the number of cases filed in federal court in 1974 was just 1,579 (Skoppek 1989).

Two recent anecdotes (discussed briefly in the introduction) highlight the importance of product liability as it relates to corporate transactions. The reorganization of General Motors during its 2009 bankruptcy was structured as a sale of assets to a new corporate entity under special provisions of the bankruptcy code (Fisher 2017). The automaker argued that forcing the new entity to retain liability for ignition-switch defects in cars manufactured by the pre-bankruptcy GM "threatens the 'free and clear' provisions of sale contracts that induce buyers to pay more for the assets of companies in

[47]For details of this case, see https://www.insurancejournal.com/news/west/2018/11/20/509843.htm.

bankruptcy." Without such protection, they argued, "buyers will offer less or refuse to bid on a bankrupt company's assets, driving it into liquidation and forcing unnecessary layoffs at the company and its suppliers."(Fisher 2017) A stark example of the potential impact from target's product liability is the ongoing litigation faced by Bayer, relating to the Roundup herbicide product produced by Monsanto, which it acquired in 2018. A Wall Street Journal article (Bender 2019) argued that this acquisition was one of the worst corporate deals ever, as the share value of the combined entity declined by 46.6% (more than for any other $M\&A$ deal ever) one year after the transaction. Starting with a first jury verdict of $289.2 million (in August 2018), two more large damage verdicts (all three reduced by judges) came in by May 2019; new cases and plaintiffs went up steeply, with the number of plaintiffs reaching 18,400 by July 2019. Reflecting the significant uncertainty associated with product liabilities, the article reported analysts' estimates of total liability costs for Bayer ranging from $5.5 billion to $27 billion (Bender 2019).

In the next section, we investigate this further and present a simple model that generates testable hypotheses on the potential economic impact of PLE.

3.3 Hypotheses

We develop our hypotheses using a simple model of acquisitions. Given our empirical focus, we intend the model to be a tool to help generate and better understand our hypotheses rather than as a full-fledged model of acquisitions. Here, we mostly focus on the underlying intuition and leave the technical details to the Appendix.

Briefly, a seller in this model faces a trade-off—wait one period in the hope of finding a better buyer (who will pay more) but potentially incur a liability during that wait, which may force them to exit. The introduction of PLE generally reduces acquisitions and increases closures, as the probability of being sold diminishes, and hence sellers are compelled to exit the market. Buyers in this model benefit from targeting a young firm because they can modify the target firm in a way to avoid future liability. PLE accentuates this benefit, thus shifting the focus of acquisitions to younger sellers.

3.3.1 Set up

We consider a three-period model. The timeline of the model is shown in Figure 3.1. A potential seller, S, chooses to pay an entry cost κ to enter the market in the beginning of period 1. The quality of its management, θ_S, is drawn from a uniform distribution from 0 to 1, $U[0,1]$. This quality is assumed to stay the same in all periods that S operates in the market.

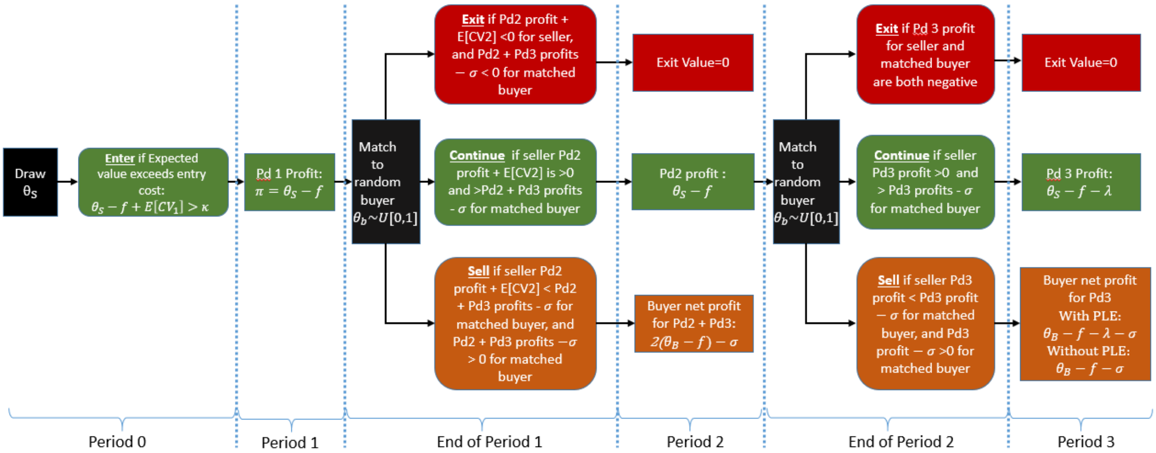


Figure 3.1: Model timeline

At the end of period 1, a potential buyer, *B1*, appears. The quality of its management, θ_{B1}, is drawn from U[0,1]. The seller then has three options at the end of period 1. It can sell to the buyer, exit the market, or continue to the next period.

If the seller continues to the second period, a new buyer, *B2*, appears at the end of that period. The quality of its management, θ_{B2}, is also drawn from $U[0,1]$ (since both θ_{B1} and θ_{B2} are drawn from a uniform distribution, we use θ_B to represent them hereafter), and independent of the quality of the buyer in the first period. As in the first period, the seller then has three options at the end of period 2. It can sell to the buyer, exit the market, or continue to the next period.

The firm exits at the end of the third period. For simplicity, we assume that if sold, firms are sold only once. Also, we assume that the buyer pays the maximum price that it is willing to pay, and that the transaction cost paid by the buyer is σ.

The firm pays a fixed cost f every period, irrespective of ownership. The profits for the firm in any period is given by $\pi = \theta - f$, where θ is the quality of the management. We assume that there are no costs to exit, and that the value of exiting in any period is equal to zero.

3.3.2 Evolution of product liability and PLE

We assume that the firm does not have any liability when it enters, and that it does not incur any liability in the first period.

If the seller S continues to operate the firm in the second period, it would incur a liability λ in that period. The liability is assumed to be observable and required to be paid in period 3 unless the firm is sold at the end of the second period and the state has no PLE. If the state has PLE, then the buying firm is required to pay the liability in period 3. If the state has no PLE, then the buying firm is not required to pay the liability in period 3.

If the firm is sold at the end of the first period to a buyer, we assume that there is no liability incurred in the second period. This assumption reflects the superior management skills of the buyer as well as the fact that the selling firm is young enough that the buyer can potentially modify its operations to avoid the liability.

For simplicity, we assume there are no new liabilities that are incurred in period 3, irrespective of ownership.

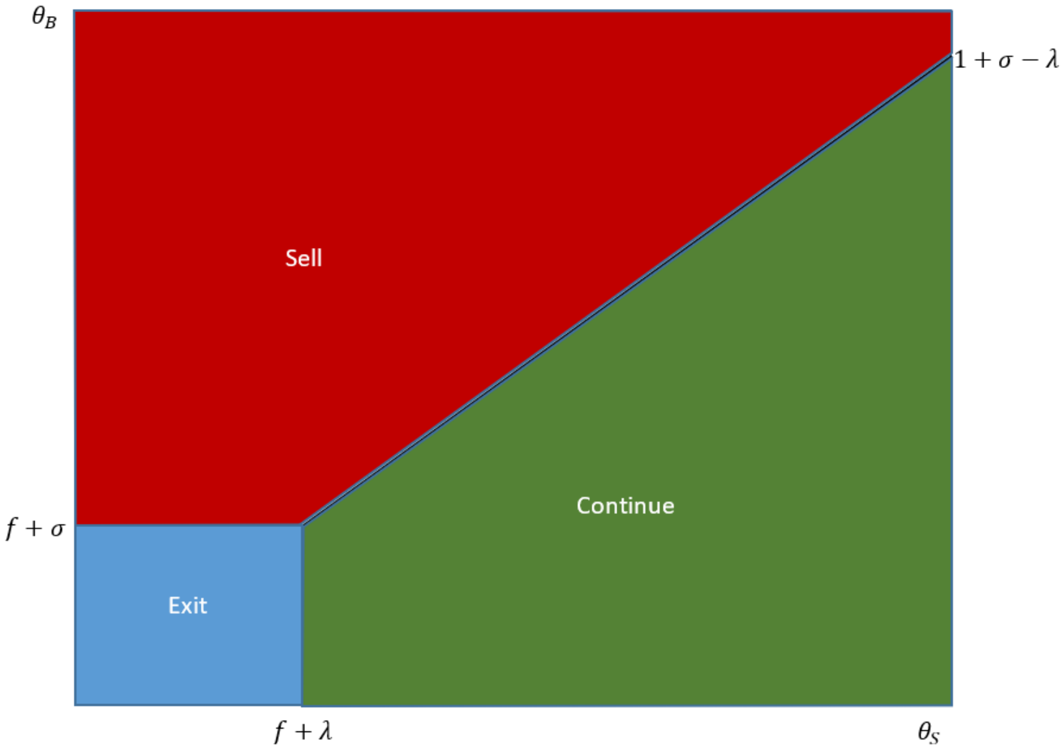
3.3.3 Buyer willingness to pay

Period 2 – Buyer B2's willingness to pay in the second period is the expected profits from operating in the third period less the transaction cost. That is (suppressing the period suffix on the quality of management parameter for brevity), $w_B^2 = \pi_{B2}^3 - \sigma = \theta_B - f - \sigma$ if the state has no PLE (which means buyer can avoid the liability), and $w_B^2 = \pi_{B2}^3 - \sigma = \theta_B - f - \sigma - \lambda$, if the state has PLE (which means buyer has to assume the liability).

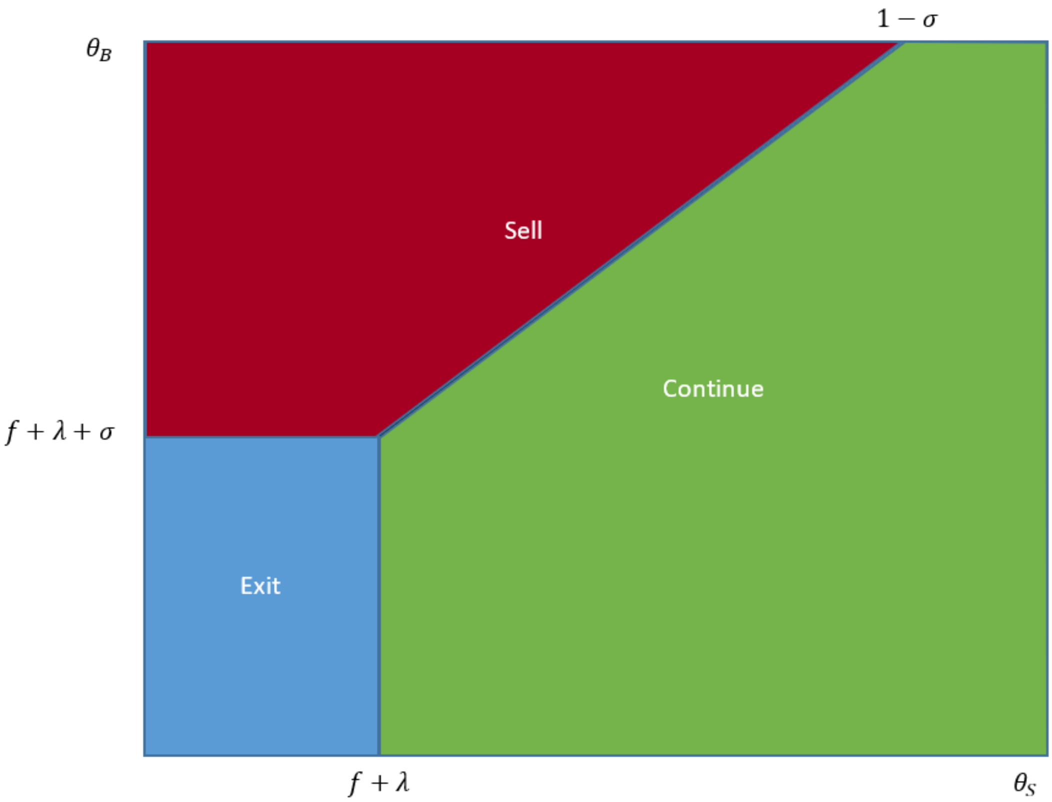
Period 1 – Buyer B1's willingness to pay in the second period is the expected profits from operating in the next two periods less the transaction cost. Since there is no accumulated liability if the firm is sold at the end of this period, $w_{B1}^1 = \pi_{B1}^2 + \pi_{B1}^3 - \sigma = 2(\theta_B - f) - \sigma$.

3.3.4 Decision rules at the end of period 2

The decision rules for end of period 2 in two scenarios: 1) without the PLE doctrine; 2) with PLE are discussed in Theory Appendix subsection C.1.1. Panels A and B of Figure 3.2 summarizes the corresponding decision regions.



(a) End of the second period decision regions without PLE



(b) End of the second period decision regions with PLE

Figure 3.2: End of the second period decision regions

3.3.5 Key predictions for end of period 2 decisions

(All proofs (and some corollaries) are presented in Theory Appendix subsection C.1.2.)

- **Lemma 1: Probability of exiting for older firms (i.e., firms at the end of period 2) is higher with PLE.**
- **Lemma 2: The probability of continuing for older firms is higher with PLE.**
- **Lemma 3: The probability of selling for older firms is lower with PLE.**

3.3.6 Decision rules at the end of period 1

The decision rules for end of period 1 in two scenarios: 1) without the PLE doctrine; 2) with PLE are discussed in Theory Appendix subsection C.1.3. Panels A and B of Figure 3.3 summarizes the corresponding decision regions.

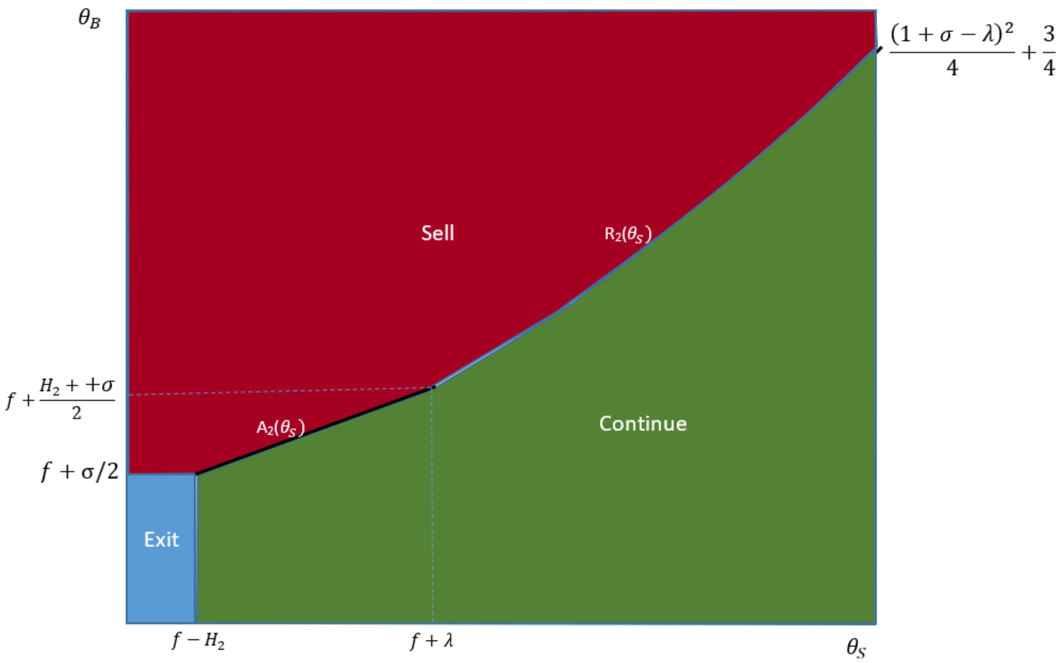
3.3.7 Key predictions for end of period 1 decisions

(All proofs and a corollary to Lemma 4 are presented in Theory Appendix Appendix C.1.4.)

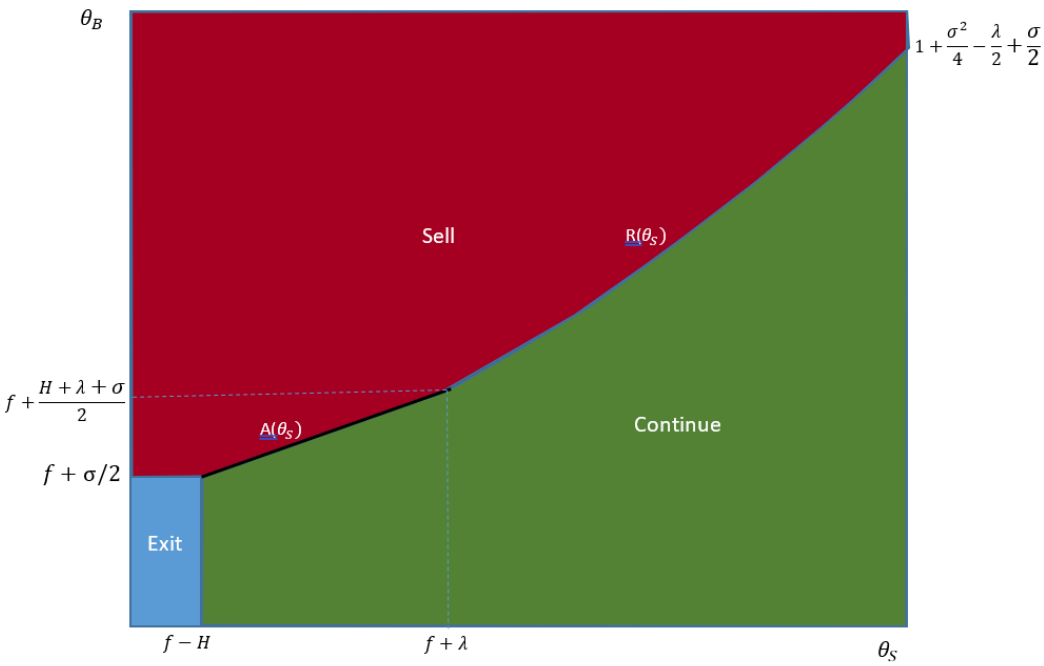
- **Lemma 4: Probability of exiting for younger firms is higher with PLE.**
- **Lemma 5: The probability of continuing for younger firms is lower with PLE if** $\lambda > 2\sigma$.
- **Lemma 6: The probability of selling for younger firms is higher with PLE if $\lambda > 2\sigma$.**

Lemma's 5 and 6 highlight the importance of transaction cost frictions within the model. In particular, if transaction costs are too high, then the probability that younger firms will sell (or continue) does not go up with PLE, as the gain from selling (or the incentive effect of the potential gain from selling next period) becomes too low.

We verify each of lemmas 1 to 6 for specific parameters in Figure C.1 (for the comparison of old firms with and without PLE) and Figure C.2 (for the comparison of young firms) below. The figures confirm that in the regime with PLE (i.e., with higher value of liability λ), (1) the region for exit or closure of the firm (blue rectangular region in the bottom corner) expands, in line with Lemma 1. In fact with the chosen parameter



(a) End of the first period decision regions without PLE



(b) End of the first period decision regions with PLE

Figure 3.3: End of the first period decision regions

values for the "Without PLE regime", we find that none of the firms chose to exit in the first period. That is, even low quality firms, even losses in period 1 (i.e., with $\theta_S < f$) chose to continue at the end of period. This is because the possibility of selling to a higher productivity firm makes it worthwhile to continue rather than exit. This feature, of firms with negative profitability choosing to operate, echoes a finding in David (2017). Thus an active corporate transactions market helps induce entry/entrepreneurship and survival of young firms. (2) The green "continue" region shrinks, in line with Lemma 5 – the left side vertical boundary line shifts to the right compressing the region horizontally, while the top cutoff curves (defined by $A(\theta_S)$ and $R(\theta_S)$ shifts downward compressing the region vertically. Thus, in the face of a higher potential liability in period 2, fewer firms choose to continue at the end of period 1. (3) The red sale region (top right corner) expands, consistent with Lemma 6. This is evident from the fact that the bottom boundary curve of the region shifts downward throughout. Thus, the probability that a firm would sell increases for every level of seller firm quality as a consequence of the PLE.

3.3.8 Key predictions for entry decisions

(All proofs and a corollary to Lemma 4 are presented in Theory Appendix C.1.5.)

- **Lemma 7: The entry rate is lower in the regime with PLE relative to the regime without PLE, if the entry cost (κ) is high enough.**

3.4 Data and Empirics

We test our hypotheses using establishment-level data obtained from the Longitudinal Business Database (LBD) of the U.S. Census Bureau. The LBD covers the universe of non-farm, tax-paying establishments and firms in the U.S. that employ at least one worker. The LBD includes annual observations beginning in 1976 and runs through 2014. It contains information on industry, location, employment and parent firm affiliation (Jarmin and Miranda 2002). We define establishment closure as 1 when it exists in the current year but never appears in the future years. We define acquisition as 1 when the firm identifier of an establishment in the current year is different from that in the preceding year. Since we need information from the preceding year and subsequent years, we drop the first and last years, 1976 and 2014, respectively. In all, we have about 150 million establishment-year observations and about 109 million firm-year observations over this period.

At the establishment level, we examine how the adoption of PLE affects the probability of acquisition and closure using the following difference-in-differences specification:

$$Y_{ekt} = \alpha_e + \gamma_{it} + \beta_1 * PLE_{k,t-1} + \delta * X_{ek,t-1} + \epsilon_{ekt} \tag{3.1}$$

where e indexes establishments, k state, t time, i industries, Y_{ekt} is the dependent variable of interest (acquisition or closure dummy), α_e and γ_{it} are establishment and industry-by-year fixed effects, X_{ekt} are control variables (specifically, the log of total employment and average wage). $PLE_{k,t-1}$ is a dummy variable that equals one if product line exception has been adopted by year t-1 in state k, and ϵ_{ekt} is the error term. All independent variables are lagged one year, because it takes time to finish the processes of acquisitions and closures. This methodology fully controls for stable differences between treated and non-treated establishments via establishments fixed effects, while the industry by year fixed effects control for aggregate time-varying fluctuations within industries.

Because PLE only applies to defective *products*, manufacturing is more likely to be affected by it than non-manufacturing firms.[48] Hence, we consider non-manufacturing industries as the benchmark and use the following difference-in- difference-in-differences (DDD) approach:

$$Y_{ekt} = \alpha_e + \gamma_{it} + \beta_1 * PLE_{k,t-1} + \beta_2 * PLE_{k,t-1} * MFG_{ek,t-1} + \delta * X_{ek,t-1} + \epsilon_{ekt} \tag{3.2}$$

where MFG is a dummy variable for establishments in NAICS 31, 32 or 33, and the remaining terms are as defined in Equation 3.1.

We compute establishment age as the difference between the current year and the first year that the establishment appears in the LBD. For those establishments that enter in 1976 (left censored), the variable age is missing, so those observations are dropped whenever we use the variable age. We use age 5 as the cutoff point to define young (< 5 years old) and old ($>= 5$ years old). We choose 5 years as the cutoff point, because this is a commonly used threshold in the literature (e.g., Fort et al. 2013). Further, based on a nationwide survey by Manchisi and Gallagher (2006), firms are usually held liable for

[48]Distributors and retailers of the product also potentially face liability, but anecdotal evidence (e.g., the Monsanto case, and numerous auto liability cases) suggests that manufacturers of the products are typically the primary defendants.

the defective products for about 5-15 years after the selling, so overall establishments having existed for more than 5 years old are likely to have accumulated liabilities.

3.5 Results

3.5.1 Descriptive Statistics

Descriptive statistics on acquisitions and closures for the different samples are provided in Table 3.1. For each sample, we show the rates of acquisition and closure for periods before and after the enactment of PLE for states with PLE. We also show the rates for states without PLE in the last column. Panel A shows statistics at the establishment level. Overall, we have about 36 million establishment-years in the states with PLE between 1977 and 2013, with about 3.2 million of them in the period before the enactment of PLE. We have about 114 million observations in the states without PLE.

Comparing the means before and after PLE is introduced (the "difference" column), we can see acquisitions and closures increase in the overall sample (by about 0.21 percentage points and 0.42 percentage points, respectively) as well as in the non-manufacturing samples. In contrast, acquisitions decline by about 0.16 percentage points in the manufacturing sample after PLE is introduced. Closure increases much more in the manufacturing sample (0.35 percentage points vs. 0.04 percentage points). This decline in acquisitions in manufacturing is entirely driven by old establishments; young manufacturing establishments show an increase. Closures for both young and old establishments increase and the increase is higher for young establishments.

At the firm level, exit increases after PLE, more so for manufacturing than for non-manufacturing. Growth declines as well, and more so for manufacturing firms. These broad patterns are consistent with the theoretical predictions discussed in section 3.3.

3.5.2 Baseline Results

Table 3.2 shows the results of estimating Equations (1) and (2) in the entire sample. Across all industries, the effect of PLE on the probability of acquisitions is negative but statistically insignificant. The effect on the probability of closure is positive, but that is also statistically insignificant. Focusing on the triple-difference specifications, the coefficient on *"PLE $\times$ Manufacturing"* shows that the probability of acquisition for a given manufacturing establishment decreases by an additional 0.19 percentage points after the enactment of PLE relative to the change in acquisition probability of non-manufacturing

Table 3.1: Summary Statistics.

	States with PLE			States without PLE
	Before change	***After change***	***Difference***	
Panel A: Establishment-level samples				
Overall	*(N=3,189,000)*	*(N=32,820,000)*		*(N=11,4100,000)*
Acquisition (Dummy × 1000)	16.17	18.27	*2.10****	17.43
	(126.10)	(133.90)	*(0.08)*	(130.90)
Closure (Dummy × 100)	6.19	6.61	*0.42****	6.21
	(24.10)	(24.85)	*(0.01)*	(24.14)
Manufacturing sample	*(N=261,000)*	*(N=2,259,000)*		*(N=7,137,000)*
Acquisition (Dummy × 1000)	19.82	18.19	*-1.63****	19.09
	(139.4)	(133.70)	*(0.28)*	(136.80)
Closure (Dummy × 100)	*6.02*	*6.57*	*0.55****	*5.69*
	(23.79)	*(24.77)*	(0.05)	*(23.16)*
Non-manufacturing sample	*(N=2,928,000)*	*(N=30,560,000)*		*(N=107,000,000)*
Acquisition (Dummy × 1000)	15.85	18.27	*2.42****	17.32
	(124.90)	(133.90)	(0.08)	(130.50)
Closure (Dummy × 100)	6.21	6.61	*0.40****	6.25
	(24.13)	(24.85)	(0.02)	(24.20)
Young manufacturing sample	*(N=174,000)*	*(N=587,000)*		*(N=2,000,000)*
Acquisition (Dummy × 1000)	19.16	20.30	*1.14****	20.53
	(137.10)	(141.00)	(0.38)	(141.80)
Closure (Dummy × 100)	6.18	9.66	*3.48****	7.81
	(24.08)	(29.55)	(0.08)	(26.84)
Old manufacturing sample	*(N=73,000)*	*(N=1,596,000)*		*(N=4,794,000)*
Acquisition (Dummy × 1000)	20.93	17.11	*-3.82****	18.37
	(143.10)	(129.70)	(0.49)	(134.30)
Closure (Dummy × 100)	5.33	5.47	*0.14*	4.85
	(22.47)	(22.74)	(0.09)	(21.48)
Panel B: Firm-level samples				
Overall	*(N=1,867,000)*	*(N=22,740,000)*		*(N=82,680,000)*
Exit (Dummy × 100)	6.14	6.70	0.56***	6.32
	(24.01)	(25.00)	(0.02)	(24.33)
Employment Growth (%)	-0.03	-2.30	-2.27***	-1.63
	(50.60)	(50.76)	(0.04)	(48.46)
Manufacturing sample	*(N=155,000)*	*(N=1,864,000)*		*(N=5,797,000)*
Exit (Dummy × 100)	6.20	7.10	0.90***	6.25
	(24.11)	(25.68)	(0.07)	(24.21)
Employment Growth (%)	1.34	-1.80	-3.14***	-1.11
	(46.27)	(45.92)	(0.12)	(43.62)
Non-manufacturing sample	*(N=1,712,000)*	*(N=20,880,000)*		*(N=76,890,000)*
Exit (Dummy × 100)	6.14	6.66	0.52***	6.32
	(24.00)	(24.94)	(0.02)	(24.34)
Employment Growth (%)	-0.15	-2.34	-2.19***	-1.67
	(50.97)	(51.17)	(0.04)	(48.81)

The sample includes all the establishments in the LBD from year 1977 to 2013. We exclude the first year of LBD (year 1976), as the variable ”Acquisition” is not defined for the first year. ”Acquired” is a dummy indicating that the establishment was acquired, and is set equal to 1 if the firm ID of an establishment is different from that in the previous year, and 0 otherwise; ”Closed” is a dummy indicating that the establishment was closed, and is set is equal to 1 if it is the last year we observe the establishment ID in the LBD, and 0 otherwise. We scaled ”Acquisition” by 1000, and ”Closure” by 100 to aid interpretation of (rounded) estimated coefficients. An establishment is defined as belonging to manufacturing, if its first 2 NAICS code is 31, 32 or 33. Age dummies ”young” and ”old” are defined using a threshold of 5 years: an establishment is young if its age is below 5; and old if its age is greater than or equal to 5. In panel B, we aggregated the establishment information to the firm level. ”Exit” is equal to 1 if it is the last year we can observe the firm ID in the LBD, and 0, otherwise. We scaled this dummy variable by 100. For defining the location and industry of multi-units firms, we choose the state and industry in which the firm has the most employment. Standard deviations are shown in the brackets for columns (1), (2) and (4). For the column (3) (Post-change mean – Pre-change Mean), the numbers in the brackets are the standard errors of the mean differences before and after the adoption of PLE. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

establishments, which is about 10% of the mean probability of acquisitions. Further, the adoption of PLE raises the probability of closure of manufacturing establishments by an extra 0.36 percentage points, i.e., 6% of the mean level in the treatment group before the adoption. Both effects are statistically significantly different from zero. These results are consistent with our hypotheses (and our sample being dominated by older establishments).

Table 3.2: Impact of Product Line Exception on Establishment Acquisitions and Closures (Overall Sample).

	(1)	(2)	(3)	(4)
	Dep: Acquired Dummy		Dep: Closed Dummy	
Product line exception	-0.351	-0.187	0.117	0.085
	(0.646)	(0.638)	(0.288)	(0.287)
Product line exception × Manufacturing		-1.865***		0.363**
		(0.355)		(0.166)
Adjusted R-squared	0.055	0.055	0.119	0.119
Controls for lags of Log (emp) and Log (average wage)	YES	YES	YES	YES
EST FE	YES	YES	YES	YES
IND by YEAR	YES	YES	YES	YES
N	150,100,000	150,100,000	150,100,000	150,100,000

All independent variables are lagged by one year, to account for the lead time needed to complete the process of mergers and acquisitions. ”Product line exception” is a dummy variable indicating whether the state where the establishment is located has this exception in a given year. Standard errors clustered by state are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.5.3 Young vs. Old Establishments

Next, we examine if the adoption of PLE might have different effects on young and old manufacturing establishments, in line with the predictions of our model. Table 3.3 shows estimates of equation (1) by age group. The probability of being acquired increases by about 0.26 percentage points among young manufacturing establishments (or about 13% of the mean level in the treatment group before PLE). The corresponding probability declines by 0.11 percentage points among old establishments though the effect is statistically insignificant. Thus, these results support Hypothesis 3 and are consistent with Hypothesis 1, and strongly suggest that younger establishments are more likely to be acquired after PLE is introduced. The probability of closure of young establishments increases by 1.17 percentage points after PLE or about 19% of the mean level among young manufacturing establishments in the treatment group. This strongly supports Hypothesis 4. The probability of closure among old manufacturing establishments increases by 0.52 percentage points, though it is statistically insignificant. This is consistent with Hypothesis 2.

Table 3.3: Young vs. Old Establishments: Impact of Product Line Exception on Establishment Acquisitions and Closures (Manufacturing Sample).

	(1)	(2)	(3)	(4)
	Dep: Acquired Dummy		**Dep: Closed Dummy**	
	Young Manufacturing	Old Manufacturing	Young	Old
Product line exception	2.574**	-1.118	1.169**	0.515
	-1.259	-0.811	-0.475	-0.334
Adjusted R-squared	0.045	0.044	0.169	0.117
Controls for lags of Log (emp) and Log (average wage)	YES	YES	YES	YES
EST FE	YES	YES	YES	YES
IND by YEAR	YES	YES	YES	YES
N	2,760,000	6,463,000	2,760,000	6,463,000

This table uses the sub-sample of manufacturing establishments only. All independent variables are lagged by one year, to account for the lead time needed to complete the process of mergers and acquisitions. "Product line exception" is a dummy variable indicating whether the state where the establishment is located has this exception in a given year. Age dummy "old" is defined as age above equal to or above 5. Standard errors clustered by state are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.5.4 Impact on Overall Firm Performance

We now examine the total impact on firm growth and exit, using specifications similar to those at the establishment level, and add employment size quintile by industry by year fixed effects to allow for a non-linear effect of firm size. Firm exit is defined as 1 if the firm identifier disappears from the LBD in the next year. Firm growth rate from one year to the next is calculated as the ratio of the change in employment to the average employment of the two years (Davis, Haltiwanger, and Schuh 1996). Results are presented in Table 3.4. PLE has a strong positive effect on manufacturing firm exit with the coefficients about 0.35-0.37 percentage points, or 5.7-6.0% of the mean level in the treatment group before the adoption. These results are consistent with those in the establishment level, and suggest firms are not simply shifting focus to non manufacturing activities (i.e., not opening non-manufacturing establishments to offset negative growth from manufacturing establishment closures). PLE generally has a negative effect on firm employment growth. The coefficients across these specifications are negative, but become smaller and less significant when we control for the log of employment and average wage.

Table 3.4: Impact of Product Line Exception on Firm Exit and Employment Growth rate (Overall Sample).

	(1)	(2)	(3)	(4)	(5)	(6)
		Dep: Firm Exit			Dep: Firm Employment Growth Rate	
Product line exception	0.098	0.092	0.202	0.155	0.434	-0.856
	(0.38)	(0.392)	(0.332)	(0.802)	(0.784)	(0.572)
Product line exception • Manufacturing	0.374**	0.352**	0.370**	-1.363***	-1.207***	-0.431
	(0.155)	(0.135)	(0.147)	(0.29)	(0.432)	(0.531)
Adjusted R-squared	0.108	0.111	0.109	0.033	0.136	0.206
Controls for lags of Log (emp) and Log (average wage)	NO	NO	YES	NO	NO	YES
FIRM FE	YES	YES	YES	YES	YES	YES
IND by YEAR	YES	NA	YES	YES	NA	YES
SIZE by IND by YEAR	NO	YES	NO	NO	YES	NO
N	107,300,000	107,300,000	107,300,000	107,300,000	107,300,000	107,300,000

All independent variables are lagged by one year, to account for the lead time needed to complete the process of mergers and acquisitions. "Product line exception" is a dummy variable indicating whether the state where the firm is located has this exception in a given year. For the location and industry of multi-units firms, we choose the state and industry where the firm has the most employment. Standard errors clustered by state are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.5.5 Impact of PLE on the aggregate entry patterns

In this part, we investigate the impacts of PLE on the entry of establishments and firms. Because we do not have any information about the establishment/firm in the period before the entry, we can not control for the establishment/firm-level variables. Therefore we undertake this analysis by aggregating the entry information to the state by industry level for each year. Specifically, we use two alternative measures: (i) the aggregate entry ratio, defined as the ratio of total entries in a year to the the total number of establishments in the previous period; and (ii) the log of the total number of entrants. We use state and industry by year fixed effects to control for the invariant differences among states and differences in industry trends.

Column (1) shows that the entry ratio of manufacturing establishments decreases by 2.94 percentage points, i.e. 21.15% of mean level in the treated states before the adoption of PLE. Estimate in the column (2) shows a similar pattern: log of the total number of entries decrease by 0.152, which is about 9.16% of the mean level for the sample of states adopting PLE.

The effect of PLE on firm entry is slightly larger. Entry ratio of firms decreases by

Table 3.5: **Aggregate Impact of Product Line Exception on Entry.**

	(1)	(2)	(3)	(4)
	Entry of Establishments		Entry of Firms	
	Dep: Entry ratio	Dep: Log (Number of entrants)	Dep: Entry ratio	Dep: Log (Number of entrants)
Product line exception	0.535	0.007	0.662	0.005
	(0.966)	(0.037)	(1.012)	(0.04)
Product line exception • Manufacturing	-2.939***	-0.152**	-4.139***	-0.147**
	(0.942)	(0.064)	(1.127)	(0.068)
Adjusted R-squared	0.467	0.892	0.409	0.891
STATE FE	YES	YES	YES	YES
IND by YEAR	YES	YES	YES	YES
N	454000	454000	438000	438000

This table shows the results in the state by industry by year level from aggregating establishment entry information. All independent variables are lagged by one year, as in previous tables. "Product line exception" is a dummy variable indicating whether the state by industry by year cell has this exception in a given year. We winsorized entry ratio at the 99th percentiles, and results are similar without winsorizing. Standard errors clustered at the state level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.139 percentage points after the adoption of PLE, i.e. 25.64% of the mean level in the treatment group (column (3)), while the result using log of the total of firm entry is similar but smaller: log of total entry decreases by 0.147, i.e. 9.13% of the mean level for the sample of states adopting PLE (column (4)).

3.6 Discussion

This study uses comprehensive US Census microdata on all U.S. firms and establishments to show that the adoption by state courts of PLE, which introduced a friction (in the form of uncertain potential liabilities) in the acquisitions market, has economically significant effects on overall firm reconfigurations. Consistent with a model we develop to predict the effects of PLE, we find broadly that individual establishments are less likely to be acquired and more likely to be closed after the adoption of PLE. This effect is strikingly different for younger establishments, who are much more likely to be acquired and closed. Older establishments, presumably because of their larger potential liabilities, tend not to be involved in reconfiguration. Importantly, PLE also appears to discourage starts of new establishments. Together, these findings not only show how frictions in one part of the reconfiguration differentially affect the propensity of individual resources to be reconfigured, but also how the broad pattern of reconfiguration changes across the firm life cycle. In this case, there is a shift in the locus of reconfiguration to younger establishments, consistent with an age-related disadvantage from potential accumulated liabilities for older firms.

Our study analyzes the impact of adoption of PLE at both the establishment and firm levels. Our firm-level analysis confirms that establishment-level results for manufacturing are not offset at the firm-level by shifts to non-manufacturing activities by firms located in PLE states. Beyond addressing potential shifts from manufacturing to non-manufacturing industries within a firm, analyzing at the firm level provides an important insight. Specifically, at the firm level, we find that the adoption of PLE tends to reduce overall firm growth. This suggests, albeit indirectly, that acquisitions as a mode of firm growth are not completely substitutable with organic growth. Our model highlights that the ability to sell an establishment provides an important incentive for young firms to persist in the market (and would likely also provides incentives for entry and investment in an extended version of the model). Thus our model and findings suggest that a friction in the corporate transactions market reduces both the ability to grow through acquisitions, and reduces incentives for entry and organic growth for younger firms. To our knowledge, no studies have explicitly highlighted this important link which generates complementarity between acquisitional and organic modes of growth.

Our results are consistent with concerns expressed by experts and some courts that PLE adoption would impose a uncertain cost on acquisitions, that cannot be offset by insurance. We note that even if fairly priced insurance was available, PLE adoption generates a substantive shift of costs from consumers to the current owners of the original producers. The insurance cost itself could lead to lower new value transferred to the buyer, discouraging investment in a similar way as in our model.[49]

Our rich dataset (covering about 150 million establishment-year and about 109 million firm-year observations) and setting (time series variation within states in PLE adoption) allow us to include a rich set of fixed effects that addresses concerns from omitted variable bias. Further, the confidential US Census data covers all employer establishments, including both public and private firms. Because most papers studying mergers and acquisitions use publicly available data on public firms , and because the vast majority of firms are private (e.g., the LBD has about five million firm records per year, compared to less than 8000 public firms in the US per year during this period), this chapter contributes to the broader literature by examining a much larger sample of firms. In particular, the full coverage of our data protects against potential selection bias in data

[49]Even with availability of insurance, the scenario with PLE would have likely a higher transaction cost (σ) compared to the scenario without PLE, which in our model is analogous to having a higher liability cost (λ) with PLE.

restricted to public firms, as potential liabilities may be a weaker deterrent for larger firms. (The Bayer acquisition of Monsanto in 2018, despite significant concerns relating to pending product liability lawsuits, is consistent with this concern.)

We note one important caveat: our focus on examining the effects of PLE on firm dynamics and growth means that we cannot evaluate aggregate welfare effects of PLE adoption. In particular, a primary objective of the PLE was to discourage poor quality products, and it is possible that the adoption of PLE improved consumer welfare by increasing product safety. Thus, from a policy evaluation perspective, our results should be interpreted cautiously; our study sheds light only on the potential costs of enacting PLE in terms of discouraging firm entry and growth, and does not evaluate potential benefits from improved product safety.

Appendix A

Employment Decline during the Great Recession: The Role of Firm Size Distribution

A.1 Derivations for the Case of N firms

In this part, I provide details behind the derivation in the case of N firms. First, I show the general formula for the expected employment growth rate conditional on a number of i firms hit by the shock. If firms 1,..., i are hit, the employment growth rate is $G * Ln(1 + (\nu - 1)\omega_1 + (\nu - 1)\omega_2 + ... + (\nu - 1)\omega_i)$, where ω_i represents the employment share of the firm i in the first period, and $G = \frac{1-\alpha}{1-\alpha+\epsilon}$. There are in total $\binom{N}{i}$ different combinations, so the conditional probability of each case is $1/\binom{N}{i}$. By summing up these cases, we can compute the expected employment growth rate conditional on a number of i firms hit by the shock as:

$$\sum g_{0,i\_firms\_hit} = G \cdot \frac{Ln[1 + (\nu - 1)\omega_1 + ... + (\nu - 1)\omega_i] + ... + Ln[1 + (\nu - 1)\omega_{N-i+1} + ... + (\nu - 1)\omega_N]}{\binom{N}{i}}$$

$$= G \cdot \frac{(\nu-1)\omega_1 + \ldots + (\nu-1)\omega_i - \frac{1}{2}(\nu-1)^2(\omega_1 + \ldots + \omega_i)^2 + \ldots + (\nu-1)\omega_{N-i+1} + \ldots + (\nu-1)\omega_N - \frac{1}{2}(\nu-1)^2(\omega_{N-i+1} + \ldots + \omega_N)^2}{\binom{N}{i}}$$

$$= G \cdot \frac{\binom{N}{i}\frac{i}{N}(\nu-1) - \binom{N}{i}\frac{i(i-1)}{N(N-1)}\frac{1}{2}(\nu-1)^2 - \binom{N}{i}\frac{(N-i)i}{N(N-1)}\frac{1}{2}(\nu-1)^2 * HHI}{\binom{N}{i}} = G \cdot \frac{\binom{N-1}{i-1}(\nu-1) - \binom{N-2}{i-2}\frac{(\nu-1)^2}{2} - \binom{N-2}{i-1}\frac{(\nu-1)^2}{2}HHI}{\binom{N}{i}} \quad (i \geq 2);$$

With this general formula, we can derive the unconditional expected growth rate through summing all these conditional expected growth rates multiplied by their probability:

$\binom{N}{0}s^0(1-s)^N * g_{0,none\_hit} + \binom{N}{1}s^1(1-s)^{N-1} * \sum_{j=1}^{N} g_{0,one\_hit} + ... + \binom{N}{N-1}s^{N-1}(1-$

$s)^1 * \sum_{j=1}^{N} g_{0,(N-1)firms\_hit} + \binom{N}{N} s^N (1-s)^0 * g_{0,all\_hit} \simeq (1-s)^N * 0 + s^1(1-s)^{N-1} * G \cdot (\nu-1) - \frac{1}{2}(\nu-1)^2 \cdot HHI + s^2(1-s)^{N-2} * G \cdot [\binom{N-1}{1}(\nu-1) - \binom{N-2}{0}\frac{1}{2}(\nu-1)^2 - \binom{N-2}{1}\frac{1}{2}(\nu-1)^2 HHI] + ... + s^{N-1}(1-s)^1 *$

$G \cdot [\binom{N-1}{N-2}(\nu-1) - \binom{N-2}{N-3}\frac{1}{2}(\nu-1)^2 - \binom{N-2}{N-2}\frac{1}{2}(\nu-1)^2 HHI] + s^N(1-s)^0 * G \cdot [(\nu-1) - \frac{(\nu-1)^2}{2}]$. Combining those terms having $(\nu-1)$, $\frac{(\nu-1)^2}{2}$, and HHI together, respectively, leads to a simplified version: $g \simeq G \cdot s(\nu-1) - G \cdot s^2 \frac{(\nu-1)^2}{2} - G \cdot s(1-s)\frac{(\nu-1)^2}{2} HHI$, which is Equation 1.10 in the main text. Following the same process, we can derive the formulas for the change rate of wage and total output.

A.2 Neoclassic Model with Capital

In this section, I provide a model with both capital and labor. The formulas and derivations are similar to the simplified version with only labor as the input. Assume there are two periods: –1 (before the crisis) and 0 (during the crisis). Firms are price-takers in both product and factor markets. In period –1, firms receive a firm-specific productivity draw z_i, which will be carried on to period 0, and then maximize the profits by choosing the labor ($L_{i,-1}$) and capital ($k_{i,-1}$) in each period. The production function is a Cobb-Douglas function with decreasing returns to scale: $Y_{i,-1} = z_i K_{i,-1}^{\beta} L_{i,-1}^{\alpha}$, where $\alpha + \beta < 1$ captures the extent of decreasing returns to production, and i indexes firm i. We can think of the decreasing returns to scale as that there is another factor in the production function, like land, which has a fixed supply. I need the assumption of decreasing returns to scale to pin down the employment size. At the beginning of period 0, each firm faces a productivity/demand shock (these two types of shocks are indistinguishable, unless we observe the price; in the following, I will just assume it is a shock to the productivity) with the same probability s, leading to a new productivity level $z_i' = \mu z_i$, with $0 \leq \mu < 1$ in the downturn and $\mu > 1$ in the recovery.[50] Firms then choose labor ($L_{i,0}$) and capital ($K_{i,0}$) given the new factor price and productivity level in period 0. I abstract from entry for simplicity.

Let us begin from period –1. For firm i, it chooses labor $L_{i,-1}$ and capital $K_{i,-1}$ to maximize the profit after receiving the productivity draw z_i.

$$\pi_{i,-1} = z_i K_{i,-1}^{\beta} L_{i,-1}^{\alpha} - W_{-1} \cdot L_{i,-1} - r \cdot K_{i,-1}.$$

W_{-1} and r index the wage level and interest rate. We assume the capital market is

[50] An extreme example of the shock in the downturn could be that productivity becomes 0, once hit by the shock, and then firms shut down.

a global market and labor market is a local market—that is, wage could differ across different areas while interest rate is constant across areas and periods, so that we focus on the wage level that clears the labor market in both periods.

These two first-order conditions with respect to capital $K_{i,-1}$ and labor $L_{i,-1}$ are

$$\begin{aligned} z_i \cdot \beta K_{i,-1}^{(\beta-1)} L_{i,-1}^{\alpha} &= r \\ z_i \cdot \alpha K_{i,-1}^{\beta} L_{i,-1}^{(\alpha-1)} &= W_{-1}. \end{aligned} \tag{A.1}$$

Using the first equation divided by the second equation on both sides gives us $\frac{\beta}{\alpha} \cdot \frac{L_{i,-1}}{K_{i,-1}} = \frac{r}{W_{-1}}$, i.e., $\frac{L_{i,-1}}{K_{i,-1}} = \frac{r \cdot \alpha}{W_{-1} \cdot \beta}$. We set $R = \frac{r \cdot \alpha}{W_{-1} \cdot \beta}$, which is a constant across firms within the same area, as firms face the same factor prices. Then, we plug this relation $\frac{L_{i,-1}}{K_{i,-1}} = \frac{r \cdot \alpha}{W_{-1} \cdot \beta}$ into Equation A.1, and derive

$$K_{i,-1} = [\frac{z_i \beta^{(1-\alpha)} \alpha^{\alpha}}{r^{(1-\alpha)} (W_{-1})^{\alpha}}]^{\frac{1}{1-\alpha-\beta}} \tag{A.2}$$

or $\quad Ln(K_{i,-1}) = (\dfrac{1}{1-\alpha-\beta})[Ln(z_i) + (1-\alpha)Ln(\beta) + \alpha Ln(\alpha) - (1-\alpha)Ln(r) - \alpha Ln(W_{-1})].$

Using the relation between capital and labor, $\frac{L_{i,-1}}{K_{i,-1}} = \frac{r \cdot \alpha}{W_{-1} \cdot \beta}$, we have

$$Ln(L_{i,-1}) = (\frac{1}{1-\alpha-\beta})Ln(z_i) - \frac{1-\beta}{1-\alpha-\beta} Ln(W_{-1}) + G \tag{A.3}$$

$$\text{where} \quad G = (\frac{1-\beta}{1-\alpha-\beta})Ln(\alpha) + (\frac{\beta}{1-\alpha-\beta})Ln(\beta) - (\frac{\beta}{1-\alpha-\beta})Ln(r).$$

Since factors' prices are given and are the same across firms, we can derive that firm size is proportional to the productivity draw

$$\frac{L_{i,-1}}{L_{j,-1}} = \frac{K_{i,-1}}{K_{j,-1}} = \frac{z_i^{1/(1-\alpha-\beta)}}{z_j^{1/(1-\alpha-\beta)}} = \frac{B_i}{B_j} \tag{A.4}$$

i.e., ratios of firm sizes are proportional to the productivity draws. We set $B_i = z_i^{1/(1-\alpha-\beta)}$ to simplify the formulas. Suppose firms' shares are represented as ω_1, ω_2, ..., ω_N:

$$\omega_i = \frac{L_{i,-1}}{L_{1,-1} + L_{2,-1} + \cdots + L_{N,-1}} = \frac{z_i^{1/(1-\alpha-\beta)}}{z_1^{1/(1-\alpha-\beta)} + z_2^{1/(1-\alpha-\beta)} + \cdots + z_N^{1/(1-\alpha-\beta)}} = \frac{B_i}{\sum_{i=1}^{N} B_i}. \tag{A.5}$$

Then, we have $HHI = \sum_{i=1}^{N} \omega_i^2$. Using this formula of firm i's employment share, labor demand function, and the labor supply function, $W = \psi(L^s)^\epsilon$, I derive the total employment in equilibrium in period –1:

$$Ln(L_{-1}) = \frac{Ln(\sum_{i=1}^{N} B_i) - \frac{1-\beta}{1-\alpha-\beta} Ln(\psi) + G}{P} \tag{A.6}$$

$$\text{where} \quad P = 1 + \frac{\epsilon(1-\beta)}{1-\alpha-\beta}; \quad \text{G has the same formula as before.}$$

Now, let us move to period 0. Since we have N firms, we have the following scenarios: (1) no firms are hit by the shock: $p = C_N^0 \cdot s^0(1-s)^N$; (2) only one firm is hit: $p = C_N^1 \cdot s^1(1-s)^{(N-1)}$; (3) only two firms are hit $p = C_N^2 \cdot s^2(1-s)^{(N-2)}$; ... ; and (N+1) all firms are hit: $p = C_N^N \cdot S^N(1-S)^0$. In the first and last scenarios, the employment growth rate is independent of size distributions, so we can ignore them. Let us start with the second scenario. We first consider the conditional employment growth rate, then the unconditional growth rate. Since the probability of each scenario is independent of size distributions, the unconditional expected growth rate will be lower, as long as the conditional expected growth rate is lower.

Suppose firm j is hit by the shock at the beginning of period 0; then its productivity becomes $z_j' = \mu z_j$. Using the same process as in period 0, we can derive the total employment in the equilibrium in period 0 as

$$Ln(L_{0,j\_hit}) = \frac{Ln[\sum_{i \neq j}^{N} B_i + \nu B_j] - \frac{1-\beta}{1-\alpha-\beta} Ln(\psi) + G}{P} \tag{A.7}$$

$$\text{where} \quad \nu = \mu^{1/(1-\alpha-\beta)}; \quad \text{and} \quad P = 1 + \frac{\epsilon(1-\beta)}{1-\alpha-\beta}.$$

Then, the employment growth rate of only firm j being hit conditional on only one firm being hit by the shock is:

$$g_{0,j\_hit} \simeq \frac{Ln(L_{0,j\_hit}) - Ln(L_{-1})}{\binom{N}{1}} = \frac{Ln[(\sum_{i \neq j}^{N} B_i + \nu B_j)/\sum_{i=1}^{N} B_i]}{P \cdot \binom{N}{1}}$$
$$= \frac{Ln[1 + (\nu - 1)\omega_j]}{P \cdot \binom{N}{1}} \tag{A.8}$$

where $1/\binom{N}{1}$ represents the probability that firm j is hit conditional on only one firm being hit, and $\binom{N}{1}$ indexes the number of combinations choosing 1 item from N items.

With this formula in hand, we can derive the expected employment growth rate conditional on only one firm being hit:

$$\sum_{j=1}^{N} g_{0,j\_hit} = \frac{Ln[1+(\nu-1)\omega_1]+...+Ln[1+(\nu-1)\omega_N]}{P\cdot\binom{N}{1}} =$$
$$\frac{(\nu-1)\omega_1-\frac{1}{2}(\nu-1)^2\omega_1^2+...+(\nu-1)\omega_N-\frac{1}{2}(\nu-1)^2\omega_N^2]}{P\cdot\binom{N}{1}} = \frac{(\nu-1)-\frac{1}{2}(\nu-1)^2\cdot HHI}{P\cdot\binom{N}{1}};$$

while the second to the last step uses a second-order Taylor series expansion of $log(1+x)$, and $\binom{N}{1}$ indexes the number of combinations choosing one item from N items, so $1/\binom{N}{1}$ is the probability that any firm is hit conditional on only one firm being hit. HHI represents the concentration level in the first (pre-crisis) period.

The same process could apply to cases in which more than one firm is hit. Suppose a number of i firms are hit by the shock, I derive that the conditional expected employment growth rate is

$$1/\left[P\cdot\binom{N}{i}\right]*\left[\binom{N-1}{i-1}(\nu-1)-\binom{N-2}{i-2}\frac{(\nu-1)^2}{2}-\binom{N-2}{i-1}\frac{(\nu-1)^2}{2}HHI\right];(i\geq 2).^{51} \tag{A.9}$$

By summing these conditional growth rates together, I can derive the unconditional employment growth rate:[52]

$$g \simeq \frac{s(\nu-1)}{P}-\frac{s^2}{P}\frac{(\nu-1)^2}{2}-\frac{s(1-s)}{P}\frac{(\nu-1)^2}{2}HHI \tag{A.10}$$

Thus, we have $\triangle g \propto -\frac{s(1-s)}{P}\frac{(\nu-1)^2}{2}*\triangle HHI$, i.e., the difference in employment growth rates is proportional to the HHI across areas, where $P=1+\frac{\epsilon(1-\beta)}{1-\alpha-\beta}$. When $\beta=0$, then $\frac{1}{P}=G=\frac{1-\alpha}{a-\alpha+\epsilon}$, and this formula becomes the same as Equation 1.10 in the main context.

A.3 Search and Matching Model

One possible concern with the neoclassical model above is that the employment level is generated by equating the labor demand to the labor supply, so there is no involuntary unemployment there, which might not be consistent with real life. To allow for the involuntary unemployment and embed the core idea from the above neoclassical model,

[51]See Section A.1 for the detailed algebra.
[52]See Section A.1 for the detailed algebra.

I build a search-matching model, based on the one in Crépon et al. (2013) and Michaillat (2012). I introduce a firm-idiosyncratic shock to the equilibrium and see how changes in employment depend on the pre-shock size distributions. The goal of this model is to see how the employment size distribution affects the drop in employment when facing a negative shock when the search friction is onsite. In the search-matching framework, the labor market is adjusted not only by wage but also by labor market tightness. That is why even if we have a constant wage level, firm size distribution would still matter. I also conduct a simple simulation in the last part of this section.

Consider a model with one sector and one type of worker in one commuting zone. In the first period, the economy is in a steady state: outflow of labor force equals inflow. At the beginning of the second period, I introduce a symmetric firm-level productivity/demand shock. (These two types of shocks are indistinguishable, unless we observe the price. In the following I will assume it is a shock to the productivity.) Once hit by the shock, the productivity level becomes $z_i' = \mu z_i$, with $0 \leq \mu < 1$ in the downturn and $\mu > 1$ in the recovery. This exogenous firm shock is in addition to each job exogenously ends with a rate h in every standard search and matching model. The job separation rate h could be considered as a shock in the job level, which is independent of firm size distributions.

Let u and n denote the number of unemployed and employed workers, and normalize the labor force to 1, so $n + u = 1$. The reduced form of matching function is given by $m(u, v)$, while v indexes the total number of vacancies. Following the standard matching model as in Pissarides (2000), we assume the m function is homogeneous of degree one and increasing in both its arguments. The labor market tightness is defined as $\theta = \frac{v}{u}$. The vacancy filling rate is $q(\theta) = \frac{m(u,v)}{v}$, and the job-finding probability is $f(\theta) = \frac{m(u,v)}{u}$. It is easy to see $f(\theta) = \theta q(\theta)$. Moreover, $q(\theta)$ and $f(\theta)$ are decreasing and increasing functions of θ, respectively.

In a steady state, inflow to unemployment $h \cdot n$ equals outflows from unemployment $u \cdot f(\theta)$. Then, we can derive the labor supply curve as a mapping between θ and the employment rate n (replacing u with $1 - n$):

$$n = \frac{f(\theta)}{f(\theta) + h}. \tag{A.11}$$

This equation also represents the Beveridge curve: When firms post more vacancies v, labor market tightness θ increases, which will raise $f(\theta)$, then increase n and decrease u. Here, I will call this equation the labor supply curve, following Crépon et al. (2013).

The implicit function, $\theta = \theta(n^S)$, is a convex and increasing function, because $f(\theta)$ is concave and increasing. See the graph below.

Next, we turn to the firm side to derive the labor demand curve. We assume the production function is in the Cobb-Douglas form, and physical capital is fixed in the short run

$$y_i = z_i n_i^{\alpha}.$$

I normalize the price of the product to be 1. Each firm i chooses employment to maximize the value of output, minus operating and recruiting costs. Let c be the per-period cost of an unfilled vacancy, and r the interest rate. The value of having a vacancy and a filled job are indexed by J_V and J_E, respectively. For each firm, we have the following two Bellman equations:

$$J_V = -c + q(\theta)E[J_E']/(1+r) + (1-q(\theta))E[J_V']/(1+r)$$

$$J_E = MPL - w + (1-h)E[J_E']/(1+r) + hE[J_V']/(1+r)$$

The free entry condition leads the value of having a vacancy to be 0: $J_V = E[J_V'] = 0$. Using this condition and the formula of J_V, we can derive:

$$\frac{c}{q(\theta)} = \frac{E[J_E']}{(1+r)}. \tag{A.12}$$

For each worker, we have two other Bellman equations:

$$J_U = b + f(\theta)E[J_W']/(1+r) + (1-f(\theta))E[J_U']/(1+r)$$

$$J_W = w + (1-h)E[J_W']/(1+r) + hE[J_U']/(1+r)$$

where J_U and J_E represent the value of unemployment and the value of job to a worker, respectively, and b indexes the value of leisure. The worker surplus from a job is $J_W - J_U = (w-b) + \frac{(1-h-f(\theta))}{1+r}(E[J_W' - J_U'])$. Similarly, the firm surplus from a job is $J_E - J_V = J_E = MPL - w + (1-h) \cdot \frac{E[J_E']}{(1+r)}$.

Assume that wage level w is determined by generalized Nash bargaining over the surplus from the marginal match, and β is workers' bargaining power. The total surplus is represented by S. Thus, we have $E[S'] = \frac{E[J_E']}{(1-\beta)} = \frac{E[J_W' - J_U']}{\beta}$. By plugging it into Equation A.12, we can derive that $\frac{E[S']}{1+r} = \frac{c}{q(\theta)(1-\beta)}$. By summing the worker and firm surpluses together, we get $S = J_W - J_U + J_E - J_V = MPL - b + \frac{c \cdot \theta \cdot (1-h-\beta f)}{f(\theta)(1-\beta)}$. Substituting into the workers' surplus derives $\beta S = (w - b) + \frac{(1-h-f(\theta))}{1+r}\beta E[S']$, which leads to the formula for wage level:

$$w = (1-\beta)b + \beta \cdot MPL + \beta c\theta = b + \beta(MPL - b) + \beta c\theta.$$

To solve for the steady state, I need to use the condition that X=X' for all variables in the model. To get the relation between θ and employment n, I plug the wage formula into the condition $J_E = E[J'_E]$:[53]

$$MPL - w + (1-h) \cdot \frac{c}{q(\theta)} = \frac{c}{q(\theta)}(1+r) \Rightarrow \frac{(r+h) \cdot c}{q(\theta)} = (z_i \alpha n_i^{(\alpha-1)} - b)(1-\beta) - \beta c\theta. \tag{A.13}$$

Given the market tightness θ, I can derive firm i's labor demand $n_i(\theta)$ based on its productivity level z_i. The summation of $n_i(\theta)$ gives us the total labor demand $n^D(\theta) = \left[\sum z_i^{(\frac{1}{1-\alpha})}\right]\left[\frac{\alpha(1-\beta)}{\beta c\theta + \frac{(r+h)c}{q(\theta)})}\right]$. Equating aggregate labor demand to the supply ($n^S(\theta) = \frac{f(\theta)}{f(\theta)+h}$) can solve for the equilibrium values of θ and n, while (1-n) gives us the unemployment rate.

Now, let us consider how size distributions affect the declines in employment when facing a firm-level idiosyncratic shock. Suppose we have two periods: -1 (before crisis), and 0 (during the crisis). Assume we are in the old equilibrium in period −1, and all areas have the same employment initially. Firm sizes (n_i) are proportional to $z_i^{\frac{1}{1-\alpha}}$, because MPL ($z_i\alpha/n_i^{(1-\alpha)}$) should be the same in the equilibrium, given the same wage, market tightness (θ), and other parameter values. At the beginning of period 0, a stochastic firm shock hits each firm with a probability s (let's focus on negative shocks), after which, firms adjust their employment, resulting in a new equilibrium. Comparing the new and old equilibriums, we can compute the changes in unemployment in this framework.

I conduct a simulation using the values of the parameters shown in Table A.1. The productivity shock is the same as that in section 1.2. I use the Cobb-Douglas matching function: $m(u, v) = \Psi u^{\phi} v^{(1-\phi)}$, so that $q(\theta) = m/v = \Psi\theta^{(-\phi)}$, and $f(\theta) = m/u = \Psi\theta^{(1-\phi)}$, following Hagedorn and Manovskii (2008), Michaillat (2012), and Toohey (2014). The simulation process is as follows.

I generate 100 random samples using the power law distribution with the parameter value equaling 1.6 (see Section 1.2.4 for the details of this distribution). Each observation has 10 firms. I randomly assign employment sizes to firms in each observation, satisfying

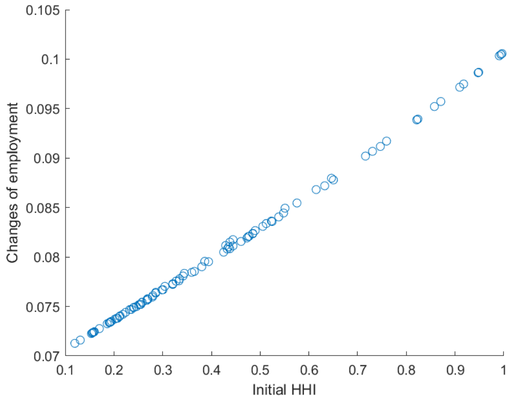
[53]The value of leisure –b is normalized to be 0.

that the initial employment in the equilibrium is the same across observations (I set the initial employment to be 0.95). Then, I infer the market tightness (θ) and productivity of each firm from the randomly assigned employment size using Equation A.13. Then, all observations face the same idiosyncratic firm shocks as in Section 1.2.4. Through summing up the changes of unemployment in all scenarios, we can get the unconditional changes in unemployment and employment shown in Figure A.1.

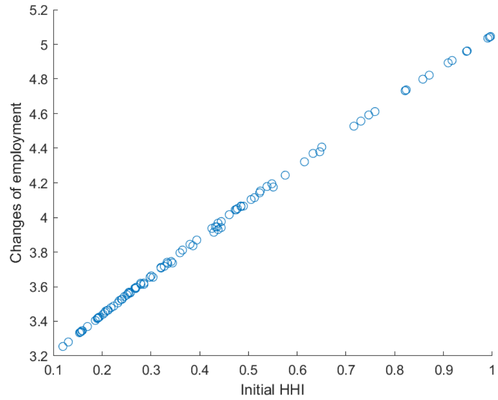
Figure A.1 shows the relationship between the expected unemployment and employment changes and the initial HHI using the simulated 100 observations. Areas with high initial HHIs experience a larger drop in employment and a bigger increase in unemployment whether the wage is sticky or not, although the relation is not exactly monotonic.[54] I also consider the case with sticky wages, because Michaillat (2012) shows that sticky wages are important to understand the rise in unemployment during recessions.[55] The magnitudes with and without sticky wages are quite different. The reason there is such a big gap in these two cases is that with sticky wages, the labor market is only adjusted by market tightness (θ), which creates a lot of rationing unemployment beacuse the marginal product of labor falls below the rigid wage level. The rationing unemployment becomes even more when large firms are hit by the idiosyncratic shocks, so the wage rigidity magnifies the effect of HHI. I would expect the real effect to be between these two cases, as wage adjusts partially downward instead of fixing at the same level .

[54]One possible reason for this relation being not exactly monotonic could be that the labor demand and supply are nonlinear functions. One caveat about the simulation results is that sometimes it has more than one solution for θ and n, when equating the total labor demand to the supply, so I choose to search for the local solution around the initial pair: $n = 0.7$ and $\theta = 0.4$.

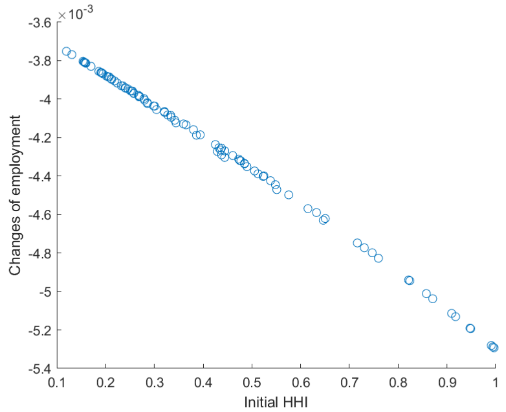
[55]Michaillat (2012) distinguishes two types of unemployment: rationing unemployment, which measures the shortage of jobs in the absence of matching frictions, and frictional unemployment, measuring additional unemployment attributable to matching frictions. He also shows that rationing unemployment is crucial to understand the rise in total unemployment in recessions, while diminishing returns to scale and wage rigidity are key factors leading to the rationing unemployment. In my simulation, I consider an extreme case of wage rigidity that wage is fixed at the initial level, even after negative shocks.



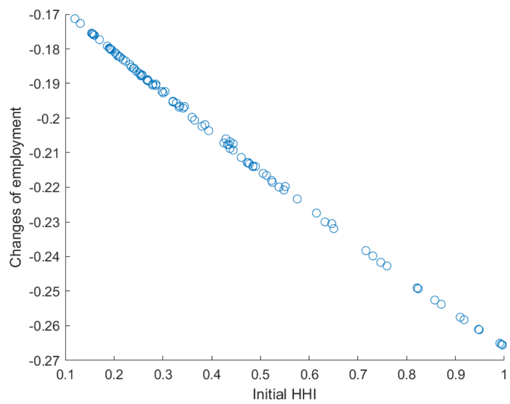
(a) Unemployment changes with flexible wages



(b) Unemployment changes with sticky wages



(c) Employment changes with flexible wages



(d) Employment changes with sticky wages

Figure A.1: The relation between changes of employment/unemployment and HHI.

These graphs show the changes in unemployment and employment in areas with different initial HHIs using the simulated data. Each observation in the simulated data has 10 firms, and there are 100 observations in total. I randomly assign firm sizes to each observation, satisfying that the initial employment in the equilibrium is the same across observations, i.e., $\sum z_i^{\left(\frac{1}{1-\alpha}\right)}$ is the same. Then, all areas face the same idiosyncratic shocks as in Section II.D, and this graph shows the expected changes of unemployment and employment. Subfigures (b) and (d) show the changes with sticky wages, i.e., wage level is fixed at the initial level regardless of negative shocks.

Table A.1: **Simulation Parameters Used in Search-matching Model.**

Symbol	Interpretation	Value	Source
h	Separation rate	0.0095	weekly frequency, Michaillat (2012)
Ψ	Efficacy of matching	0.233	Michaillat (2012)
c	Recruiting cost	0.215	Michaillat (2012)
α	Marginal returns to labor	0.65	Hsieh and Moretti (2019)
ϕ	Unemployment elasticity of matching	0.5	Petrongolo and Pissarides (2001)
β	Bargaining power of workers	0.443	Elsby and Michaels (2013)
μ	Magnitude of productivity shock	0.68	LBD, 2006-2010
s	Probability of being hit	0.46	LBD, 2006-2010

A.4 Additional Figures and Tables

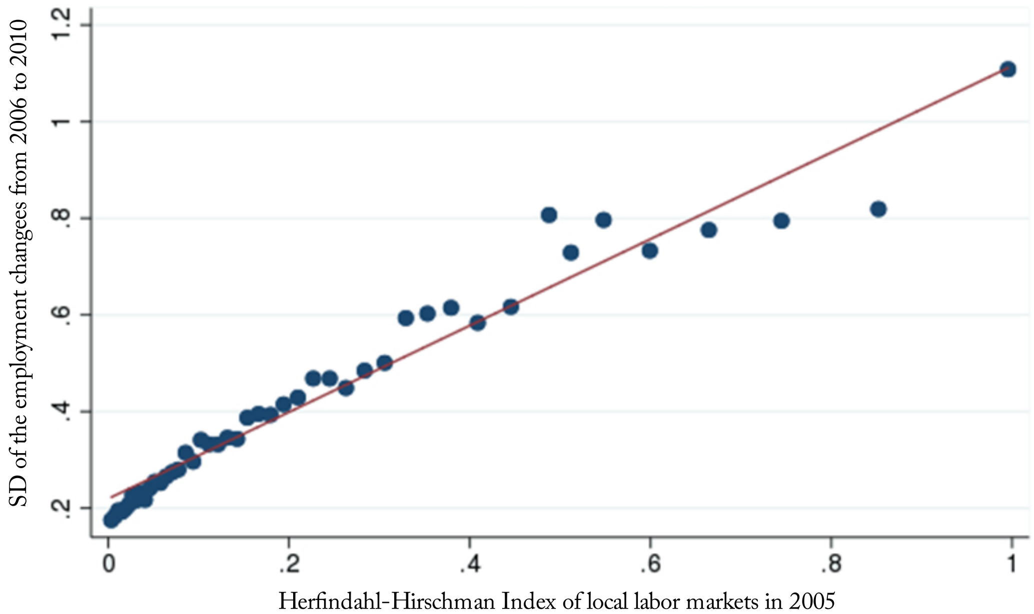


Figure A.2: Standard deviation of employment growth rate from 2006 to 2010 and Herfindahl-Hirschman Index (HHI) of local labor market in 2005.

There are about 51,500 commuting zone (CZ)-industry observations. I use the three-digit NAICS code to define the industry. I group these observations into 50 equal-sized bins based on the concentration level (HHI), compute the mean of HHI and standard deviation of employment growth rates within each bin, then create a scatter plot of these 50 bins. It also plots a linear fit line using OLS.

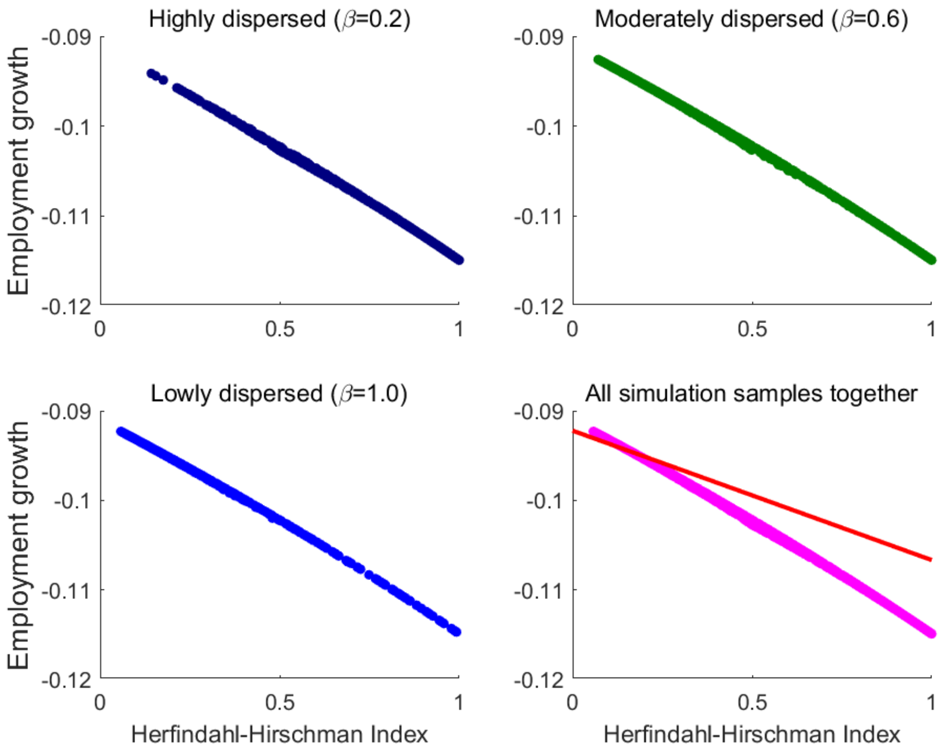


Figure A.3: Simulation results: The impact of pre-crisis HHI ($\epsilon = 1$).

These graphs show the simulation result using $\epsilon = 1$. The upper left, upper right, and lower left graphs employ different parameters in generating firm size distributions. The lower value of β corresponds to a more dispersed distribution, and usually high HHI. That is why it is more dense among high HHI in the upper left graph, and relatively sparse in the bottom left graph. Each of these three graphs includes 1,000 random samples, each of which has 20 firms. The bottom right graph packs these three graphs together and also shows the analytical solution with the red solid line.

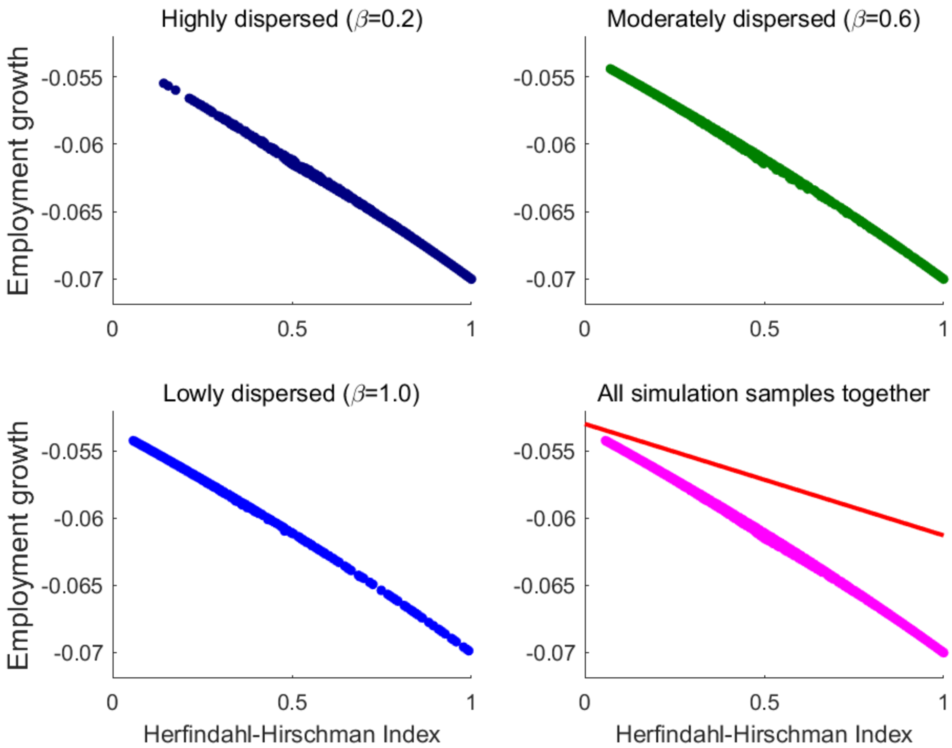


Figure A.4: Simulation results: The impact of pre-crisis HHI ($\epsilon = 2$).

These graphs show the simulation result using $\epsilon = 2$. For the details about each sub-plot, see the above note.

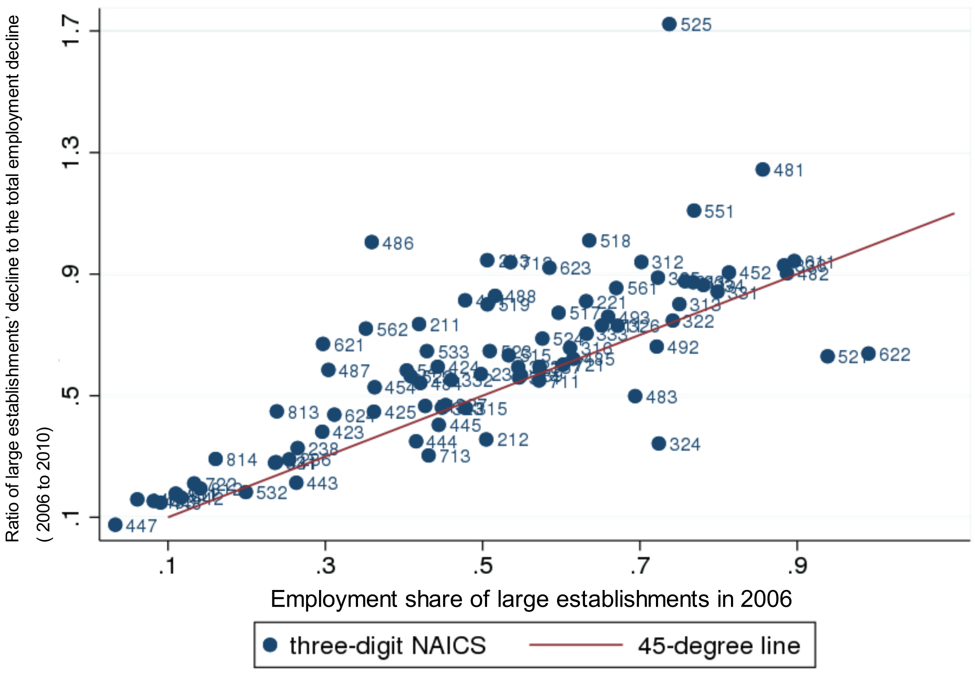


Figure A.5: Employment declines by sectors: Large vs. small firms.

This figure shows the employment declines of large vs. small establishments by three-digit NAICS industry, with employment shares of large establishments (having more than 100 workers) in 2006 in the x-axis, and the ratios of these large establishments' decline to the total employment declines from 2006 to 2010 in each industry as the y-axis. If an industry is above the 45-degree line, it means employment declined more in those large establishments during the Great Recession. In most industries, employment declines more in large establishments compared to small establishments, as most points are above the 45-degree line.

Table A.2: The Effect of HHI on Employment Growth Rate (Weighted).

	Dependent variable: Employment change from 2006 to 2010							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Herfindahl-Hirschman Index in 2005	-0.247***	-0.289***	-0.184***	-0.222***	-0.318***	-0.358***	-0.155***	-0.130***
	(0.043)	(0.050)	(0.040)	(0.051)	(0.053)	(0.058)	(0.045)	(0.046)
Log (total employment in 2005)					0.031***	0.051***	-0.042***	-0.049***
					(0.003)	(0.003)	(0.009)	(0.009)
Log (the number of establishments in 2005)					-0.026***	-0.022***	0.040***	0.050***
					(0.003)	(0.003)	(0.009)	(0.011)
Observations	51,500	51,500	51,500	51,500	51,500	51,500	51,500	51,500
Adjusted R^2	0.017	0.060	0.331	0.366	0.036	0.097	0.337	0.372
CZ FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.3: The relation between HHI and market thickness and large establishments' employment shares.

Dependent variable: Herfindahl-Hirschman Index (HHI) in 2005				
	(1)	(2)	(3)	(4)
Panel A: The relation between HHI and total employment				
Log (total employment in 2005)	-0.087***	-0.092***	-0.079***	-0.048***
	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: The relation between HHI and total number of establishments				
Log (the number of establishments in 2005)	-0.136***	-0.153***	-0.126***	-0.168***
	(0.002)	(0.002)	(0.003)	(0.003)
Panel C: The relation between HHI and employment shares of large establishments				
Employment share of establishments with 51-100 workers	-0.117***	-0.000	-0.181***	0.027***
	(0.012)	(0.009)	(0.012)	(0.007)
Employment share of establishments with 101-250 workers	-0.052***	0.072***	-0.175***	0.059***
	(0.010)	(0.007)	(0.012)	(0.006)
Employment share of establishments with more than 250 workers	0.027***	0.172***	-0.131***	0.157***
	(0.009)	(0.006)	(0.014)	(0.006)
Observations	51,500	51,500	51,500	51,500
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: The relation between Herfindahl-Hirschman Index (HHI) and firm leverage ratios.

Dependent variable:	Weighted book leverage in 2005				Weighted market leverage in 2005			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Herfindahl-Hirschman Index in 2005	-0.075***	-0.082***	-0.019***	-0.008	-0.089***	-0.112***	-0.040***	-0.024**
	(0.007)	(0.008)	(0.007)	(0.008)	(0.011)	(0.012)	(0.010)	(0.010)
Log (total employment in 2005)	0.008***	0.007***	0.001	-0.000	-0.010***	-0.018***	0.002	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Log (the number of establishments in 2005)	-0.018***	-0.020***	-0.002	0.002	-0.013***	-0.019***	-0.006**	-0.002
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	24000	24000	24000	24000	24000	24000	24000	24000
Adjusted R^2	0.007	0.005	0.362	0.366	0.020	0.024	0.435	0.439
CZ FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES

Each observation represents a CZ by industry cell. Leverage ratios are the weighted mean of leverage ratios of establishments belonging to public firms. Columns (1)-(4) use the book leverage ratio in 2005 as the dependent variable, while columns (5)-(8) use the market leverage ratio. The book leverage is defined as the ratio of the sum of debt in current liabilities (dlc) and long-term debt (dltt) to book value of assets (at), while the market leverage is the ratio of debt in current liabilities (dlc) plus long-term debt (dltt) divided by market value of debt and equity (long-term debt (dltt) plus debt in current liability (dlc) plus market value of equity (prcc_f*csho)). I also use another definition of market leverage ratio as the ratio of debt in current liabilities (dlc) plus long-term debt (dltt) to the total assets minus the book value of equity plus the market value of equity. Results using this definition of market leverage are similar to those using the first definition, so I do not report them. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.5: Control for Shares of Large Firms.

Dependent variable: Employment change from 2006 to 2010				
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	-0.221***	-0.251***	-0.157***	-0.113***
	(0.013)	(0.014)	(0.015)	(0.019)
Employment share of establishments with 51-100 workers	-0.082***	-0.066***	-0.098***	-0.116***
	(0.015)	(0.016)	(0.017)	(0.017)
Employment share of establishments with 101-250 workers	-0.114***	-0.087***	-0.124***	-0.139***
	(0.013)	(0.014)	(0.015)	(0.016)
Employment share of establishments with more than 250 workers	-0.083***	-0.050***	-0.160***	-0.183***
	(0.009)	(0.010)	(0.013)	(0.015)
Observations	51,500	51,500	51,500	51,500
Adjusted R^2	0.018	0.027	0.083	0.091
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.6: The Effect on the Change of Non-Employment: ACS full sample.

Dependent variable: Changes in non-employment (unemployment + out of labor force)

	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	0.029	0.029	-0.014	0.011
	(0.023)	(0.023)	(0.027)	(0.028)
Log (total employment in 2005)	-0.015***	-0.026***	-0.008*	-0.015***
	(0.003)	(0.004)	(0.005)	(0.005)
Log (the number of establishments in 2005)	0.021***	0.020***	0.015***	-0.004
	(0.002)	(0.002)	(0.006)	(0.007)
Observations	48,702	48,702	48,702	48,702
Adjusted R^2	0.001	0.007	0.074	0.080
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: The Effect on the Change in Unemployment.

Dependent variable: Changes in unemployment from 2007 to 2010

	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	0.419***	0.463***	0.139***	0.239***
	(0.039)	(0.037)	(0.042)	(0.043)
Log (total employment in 2005)	-0.025***	-0.098***	-0.035***	-0.070***
	(0.005)	(0.006)	(0.007)	(0.008)
Log (the number of establishments in 2005)	0.028***	0.030***	0.057***	0.004
	(0.002)	(0.002)	(0.008)	(0.007)
Observations	28,311	28,311	28,311	28,311
Adjusted R^2	0.009	0.040	0.091	0.113
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

Unemployment information comes from three-year ACS in the years 2007 (covers 2005-2007) and 2010 (covers 2008-2010). Each year consists of 3% of the total population. I drop those CZ by industry cells, if the number of interviewees in 2007 is below 30, because the information about unemployment might be imprecise if the number of interviewees is too small. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.8: The Effect on the Change in the Number of People out of the Labor Force.

	Dependent variable: Changes in the number of people who are out of the labor force from 2007 to 2010			
	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2005	0.328***	0.360***	0.195***	0.278***
	(0.030)	(0.029)	(0.031)	(0.033)
Log (total employment in 2005)	-0.066***	-0.101***	-0.053***	-0.083***
	(0.003)	(0.005)	(0.006)	(0.007)
Log (the number of estabs in 2005)	0.035***	0.037***	0.035***	0.010*
	(0.002)	(0.002)	(0.006)	(0.006)
Observations	28,311	28,311	28,311	28,311
Adjusted R^2	0.037	0.058	0.186	0.202
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

Information about people out of the labor force comes from the three-year ACS in the years 2007 (covers 2005-2007) and 2010 (covers 2008-2010). Each year consists of 3% of the total population. I drop those CZ by industry cells if the number of interviewees in 2007 is below 30, because the information about people out of the labor force might be imprecise if the number of interviewees is too small. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.9: The Effect on the Change of Non-Employment: Homeowners vs. Renters.

Dependent variable: Changes in non-employment (unemployment + out of labor force)

	(1)	(2)	(3)	(4)
Panel A: Homeowners				
Herfindahl-Hirschman Index in 2005	0.412***	0.442***	0.197***	0.278***
	(0.030)	(0.029)	(0.031)	(0.033)
Log (total employment in 2005)	-0.056***	-0.107***	-0.050***	-0.084***
	(0.003)	(0.005)	(0.005)	(0.007)
Log (the number of establishments in 2005)	0.039***	0.042***	0.045***	0.011**
	(0.002)	(0.002)	(0.006)	(0.005)
Panel B: Renters				
Herfindahl-Hirschman Index in 2005	0.360***	0.390***	0.141***	0.224***
	(0.041)	(0.041)	(0.045)	(0.047)
Log (total employment in 2005)	-0.037***	-0.096***	-0.037***	-0.067***
	(0.005)	(0.007)	(0.008)	(0.009)
Log (the number of establishments in 2005)	0.034***	0.036***	0.050***	0.011
	(0.003)	(0.002)	(0.008)	(0.008)
Observations	28,311	28,311	28,311	28,311
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

This table uses data from three-year ACS in the years 2007 and 2010 and the CBP data set. I drop those CZ by industry cells if the number of interviewees in 2007 is below 30, because the information about people out of the labor force might be imprecise if the number of interviewees is too small. Panel A uses the changes in the number of homeowners who are out of the labor force between ACS 2007 (covering years 2005-2007) and 2010 (covering years 2008-2010), while Panel B uses the changes among renters. Homeowners are less likely to move than renters, so their response to unemployment is more likely to be staying unemployed or dropping out of the labor force. The effect of HHI is higher among homeowners, although the difference is not significantly different from 0. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.10: Heterogeneity across Categories of Industry.

Dependent variable: Employment change from 2006 to 2010				
	(1)	(2)	(3)	(4)
Panel A: Tradeable				
Herfindahl-Hirschman Index in 2005	-0.138***	-0.082*	-0.131***	-0.090**
	(0.039)	(0.043)	(0.039)	(0.044)
Panel B: Non-tradeable				
Herfindahl-Hirschman Index in 2005	-0.098	-0.027	-0.123*	-0.098
	(0.067)	(0.075)	(0.067)	(0.071)
Panel C: Construction				
Herfindahl-Hirschman Index in 2005	-0.383***	-0.404***	-0.278***	-0.318***
	(0.076)	(0.078)	(0.078)	(0.082)
Panel D: Others				
Herfindahl-Hirschman Index in 2005	-0.328***	-0.328***	-0.213***	-0.246***
	(0.025)	(0.026)	(0.027)	(0.027)
Control for total employment and the number of establishments	YES	YES	YES	YES
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

I define tradeable, non-tradeable, construction, and other sectors, as in Mian and Sufi (2014). The differences between the 25th and 75th percentiles of HHI for Tradeable, Non-tradeable, Construction, and Others are 0.560, 0.133, 0.185, and 0.369 respectively. The differences between the 25th and 75th percentiles of the employment growth rate are 0.543, 0.226, 0.410, and 0.348, respectively. Thus, going from the 25th to 75th percentile could explain 9.28%, 5.77%, 14.35% and 26.08% of the variation in Tradeable, Non-tradeable, Construction, and Others, respectively. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.11: The Effect of HHI on Employment Change Caused by Entry.

Dependent variable: Employment changes caused by new entry from 2006 to 2010				
	(1)	(2)	(3)	(4)
VARIABLES				
Herfindahl-Hirschman Index in 2005	0.028***	0.005	0.020**	-0.001
	(0.007)	(0.007)	(0.008)	(0.008)
Log (employment in 2005)	-0.044***	-0.050***	-0.045***	-0.047***
	(0.001)	(0.001)	(0.002)	(0.002)
Log (the number of establishments in 2005)	0.049***	0.043***	0.055***	0.021***
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	51,500	51,500	51,500	51,500
CZ FE	NO	YES	NO	YES
IND FE	NO	NO	YES	YES

I define employment changes caused by entry as 2 * (total employment of establishments that existed in 2010 but not in 2006)/(the total employment in 2006+the total employment in 2010) for each CZ by industry cell. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.12: The Effect of Concentration Level on Employment Change during the Other Recession – 2001.

	Dependent variable: Employment change from 2001 to 2002			
	(1)	(2)	(3)	(4)
Panel A: Unweighted				
Herfindahl-Hirschman Index in 2000	0.003	-0.015	0.029**	0.007
	(0.012)	(0.013)	(0.013)	(0.013)
Log (total employment in 2000)	-0.038***	-0.043***	-0.061***	-0.064***
	(0.002)	(0.002)	(0.003)	(0.003)
Log (the number of establishments in 2000)	0.038***	0.033***	0.074***	0.029***
	(0.002)	(0.002)	(0.004)	(0.005)
Adjusted R^2	0.015	0.018	0.053	0.061
Panel B: Weighted by the total employment of each cell				
Herfindahl-Hirschman Index in 2000	-0.156***	-0.161***	-0.089**	-0.081**
	(0.050)	(0.051)	(0.035)	(0.033)
Log (total employment in 2000)	0.001	0.002	-0.025***	-0.028***
	(0.002)	(0.002)	(0.005)	(0.005)
Log (the number of establishments in 2000)	-0.004**	-0.005**	0.026***	0.025***
	(0.002)	(0.002)	(0.006)	(0.008)
Adjusted R^2	0.011	0.034	0.165	0.186
Observations	49,500	49,500	49,500	49,500
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

This sample consists of about 49,500 observations. Each observation represents a commuting zone by industry cell. The dependent variable is the employment growth rate from 2001 to 2002. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.13: The Effect of Concentration Level on Wage Change during the Other Recession – 2001.

Dependent variable: Wage change from 2001 to 2002

	(1)	(2)	(3)	(4)
Herfindahl-Hirschman Index in 2000	-0.060***	-0.053***	-0.063***	-0.061***
	(0.010)	(0.010)	(0.010)	(0.010)
Log (total employment in 2000)	0.010***	0.011***	0.009***	0.009***
	(0.001)	(0.001)	(0.002)	(0.002)
Log (the number of establishments in 2000)	-0.023***	-0.021***	-0.025***	-0.025***
	(0.002)	(0.002)	(0.003)	(0.004)
Adjusted R^2	0.004	0.005	0.021	0.022
Observations	49,500	49,500	49,500	49,500
CZ FE	NO	YES	NO	YES
Industry FE	NO	NO	YES	YES

This sample consists of about 49,500 observations. Each observation represents a commuting zone by industry cell. The dependent variable is the wage growth rate from 2001 to 2002. All standard errors are clustered at the commuting zone level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix B

Social Insurance and Entrepreneurship: The Effect of Unemployment Benefits on New-Business Formation

Additional Tables:

Table B.1: Effects of Big Changes of UI Benefits on Self-employment (Linear Probability Model).

	Switch from unemployment to self-employment			
	Max UI benefits increased by more than 20%		Decreased by more than 20%	
	(1)	(2)	(3)	(4)
Dummy - Big change of max UI benefit	-0.217	-0.071	0.434	0.093
	(0.171)	(0.190)	(0.259)	(0.308)
Big change of max UI benefit × Layoff		-0.317*		0.791*
		(0.174)		(0.452)
Layoff	-0.237**	-0.173*	-0.236**	-0.253***
	(0.089)	(0.091)	(0.089)	(0.090)
Married	0.229**	0.230**	0.229**	0.228**
	(0.090)	(0.090)	(0.090)	(0.090)
Spouse has a job	0.183**	0.183**	0.183**	0.184**
	(0.089)	(0.089)	(0.089)	(0.089)
Annual family income below $20,000	-0.001	-0.002	-0.001	-0.001
	(0.104)	(0.104)	(0.105)	(0.105)
Annual family income between $20,000 and $50,000	-0.308**	-0.309**	-0.309**	-0.309**
	(0.125)	(0.126)	(0.125)	(0.125)
Annual family income between $50,000 and $75,000	-0.417***	-0.418***	-0.418***	-0.417***
	(0.128)	(0.128)	(0.128)	(0.128)
Control for unemployment rates and demographic characteristics	YES	YES	YES	YES
State fixed effects	YES	YES	YES	YES
Year by Month fixed effects	YES	YES	YES	YES
Number of observations	252,791	252,791	252,791	252,791
Adjusted R2	0.009	0.009	0.009	0.009

This table uses CPS monthly data from 1995 to 2016. The sample includes only people who were unemployed in at least one period of the sample, and not self-employed before losing a job, so that they could be eligible for UI benefits during the unemployment period. The age restriction is between 20 and 70. I also set a restriction that unemployed people who do not switch to self-employment have to stay in the sample for at least three months after losing a job, to ensure reasonably long periods to observe their choice (results are robust without this restriction, but a little smaller in magnitude). I keep one observation for each individual, because according to the survey results I collected, UI benefits will not change once unemployed people start to receive them, which means there is no variation in UI benefit for each unemployment period. The dependent variable is equal to 100 (scaled by 100 so that we can see the coefficients more clearly) if the unemployed person switches from unemployment to self-employment, and equal to 0 if the person switches from unemployment to another option except self-employment in the sample period. Layoff is a dummy variable indicating the unemployed person falls into the categories "Job loser/On layoff" or "Other job loser," instead of "Temporary job ended," "Job leaver," "Re-entrant," or "New entrant," so Layoff likely represents the group of people who are eligible for UI benefits and thus might be affected by changes in UI benefits. Instead of using the continuous variable, log(max UI benefit), I separated the changes of UI benefits into two dummies: (1) Max UI benefit has increased by more than 20% (including 20%), and (2) Max UI benefit has decreased by more than 20% (including 20%). I then look at the effects of each dummy. All coefficients are from the linear probability model. All benefits are in 1995 dollars. The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2. I do not report these coefficients to save the space. All standard errors are clustered at state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table B.2: Effects of UI Benefits on the Duration before Switching to Self-employment.

	Self-employment	Unincorporated	Incorporated
	(1)	(2)	(3)
log (max UI benefit)	-0.755	-0.838	0.704
	(0.833)	(0.885)	(3.752)
log (max UI benefit) $\times$ Layoff	1.448*	1.597*	-0.807
	(0.800)	(0.818)	(2.643)
Layoff	-0.364	-0.546**	-0.017
	(0.238)	(0.253)	(0.629)
Married	-0.675***	-0.728***	0.403
	(0.188)	(0.184)	(0.930)
Spouse has a job	0.158	0.148	0.154
	(0.211)	(0.219)	(0.699)
Annual family income below $20,000	2.410***	2.387***	4.423***
	(0.419)	(0.448)	(1.370)
Annual family income between $20,000 and $50,000	1.182***	1.184**	2.204**
	(0.368)	(0.444)	(0.955)
Annual family income between $50,000 and $75,000	0.996***	1.083**	2.138*
	(0.364)	(0.449)	(1.185)
Control for unemployment rates and demographic characteristics	YES	YES	YES
State fixed effects	YES	YES	YES
Year by Month fixed effects	YES	YES	YES
Number of observations	6,421	5,901	604
Adjusted R2	0.085	0.087	0.055

This table uses duration before the transition to self-employment as the dependent variable. The sample includes only those who made the transition from unemployment to self-employment. Columns (2)-(3) focus on the duration before switching to unincorporated and incorporated self-employment, respectively. The same demographic variables: gender, age and education, and unemployment rates are controlled for as in the Table 2.2. I do not report these coefficients to save the space. All standard errors are clustered at state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table B.3: Questionnaire.

Question 1. Suppose an unemployed worker satisfies all of the eligibility requirements (e.g., having sufficient work history and covered earnings in the previous year) to receive UI benefits. If this person starts his/her own business, would s/he still be eligible for unemployment benefits?
Question 2. If this unemployed person can receive benefits while starting a business in your state, would s/he still need to satisfy the job search requirements?
Question 3. If this unemployed person is receiving unemployment benefits while starting a business, would the gross revenue or profit from the business affect his/her unemployment benefits? If so, how will the revenue or profit change the unemployment benefits in your state?
Question 4. If there is a change in the maximum weekly benefits or maximum duration of receiving benefits in your state, would it only apply to the new claimants or also apply to the people who claimed benefits before the change and are still receiving benefits? For example, suppose I lost my job in December of 2009, and started to receive the maximum weekly benefit in that month. In January of 2010, the maximum benefits rose. Will the benefits I received in January be increased (assuming my previous earnings were high enough)?
Question 5. If there is an increase in the maximum weekly benefit in your state, would the benefits of an unemployed worker whose benefit is below the maximum weekly benefits also increase at the same time?
Question 6. Has there been any change in the eligibility requirements discussed in question 1 since 1995 (that you are aware of)? If yes, could you briefly explain the change?

Table B.4: Variable Explanation.

Variables	Explanation
A. Labor Market Status	
Switch from unemployment to self-employment	It is equal to 1 if this unemployed person has became self-employed during the sample period, and 0 otherwise. In all the regressions, it is scaled by100.
Switch from unemployment to unincorporated self-employment (%)	It is equal to 1 if this unemployed person has started an unincorporated business during the sample period, and 0 otherwise. In all the regressions, it is scaled by100.
Switch from unemployment to incorporated self-employment (%)	It is equal to 1 if this unemployed person has started an incorporated business during the sample period, and 0 otherwise. In all the regressions, it is scaled by100.
Dummy: Layoff	It is equal to 1, if respondents report the reason as "Job loser/ on layoff ", or " Other job loser"; and equal to 0 if the reason is "Temporary job ended", " Job leaver ", "Re-entrant", or "New-entrant".
Having SEA program	It is equal to 1, if a state in that month of year has this SEA program, otherwise, it equals to 0.
Unemployment rate in the current month (%)	Unemployment rate in the month that the employed lost their job
Unemployment rate in the past 3 months (%)	Average of the unemployment rate in the past three months before the employed lost their job
Nonspecific work-search requirements	It equals to 1, if a state does not indicate the search requirments, otherwise, equals to 0.
Low work-search requirements	It equals to 1, if a state requires 0-2 employer contacts per week; equals to 0, otherwise.
High work-search requirements	It equals to 1, if a state requires 3 or more employer contacts per week; equals to 0, otherwise.
B. Unemployment Insurance Benefits	
Max UI benefit (adjusted for inflation)	It is the product of the maximum weekly benefit and the maximum duration adjusted by the monthly inflation rate.
Log (max benefit)	Log of the product of the maximum weekly benefit and the maximum duration adjusted by the monthly inflation rate.
Dummy - max UI benefits increase by more than 20%	It is equal to 1 if maximum UI benefit has increased by more than 20% in that year and that state; otherwise, equals to 0
Dummy - max UI benefits decrease by more than 20%	It is equal to 1 if maximum UI benefit has decreased by more than 20% in that year and that state; otherwise, equals to 0
C. Demographics	
Age	respondent's age
Female	respondent's gender
Have College Degree or Above	It equals to 1 if the respondent has college degree or above; equals to 0, otherwise.
Married, Spouse Present	It equals to 1 if the respondent has gotten married and their spouse is present; equals to 0, otherwise.
Spouse has a job	It equals to 1 if the respondent's spouse has a job; and 0, otherwise.
Annual family income below $20,000	It is equal to 1 if the family annual income is below $20,000; otherwsie, equal to 0.
Annual family income between $20,000 and $50,000	It is equal to 1 if the family annual income is between $20,000 and $50,000; otherwsie, equal to 0.
Annual family income between $50,000 and $75,000	It is equal to 1 if the family annual income is between $50,000 and $75,000; otherwsie, equal to 0.
Annual family income above $75,000	It is equal to 1 if the family annual income is above $75,000; otherwsie, equal to 0.
Annual family income is missing	It is equal to 1 if the family annual income is missing; otherwsie, equal to 0.

Appendix C

Caveat Emptor: The Impact of Product Line Exceptions on Firm Acquisitions and Performance

C.1 Theory Appendix

C.1.1 Period 2 decision rules

The table below summarises the optimal decision rules for end of period 2.

C.1.2 Proofs of predictions about Period 2 decisions

Proof of Lemma 1 and Corollary 1

Lemma 1: Probability of exiting for older firms (i.e., firms at the end of period 2) is higher with PLE.

Proof: Because some firms sell/exit in period 1, seller quality is not likely to be uniformly distributed in period 2. Nevertheless, assuming $\theta_B \sim U[0,1]$, and sellers match randomly with buyers for any given seller θ_s, the probability of exit for any seller conditional on their quality is given by:

For Scenario without PLE:

$$P[\text{Exit}|\theta_S] = \begin{cases} (f+\sigma\ ) & \text{if } \theta_S < f+\lambda \\ 0 & \text{if } \theta_S \geq f+\lambda \end{cases}$$

Table C.1: Decision rules and regions for end of Period 2.

Decision	Scenario without PLE	Scenario with PLE
(1) Exit if seller profit and matched buyer profit are both negative	$\theta_S - f - \lambda < 0$ and $\theta_B - f - \sigma < 0$	$\theta_S - f - \lambda < 0$ and $\theta_B - f - \lambda - \sigma < 0$
	i.e., $\theta_S < f + \lambda$ and $\theta_B < f + \sigma$. This corresponds to the blue rectangular region in the bottom left corner in Panel A of Figure 3.2.	i.e., $\theta_S < f + \lambda$ and $\theta_B < f + \lambda + \sigma$. This corresponds to the blue rectangular region in the bottom left corner in Panel B of Figure 3.2.
(2) Sell if: (a) Seller unprofitable, but matched buyer profitable	$\theta_S < f + \lambda$ but $\theta_B \geq f + \sigma$	$\theta_S < f + \lambda$ but $\theta_B \geq f + \lambda + \sigma$
	This corresponds to the red region above the blue rectangular region in Panel A of Figure 3.2.	This corresponds to the red region above the blue rectangular region in Panel B of Figure 3.2.
(b) Seller profitable, but buyer more profitable	$\theta_S \geq f + \lambda$ and $\theta_B - f - \sigma \geq \theta_S - f - \lambda$	$\theta_S \geq f + \lambda$ and $\theta_B - f - \lambda - \sigma \geq \theta_S - f - \lambda$
	i.e., $\theta_S \geq f + \lambda$ and $\theta_B \geq \theta_S + \sigma - \lambda$ This corresponds to the red region above the line defined by $\theta_B = \theta_S + \sigma - \lambda$ in Panel A of Figure 3.2.	i.e., $\theta_S \geq f + \lambda$ and $\theta_B \geq \theta_S + \sigma$ This corresponds to the red region above the line defined by $\theta_B = \theta_S + \sigma - \lambda$ in Panel B of Figure 3.2.
(3) Continue if seller profitable, and more so than matched buyer	$\theta_S \geq f + \lambda$ and $\theta_B - f - \sigma < \theta_S - f - \lambda$	$\theta_S \geq f + \lambda$ and $\theta_B - f - \lambda - \sigma < \theta_S - f - \lambda$
	i.e., $\theta_S \geq f + \lambda$ and $\theta_B < \theta_S + \sigma - \lambda$ This corresponds to the green region below the line defined by $\theta_B = \theta_S + \sigma - \lambda$ in Panel A of Figure 3.2.	i.e., $\theta_S \geq f + \lambda$ and $\theta_B < \theta_S + \sigma$ This corresponds to the green region below the line defined by $\theta_B = \theta_S + \sigma$ in Panel B of Figure 3.2.

For Scenario with PLE:

$$P[\text{Exit}|\theta_S] = \begin{cases} (f + \lambda + \sigma\ ) \text{ if } \theta_S < f + \lambda \\ 0 \qquad\qquad\quad\ \text{if } \theta_S \geq f + \lambda \end{cases}$$

Lemma 1 follows immediately from the expressions for probability of exit above –- the exit probability with PLE is greater for region $\theta_S < f + \lambda$, and the same for the other region.

Corollary 1: The probability that a firm exits at the end of period 2 is non-decreasing in liability (λ).

Proof: Follows directly from that fact that $\frac{\partial P[\text{Exit}|\theta_S]}{\partial \lambda} \geq 0$ for all θ_S, and the region with positive exit probability expands with λ.

Proof of Lemma 2 and Corollary 2

Lemma 2: The probability of continuing for older firms (i.e., firms at the end of period 2) is higher with PLE.

Proof: For Scenario without PLE:

$$P[\text{Continue}|\theta_S] = \begin{cases} 0 & \text{if} \quad \theta_S < f + \lambda \\ \theta_S + \sigma - \lambda & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

For Scenario with PLE:

$$P[\text{Continue}|\theta_S] = \begin{cases} 0 & \text{if} \quad \theta_S < f + \lambda \\ \theta_S + \sigma & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

Comparing these two probabilities yields the result that the overall probability of continuing is greater in states with PLE than other states, although it is the same for region $\theta_S < f + \lambda$.

Corollary 2: The probability that a firm continues at the end of period 2 is non-increasing in λ.

Proof: Follows from the fact that the cutoff for continuation shifts to the right, so $\frac{\partial P[\text{Continue}|\theta_S]}{\partial \lambda} \leq 0$.

Proof of Lemma 3 and Corollary 3

Lemma 3: The probability of selling for older firms (i.e., firms at the end of period 2) is lower with PLE.

Proof: For Scenario without PLE:

$$P[\text{Sell}|\theta_S] = \begin{cases} (1 - f - \sigma) & \text{if} \quad \theta_S < f + \lambda \\ 1 - (\theta_S + \sigma - \lambda) & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

For Scenario with PLE:

$$P[\text{Sell}|\theta_S] = \begin{cases} (1 - f - \sigma - \lambda) & \text{if} \quad \theta_S < f + \lambda \\ 1 - (\theta_S + \sigma) & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

Through comparing these two expressions, it is easy to see that the probability of selling is lower in states with PLE.

Corollary 3: The probability that a firm is sold (i.e., acquired) at the end of period 2 in states with PLE is non-increasing in λ.

Proof: Follows from the fact that $\frac{\partial P[\text{Sell}|\theta_S]}{\partial \lambda} \leq 0$, and the region where $\frac{\partial P[\text{Sell}|\theta_S]}{\partial \lambda} < 0$, i.e. the region $\theta_S < f + \lambda$ expands with λ.

C.1.3 Period 1 decision rules

At the end of period 1, the firm would base decisions on expected continuation value at the end of period 2, as discussed below. The firm would:

- Exit if: (a) Profit in period 2 + Expected Continuation value at end of period 2 < 0; and (b) (Period 2 +Period 3) profits of buyer < 0.

- Continue if: (a) Profit in period 2 of seller + Expected Continuation value at end of period 2 of seller > 0; and (b) Profit in period 2 of seller + Expected Continuation value at end of period 2 of seller $>$(Period 2 +Period 3) profits of buyer.

- Sell if: (a) (Period 2 + Period 3) profits of buyer $>$ Profit in period 2 of seller + Expected Continuation value at end of period 2 of seller; and (b) (Period 2 +Period 3) profits of buyer > 0.

Because decisions involve expected continuation values at end of period 2, which in turn differs between the regions $\theta_S < f + \lambda$ and $\theta_S \geq f + \lambda$ in Figure 3.2 above, it is useful to consider those cases separately.

Scenario 1: without PLE

When $\theta_S < f + \lambda$**:**

The expected value at end of period 2 evaluated at the end the first period is:
$H_2(\theta_S) \equiv E\left[CV_2|\theta_S \leq (f+\lambda)\right] = P\left[\theta_B < (f+\sigma)\right] \times E\left[CV_2|\theta_B < (f+\sigma)\right]$
$+P\left[\theta_B \geq (f+\sigma)\right] \times E\left[CV_2|\theta_B \geq (f+\sigma)\right] = (f+\sigma) \times 0 + \left[1-(f+\sigma)\right] \times$
$E[(\theta_B - f - \sigma)\,|\theta_B > (f+\sigma)] = [1-(f+\sigma)] \times \left[\frac{1+(f+\sigma)}{2} - f - \sigma\right] = \frac{[1-(f+\sigma)]^2}{2}$

- If $\theta_S < f - H_2$ & $\theta_B < f + \sigma/2$, firm chooses to exit.
- If $\theta_S < f - H_2$ & $\theta_B > f + \sigma/2$, firm would sell to the buyer.
- If $f - H_2 \leq \theta_S < f + \lambda$, firm will not exit. Instead, it chooses either continue or sell in the end of the first period. The decision depends on the relative value of continuing $(\theta_S - f + H_2)$ and selling $[2(\theta_B - f) - \sigma]$, i.e. if $\theta_B \geq A_2(\theta_S) \equiv \frac{f+H_2+\theta_S+\sigma}{2}$, firm chooses to sell, otherwise chooses to continue operating.

When $\theta_S \geq f + \lambda$**:**

The present value from period 2 is:
$J_2(\theta_S) \equiv E[CV_2|\theta_S \geq f+\lambda] = P\left[\theta_B < (\theta_S + \sigma - \lambda)\right] \times (\theta_S - f - \lambda)$
$+P\left[\theta_B \geq (\theta_S + \sigma - \lambda)\right] \times E\left[(\theta_B - f - \sigma)\,|\theta_B \geq (\theta_S + \sigma - \lambda)\right] = (\theta_S + \sigma - \lambda) \times$
$(\theta_S - f - \lambda) + [1 - (\theta_S + \sigma - \lambda)] \times \left[\left(\frac{1+\theta_S+\sigma-\lambda}{2}\right) - (f+\sigma)\right] = \frac{(\theta_S+\sigma-\lambda)^2}{2} + \frac{1-2\sigma-2f}{2}.$

Thus the equation for the boundary demarcating the sell region from the continue region is given by: $2(\theta_B - f) - \sigma \geq (\theta_S - f) + J_2(\theta_S)$, i.e., $\theta_B \geq \frac{(\theta_S+\sigma-\lambda)^2}{4} + \frac{1+2\theta_S}{4} \equiv R_2(\theta_S)$. It is easy to see the y axis values of two key points, which are also depicted in Figure 3.3:

$R_2(f+\lambda) = \frac{(f+\sigma)^2}{4} + \frac{1+2(f+\sigma)}{4} = f + \frac{H_2+\lambda+\sigma}{2}$, and $R(1) = \frac{(1+\sigma-\lambda)^2}{4} + \frac{3}{4}$

Scenario 2: with PLE

When $\theta_S < f + \lambda$

Because the seller quality is low in this case, it may be optimal for the firm to exit. Because profit in period 2 is $(\theta_S - f)$, and the per period profit for the buyer is $(\theta_B - f)$, per rule discussed above this means firm would exit only if: (a) $(\theta_S - f) + E\left[CV_2|\theta_S\right] < 0$ and (b) $2(\theta_B - f) - \sigma < 0$. Now because the firm can exit at end of period 2 with zero value, this means Expected Continuation value at end of period 2 >= 0 for all values of θ_S. Then the region for firm exit is given by $\theta_S < f - E\left[CV_2|\theta_S\right]$ & $\theta_B < f + \sigma/2$.

We define: $H \equiv E[CV_2|\theta_S \leq (f+\lambda)]$, then $H = P[\theta_B < (f+\lambda+\sigma)] \times E[CV_2|\theta_B < (f+\lambda+\sigma)] + P[\theta_B \geq \ (f+\lambda+\sigma)] \times E[CV_2|\theta_B \geq (f+\lambda+\sigma)] = (f+\lambda+\sigma) \times 0 + \ [1-(f+\lambda+\sigma)] \times E[(\theta_B - f - \lambda - \sigma)\,|\theta_B > (f+\lambda+\sigma)] = [1-(f+\lambda+\sigma)] \times \left[\frac{1+(f+\lambda+\sigma)}{2} - f - \lambda - \sigma\right] = \frac{[1-(f+\lambda+\sigma)]^2}{2}$.

- Case 1 sub-region: $\theta_S < f - H$

Then the exit region is given by $\theta_S < f - H$ & $\theta_B < f + \sigma/2$, which is the blue rectangular region in the bottom-left of Panel B of Figure 3.3.

For $\theta_S < f - H$, if the buyer quality is high enough, i.e., $\theta_B > f + \sigma/2$ (region above the blue rectangular region in Figure 3.3), the buyer firm would be profitable, so the firm would sell to the buyer.

- Case 2 sub-region: $f - H \leq \ \theta_S < f + \lambda$

For all $\theta_S \geq f - H$, the firm would not exit, but instead choose between continuing as an independent firm or sell to the buyer. When $f - H \leq \theta_S < f + \lambda$, the decision to sell happens if: (Period 2 +Period 3) profits of buyer > Profit in period 2 of seller + Expected Continuation value at end of period 2 of seller; and (b) (Period 2 +Period 3) profits of buyer >0, i.e., $2(\theta_B - f) - \sigma \geq \ \theta_S - f + H$ i.e., $\theta_B \geq \ A(\theta_S) \equiv \frac{f+H}{2} + \frac{\theta_S}{2} + \frac{\sigma}{2}$. Because $\theta_S > f - H$, the condition (b) (Period 2 +Period 3) profits of buyer >0 holds. Thus in the region $f - H \leq \ \theta_S < f + \lambda$, the line $A(\theta_S)$ demarcates the separation between region where firm continues independently, and the region where the firm sells to the buyer.

When $\theta_S \geq f + \lambda$

The decision to sell happens if: (Period 2 +Period 3) profits of buyer > Profit in period 2 of seller + Expected Continuation value at end of period 2 of seller; and (b) (Period 2 +Period 3) profits of buyer >0 i.e., $2(\theta_B - f) - \sigma \geq (\theta_S - f) + E[CV_2\ |\theta_S \geq \ f + \lambda]$ & $\theta_B > f + \sigma/2$. Suppressing the dependence on $\theta_S \geq \ f + \lambda$ and referring to figure 1 above, we get: $E[CV_2|\theta_S \geq \ f + \lambda] \equiv J(\theta_S)$ = Probability firm continues at end of Period 2 $\times$ Expected value conditional on continuing + Probability firm sells at end of Period 2 $\times$ Expected value conditional on selling $= P\left[\theta_B < (\theta_S + \sigma)\right] \times (\theta_S - f - \lambda) + P\left[\theta_B \geq (\theta_S + \sigma)\right] \times E\left[\left(\theta_B - f - \lambda - \sigma\right)|\theta_B \geq (\theta_S + \sigma)\right] = (\theta_S + \sigma) \times (\theta_S - f - \lambda) + [1 - (\theta_S + \sigma)] \times [(\frac{1+\theta_S+\sigma}{2}) - (f+\lambda+\sigma)] = \frac{\theta_S^2}{2} + \sigma\theta_S + \left[\frac{1}{2} + \frac{\sigma^2}{2} - (f+\lambda+\sigma)\right]$. Thus the equation for the boundary demarcating the sell region from the continue region is given by: $2(\theta_B - f) - \sigma \geq (\theta_S - f) + J(\theta_S)$ (The condition $\theta_B > f + \sigma/2$ will be automatically satisfied, because $(\theta_S - f) + J(\theta_S) > 0$).

$$\theta_B \geq \frac{\theta_S}{2} + \frac{f}{2} + \frac{J(\theta_S)}{2} + \frac{\sigma}{2} = \frac{\theta_S^2}{4} + \frac{(\sigma+1)\theta_S}{2} + \ \left[\frac{1}{4} + \frac{\sigma^2}{4} - \frac{\lambda}{2}\right] \equiv R(\theta_S)$$

At the two boundaries we get:
$R\left(f+\lambda\right)=f+\frac{H+\lambda+\sigma}{2}$, and $\quad R\left(1\right)=1+\frac{\sigma^2}{4}-\frac{\lambda}{2}+\frac{\sigma}{2}$.

The above expressions are shown in Figure 3.3, with the top panel showing the decision rule in states without PLE, and bottom panel with PLE.

C.1.4 Proofs of predictions about Period 1 decisions

Proof of Lemma 4 and Corollary 4

Lemma 4: Probability of exiting for younger firms is higher with PLE.

Proof: Assuming $\theta_B \sim U[0,1]$, and sellers match randomly with buyers for any given seller θ_s, the probability of exit for any seller in period 1 is given by:

For Scenario with PLE:

$$P[\text{Exit}|\theta_S]=\begin{cases}(f+\sigma/2) & \text{if} \quad \theta_S<f-H\\ 0 & \text{if} \quad \theta_S\geq f-H\end{cases}$$

For Scenario without PLE:

$$P[\text{Exit}|\theta_S]=\begin{cases}(f+\sigma/2) & \text{if} \quad \theta_S<f-H_2\\ 0 & \text{if} \quad \theta_S\geq f-H_2\end{cases}$$

Because $H_2=\frac{[1-(f+\sigma)]^2}{2}>H=\frac{[1-(f+\lambda+\sigma)]^2}{2}$, this implies $f-H_2<f-H$, so the exit probability with PLE for younger firms is greater than that without PLE.

Corollary 4: The probability that a firm exits at the end of period 1 is non-decreasing in liability (λ).

Proof: Follows directly from that fact that $\frac{\partial P[\text{Exit}|\theta_S]}{\partial\lambda}=0\ \forall\theta_S$, and the region with positive exit probability expands with λ, as $\frac{\partial H}{\partial\lambda}=-[1-(f+\lambda+\sigma)]<0$ in the scenario with PLE, while $\frac{\partial H_2}{\partial\lambda}=0$ in the scenario without PLE, since the amount of liability will not affect the decision of buyer in the end of the second period.

Proof of Lemma 5

Lemma 5: The probability of continuing for younger firms is lower with PLE if $\lambda>2\sigma$.

Proof: For Scenario with PLE:

$$P[\text{Continue}|\theta_S] = \begin{cases} 0 & \text{if} \quad \theta_S < f - H \\ A(\theta_S) & \text{if} \quad f - H \leq \theta_S < f + \lambda \\ R(\theta_S) & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

For Scenario without PLE:

$$P[\text{Continue}|\theta_S] = \begin{cases} 0 & \text{if} \quad \theta_S < f - H_2 \\ A_2(\theta_S) & \text{if} \quad f - H_2 \leq \theta_S < f + \lambda \\ R_2(\theta_S) & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

For the region, $\theta_S < f - H_2$, these probabilities are equal to 0. For the region, $f - H_2 < \theta_S < f - H$, the probability of continuing in states with PLE is 0, less than that in the states without PLE, which is $A_2(\theta_S)$. In the region, $f - H < \theta_S < f + \lambda$, since $A_2(\theta_S) = \frac{f+H_2+\theta_S+\sigma}{2} > \frac{f+H+\theta_S+\sigma}{2} = A(\theta_S)\,(H_2 > H)$, the probability of continuing is lower in states with PLE. In the region, $f + \lambda \leq \theta_S$, $R_2(\theta_S) - R(\theta_S) = \frac{\lambda(\lambda+2-2\theta_S-2\sigma)}{4} > 0$ for any θ_S if $\lambda > 2\sigma$. (We can relax this condition: $\lambda > 2\sigma$, if we can only care about the relative total area of continuing regions (green color) in Figure 4 instead of relative value of these two probabilities for each θ_S.)

Proof of Lemma 6

Lemma 6: The probability of selling for younger firms is higher with PLE if $\lambda > 2\sigma$.

Proof: For Scenario with PLE:

$$P[\text{Sell}|\theta_S] = \begin{cases} 1 - f - \sigma/2 & \text{if} \quad \theta_S < f - H \\ 1 - A(\theta_S) & \text{if} \quad f - H \leq \theta_S < f + \lambda \\ 1 - R(\theta_S) & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

For Scenario without PLE:

$$P[\text{Sell}|\theta_S] = \begin{cases} 1 - f - \sigma/2 & \text{if} \quad \theta_S < f - H_2 \\ 1 - A_2(\theta_S) & \text{if} \quad f - H_2 \leq \theta_S < f + \lambda \\ 1 - R_2(\theta_S) & \text{if} \quad \theta_S \geq f + \lambda \end{cases}$$

The arguments here follow exactly as in the previous proof, as the three regions are identical to those for the Continue decision.

C.1.5 Period 0 decision rules

We assume the timing of the entry process is as follows (see Figure 3.1): in a period 0 before the start of the first period, each seller receives a quality of management draw, θ_S. Then, they choose whether to pay an entry cost κ to enter the market. The entry decision depends on the relative value of the expected payoff of entering, i.e., $\theta_S - f + E[CV_1 \mid \theta_S]$ and the entry cost, i.e., κ, where $E[CV_1 \mid \theta_S]$ represents the expected continuation value at the end of period 1 looking forward from the beginning of period 1. In particular, potential entrants will enter the market only if:

$$\theta_S - f + E[CV_1 \mid \theta_S] > \kappa;$$

otherwise they would choose to stay out.

We discuss the decision of entry in two scenarios without and with PLE, separately below, and show that the probability of entry is lower with PLE (i.e., the cutoff productivity level θ_S is higher with PLE).

Scenario 1: without PLE

- If $\theta_S < f - H_2$, then $E[CV_1 \mid \theta_S] = (1 - f - \frac{\sigma}{2})^2$, where $H_2 \equiv E[CV_2 \mid \theta_S] = \frac{(1-f-\sigma)^2}{2}$ indexes the expected value at the end of period 2 as viewed from the end of the first period (or beginning of the second period).

  Proof: Based on the discussion about the decision rule in the end of period 1, we know that:

  - (1) If $\theta_B < f + \frac{\sigma}{2}$, then sellers exit in the end of period 1, hence $E[CV_1 \mid \theta_S] = 0$;

- (2) If $\theta_B \geq f + \frac{\sigma}{2}$, firms choose to sell to the buyers, hence $E[CV_1 \mid \theta_S] = E[2\theta_B - 2f - \sigma \mid \theta_B > f + \frac{\sigma}{2}] = 1 - f - \frac{\sigma}{2}$ (≥ 0, because $f + \frac{\sigma}{2} < \theta_B \leq 1$).

Combining these two cases together gives us:

$E[CV_1 \mid \theta_S] = Prob\{\theta_B < f + \frac{\sigma}{2}\} \times E[CV_1 \mid \theta_S, \theta_B < f + \frac{\sigma}{2}] + Prob\{\theta_B \geq f + \frac{\sigma}{2}\} \times E[CV_1 \mid \theta_S, \theta_B \geq f + \frac{\sigma}{2}] = (1 - f - \frac{\sigma}{2})^2$

- If $f - H_2 \leq \theta_S \leq f + \lambda$, then $E[CV_1 \mid \theta_S] = [1 - A_2(\theta_S)] \times [1 + A_2(\theta_S) - 2f - \sigma] + A_2(\theta_S)(\theta_S - f + H_2)$, where $A_2(\theta_S) \equiv \frac{f+H_2+\theta_S+\sigma}{2}$ represents the boundary demarcating the sell region from the continue region in the end of period 1.

  Proof: From the decision rule in period 1, we know that:

  - (1) If $\theta_B \geq A_2(\theta_S)$, firms choose to sell, hence the expected value is: $2E[\theta_B \mid \theta_B \geq A_2(\theta_S)] - 2f - \sigma = 1 + A_2(\theta_S) - 2f - \sigma$;
  - (2) If $\theta_B < A_2(\theta_S)$, firms choose to continue, and the expected value becomes: $\theta_S - f + E[CV_2 \mid \theta_S] = \theta_S - f + H_2$.

  Hence, we have the expected value in this scenario:

  $E[CV_1 \mid \theta_S] = Prob\{\theta_B \geq A_2(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B \geq A_2(\theta_S)] + Prob\{\theta_B < A_2(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B < A_2(\theta_S)] = [1 - A_2(\theta_S)] \times [1 + A_2(\theta_S) - 2f - \sigma] + A_2(\theta_S)(\theta_S - f + H_2)$.

- If $\theta_S \geq f + \lambda$, then $E[CV_1 \mid \theta_S] = [1 - R_2(\theta_S)][1 + R_2(\theta_S) - 2f - \sigma] + R_2(\theta_S)[\theta_S - f + J_2(\theta_S)]$, where $R_2(\theta_S) \equiv \frac{(\theta_S+\sigma-\lambda)^2+1+2\theta_S}{4}$, indexes the boundary between the selling and continuing regions, and $J_2(\theta_S) \equiv E[CV_2 \mid \theta_S] = \frac{(\theta_S+\sigma-\lambda)^2}{2} + \frac{1-2\sigma-2f}{2}$, represents the present value from the end of period 2.

  Proof: Based on the decision rule in the end of period 1, we know that in this scenario:

  - (1) If $\theta_B \geq R_2(\theta_S)$, firms choose to sell, and its expected payoff is: $2E[\theta_B \mid \theta_B \geq R_2(\theta_S)] - 2f - \sigma = 1 + R_2(\theta_S) - 2f - \sigma$;
  - (2) If $\theta_B < R_2(\theta_S)$, firms choose to continue in the end of period 1, and then expected overall payoff is: $\theta_S - f + J_2(\theta_S)$.

  Hence, in this case:

  $E[CV_1 \mid \theta_S] = Prob\{\theta_B \geq R_2(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B \geq R_2(\theta_S)] + Prob\{\theta_B < R_2(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B < R_2(\theta_S)] = [1 - R_2(\theta_S)] \times [1 + R_2(\theta_S) - 2f - \sigma] + R_2(\theta_S)(\theta_S - f + J_2(\theta_S))$.

Thus, for the scenario without PLE, we get:

$$E[CV_1 \mid \theta_S] = \begin{cases} (1-f-\frac{\sigma}{2})^2 & \text{if} \quad \theta_S < f - H_2 \\ A_2(\theta_S)^2 - 2f - \sigma + 1 & \text{if} \quad f - H_2 \leq \theta_S < f + \lambda \\ 1 - 2f - \sigma + R_2(\theta_S)^2 & \text{if} \quad \theta_S \geq f + \lambda \end{cases} \tag{C.1}$$

Scenario 2: with PLE

Here we use notation $E_p[\ ]$ to denote expectations in the regime with PLE.

- If $\theta_S < f - H$, then $E_P[CV_1 \mid \theta_S] = (1-f-\frac{\sigma}{2})^2$, where $H \equiv E_P[CV_2 \mid \theta_S] = \frac{(1-f-\sigma-\lambda)^2}{2}$ indexes the expected value of period 2 standing in the first period.

  Proof: Based on the discussion about the decision rule in the case with PLE in the end of period 1, we know that:

  - (1) If $\theta_B < f+\frac{\sigma}{2}$, then sellers exit in the end of period 1, hence $E[CV_1 \mid \theta_S] = 0$;
  - (2) If $\theta_B \geq f+\frac{\sigma}{2}$, firms choose to sell to the buyers, hence $E[CV_1 \mid \theta_S] = E[2\theta_B - 2f - \sigma \mid \theta_B > f + \frac{\sigma}{2}] = 1 - f - \frac{\sigma}{2}$ (≥ 0, because $f + \frac{\sigma}{2} < \theta_B \leq 1$).

  Combining these two cases together gives us:

  $E[CV_1 \mid \theta_S] = Prob\{\theta_B < f+\frac{\sigma}{2}\} \times E[CV_1 \mid \theta_S, \theta_B < f+\frac{\sigma}{2}] + Prob\{\theta_B \geq f+\frac{\sigma}{2}\} \times E[CV_1 \mid \theta_S, \theta_B \geq f+\frac{\sigma}{2}] = (1-f-\frac{\sigma}{2})^2$

- If $f - H \leq \theta_S < f + \lambda$, then $E_P[CV_1 \mid \theta_S] = [1 - A(\theta_S)] \times [1 + A(\theta_S) - 2f - \sigma] + A(\theta_S)(\theta_S - f + H)$, where $A(\theta_S) \equiv \frac{f+H+\theta_S+\sigma}{2}$ represents the boundary demarcating the sell region from the continue region in the end of period 1.

  Proof: From the decision rule in period 1, we know that:

  - (1) If $\theta_B \geq A(\theta_S)$, firms choose to sell, hence the expected value is: $2E[\theta_B \mid \theta_B \geq A(\theta_S)] - 2f - \sigma = 1 + A(\theta_S) - 2f - \sigma$;
  - (2) If $\theta_B < A(\theta_S)$, firms choose to continue, and the expected value becomes: $\theta_S - f + E_P[CV_2 \mid \theta_S] = \theta_S - f + H$.

  Hence, we have the expected value in this scenario:

$E_P[CV_1 \mid \theta_S] = Prob\{\theta_B \geq A(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B \geq A(\theta_S)] + Prob\{\theta_B < A(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B < A(\theta_S)] = [1 - A(\theta_S)] \times [1 + A(\theta_S) - 2f - \sigma] + A(\theta_S)(\theta_S - f + H)$.

- If $\theta_S \geq f + \lambda$, then $E_P[CV_1 \mid \theta_S] = [1 - R(\theta_S)][1 + R(\theta_S) - 2f - \sigma] + R(\theta_S)[\theta_S - f + J(\theta_S)]$, where $R(\theta_S) \equiv \frac{\theta_S^2 + 2(\sigma+1)\theta_S + 1 + \sigma^2 - 2\lambda}{4}$, indexes the boundary between the selling and continuing regions, and $J(\theta_S) \equiv E_P[CV_2 \mid \theta_S] = \frac{\theta_S^2 + 2\sigma\theta_S + 1 + \sigma^2 - 2f - 2\lambda - 2\sigma}{2}$, represents the present value from the end of period 2.

  Proof: Based on the decision rule in the end of period 1, we know that in this scenario:

  - (1) If $\theta_B \geq R(\theta_S)$, firms choose to sell, and its expected payoff is: $2E[\theta_B \mid \theta_B \geq R(\theta_S)] - 2f - \sigma = 1 + R(\theta_S) - 2f - \sigma$;
  - (2) If $\theta_B < R(\theta_S)$, firms choose to continue in the end of period 1, and then expected overall payoff is: $\theta_S - f + J(\theta_S)$.

  Hence, in this case:

  $E_P[CV_1 \mid \theta_S] = Prob\{\theta_B \geq R(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B \geq R(\theta_S)] + Prob\{\theta_B < R(\theta_S)\} \times E[CV_1 \mid \theta_S, \theta_B < R(\theta_S)] = [1 - R(\theta_S)] \times [1 + R(\theta_S) - 2f - \sigma] + R(\theta_S)(\theta_S - f + J(\theta_S))$.

Simplify these formulas, for the scenario with PLE we get:

$$E_P[CV_1 \mid \theta_S] = \begin{cases} (1 - f - \frac{\sigma}{2})^2 & \text{if} \quad \theta_S < f - H \\ A(\theta_S)^2 - 2f - \sigma + 1 & \text{if} \quad f - H \leq \theta_S < f + \lambda \\ 1 - 2f - \sigma + R(\theta_S)^2 & \text{if} \quad \theta_S \geq f + \lambda \end{cases} \tag{C.2}$$

Lemma 7: The entry rate is lower in the regime with PLE relative to the regime without PLE, if the entry cost (κ) is high enough.

Proof:

Examining expressions in equation C.1 (scenario without PLE) to that in equation C.2 (scenario with PLE):

- Case 1: If $f + \kappa - (1 - f - \frac{\sigma}{2})^2 < 0$, then the entry constraint is not binding, so then all potential entrants do enter, and the entry rate would be the same across regimes.

- Case 2: If $f + \kappa - (1 - f - \frac{\sigma}{2})^2 > 0$ and $f + \kappa - (1 - f - \frac{\sigma}{2})^2 < f - H_2$, then the entry constraint is binding, but then the same fraction of firms with $\theta_S < f + \kappa - (1 - f - \frac{\sigma}{2})^2$ will choose not to enter in both regimes with and without PLE, so the entry rate is the same across regimes.

- Case 3: If $f + \kappa - (1 - f - \frac{\sigma}{2})^2 \geq f - H_2$, then the fraction of entrants differs across regimes with and without PLE. Because $H < H_2$, $A(\theta_S) < A_2(\theta_S)$, and $R(\theta_S) < R_2(\theta_S)$, it follows that $E_P[CV_1 \mid \theta_S] \leq E[CV_1 \mid \theta_S]$. Then because only those potential entrants with $\theta_S > f + \kappa - E[CV_1 \mid \theta_S]$ (in the regime without PLE, and $\theta_S > f + \kappa - E_P[CV_1 \mid \theta_S]$ in the regime with PLE), choose to enter the market, it follows that the entry rate is lower in the regime with PLE relative to the one without PLE.

A technical note: If κ is high enough that entry rate is lower with PLE (i.e., if $f + \kappa - (1 - f - \frac{\sigma}{2})^2 \geq f - H_2$), then given the assumption we have that θ_S is fixed over time we get the implication that there would be no exit in the end of period 2 in the regime without PLE, because those sellers with $\theta_S < f - H_2$ already chose not to enter the market in period 0. This does not impact the results derived earlier as they hold even if a slice of the sub-figures in Figure 1 and 2 for low θ_S is removed. More generally, we could assume a mean zero shock to the management quality occurs at the end of period 1 and period 2, such that forward looking (linear) expectations and hence all of the results stay unchanged, but there is full support over [0,1] for θ_S at the end of both period 1 and period 2.

C.2 Additional Figures and Tables

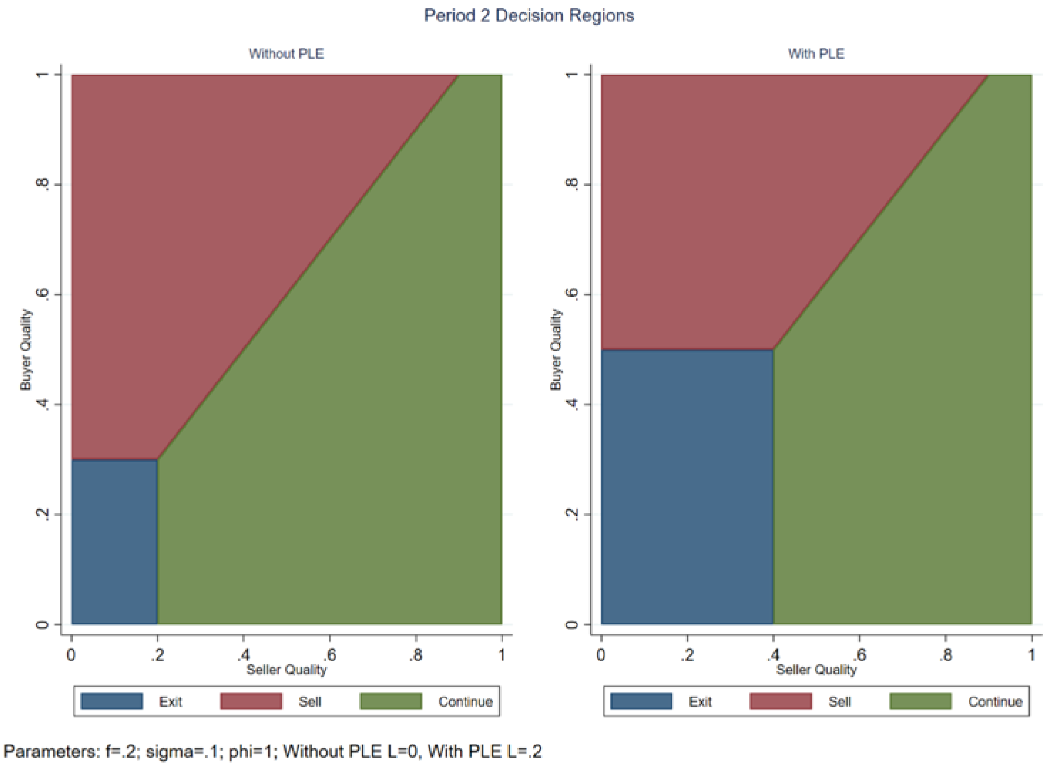


Figure C.1: Simulation results for old firms (firms in period 2)

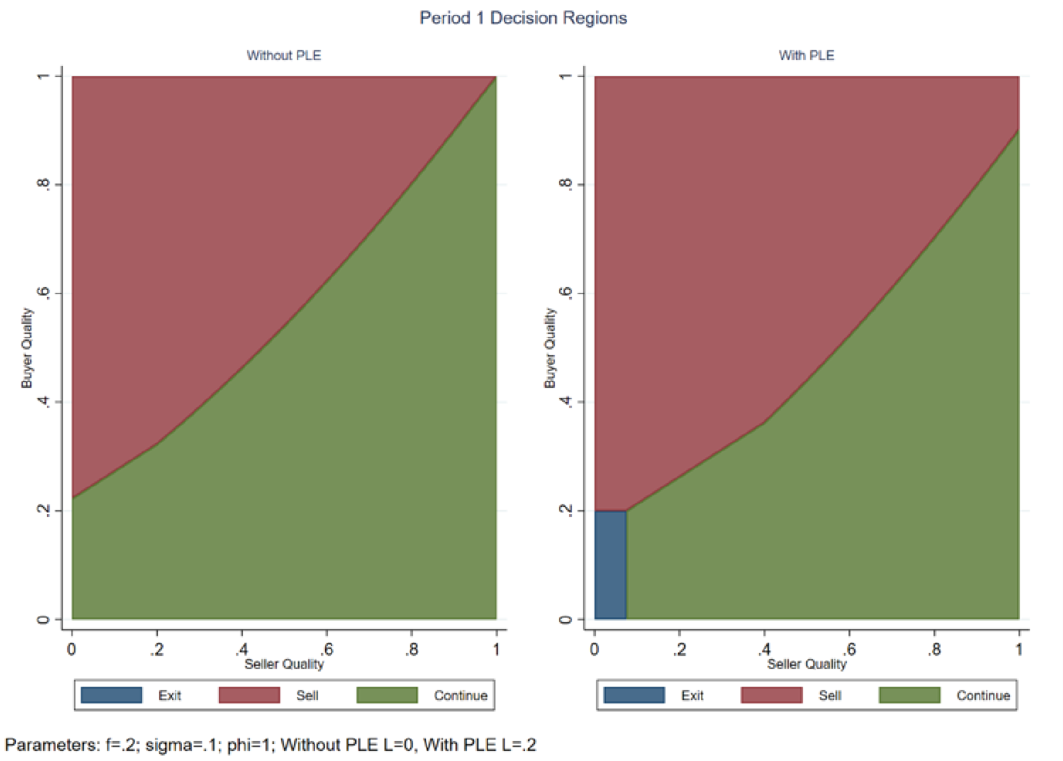


Figure C.2: Simulation results for young firms (firms in period 1)

Table C.2: State Adoption of Production Liability Exemption.

State	Year	Case	Share of national manufacturing employment (2000)	Share of national aggregate employment (2000)
California	1977	Ray v. Alad Corp., 560 P.2d 3, 10 (Cal. 1977)	10.70%	11.40%
Connecticut	1996	Sullivan v. A.W. Flint Co., No. CV 920339263	1.40%	1.40%
New Jersey	1981	Ramirez v. Amsted Indus., Inc., 431A.2d 811	2.40%	3.10%
New Mexico	1997	Garcia v. Coe Mfg. Co., 933 P.2d 243, 248-50	0.20%	0.50%
Pennsylvania	1981	Dawejko v. Jorgensen Steel Co., 434 A.2d 106	4.90%	4.50%
Washington	1984	Martin v. Abbott Labs., 689 P.2d 368	1.90%	2.00%
Total			21.50%	22.90%

This table is constructed from information in footnote 20 of Frost (2007), crosschecked with the detailed appendix in Kuney 2013. The shares of manufacturing and aggregate employment are based on County Business Patterns data for year 2000.

Table C.3: Taxonomy of Types of Successor Liability, per Kuney (2013).

Type	Key cases and tests
(1) Intentional Assumption of Liabilities	1) [Kessinger v. Grefco, Inc., 875 F.2d 153, 154 (7th Cir. 1989)]:Asset purchaser impliedly assumed a seller's unforeseen liability for certain tort claims where the purchaser agreed "to pay, perform and discharge all debts, obligations, contracts and liabilities" of the seller); · [Carlos R. Leffler, Inc. v. Hutter, 696 A.2d 157 (Pa. Super. Ct. 1997)]: Asset purchaser impliedly assumed a liability where other liabilities were expressly assumed). · [Schwartz v. Pillsbury, Inc., 969 F.2d 840, 845 (9th Cir. 1992)]: Asset purchaser that acquired franchiser did not expressly or impliedly assume seller's tort liability when acquisition agreement expressly limited obligations assumed to certain specified contracts and agreements of seller;
(2) Fraudulent Schemes to Escape Liability	[Schmoll v. ACandS, Inc., 703 F. Supp. 868, 873 (D. Or. 1988)]: Corporate restructuring was undertaken to avoid liabilities from asbestos claimants and imposing liability on transferee [Reddy v. Gonzalez, 8 Cal. App. 4th 118, 122 (1992): Under Uniform Fraudulent Transfer Act actual intent and inadequate consideration are alternative requirements for successor liability based upon fraudulent transfer
(3) de facto Merger	Five factor test for de facto merger [Marks v. Minn. Mining & Mfg. Co., 187 Cal. App. 3d 1429, 1435–36 (Cal. Ct. App. 1986)]: 1) consideration paid for the assets solely belonging to the purchaser or its parent; 2) continues the same enterprise after the sale; 3) shareholders of the seller corporation become shareholders of the purchaser; 4) the seller liquidates; and 5) the buyer assumes the liabilities of the seller necessary to carry on the business)
(4) The Continuity Exceptions: Mere Continuation and Continuity of Enterprise	Mere continuation successor liability [Stanford Hotel Co. v. M. Schwind Co., 181 P. 780 (Cal. 1919)]: 1) no adequate consideration was given for the acquired assets, and 2) where one or more persons were officers, directors, or stockholders of both corporations) Continuation of Enterprise successor liability [Turner v. Bituminous Cas. Co., 244 N.W.2d 873, 882 (Mich. 1976)]: Four considerations: 1) there is a continuity of management, personnel, physical location, assets, and general business operations 2) the seller corporation ceases its ordinary business operations, liquidates, and dissolves as soon as legally and practically possible 3) the purchasing corporation assumes those liabilities and obligations of the seller ordinarily necessary for the interrupted continuation of normal business operations of the seller corporation 4) The purchasing corporation [holds] itself out to the world as the effective continuation of the seller corporation.
(5) The Product Line Exception	[Ray v. Alad Corp., 560 P.2d 3 (Cal. 1977)]: Following "justifications" for imposing liability: 1) the virtual destruction of the plaintiff's remedies against the original manufacturer caused by the successor's acquisition of the business, 2) the successor's ability to assume the original manufacturer's risk-spreading role, and 3) the fairness of requiring the successor to assume a responsibility for defective products that was a burden necessarily attached to the original manufacturer's goodwill being enjoyed by the successor in the continued operation of the business

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