Job Loss and the Distributional Effects of Self-Employment Spells

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Abstract

It is well established that job loss has a negative impact on workers' career trajectories, but little is known about the mediating effect of transitions into self-employment. Using a rich data set of the universe of formal employment records in Brazil matched with detailed data on business ownership, I leverage mass displacement events to investigate the link between job loss, self-employment, and reemployment. I focus my analysis around a policy change in 2009 that significantly reduced barriers to microenterprise formation (i.e. formal self-employment). Prior to the policy change, the self-employment path after a job dismissal was primarily followed by high-income workers. After the reform, low-income workers closed one-third of this gap. While both high- and low-income workers who take the self-employment path are 63-65p.p. less likely to return to wage employment, there are significant distributional effects for those who eventually do return. High-income workers face a wage penalty of 12 log points, while the estimates are non-significant for low-income workers, who are partially shielded from large losses due to minimum wage regulations. The 2009 policy change, while making formal self-employment more attractive, does not appear to alter these reemployment patterns. My results are consistent with self-employment being an important option for distressed workers facing job loss, especially those at the bottom of the income distribution.

Keywords: job loss; wages; self-employment; business registration.
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1 Introduction

It is well established that job loss has a negative impact on workers' career trajectories, with displaced individuals often facing persistently lower wages and employment probabilities. Among the factors behind such finding lie the loss of firm-specific capital workers had accumulated with their pre-displacement firms (e.g., Topel 1990, Jacobson et al. 1993, Lachowska et al. 2020), workers moving into lower-paying firms (e.g., Bertheau et al. 2022, Schmieder et al. 2023), and a potential low-ability signal that hiring firms might infer from displaced workers (e.g., Gibbons and Katz 1991). Exploring unemployment insurance extensions, Schmieder et al. (2016) also show that non-employment duration is positively associated with wage losses, implying that workers' path in-between two wage employment spells matters for their reemployment outcomes.

In this paper, I focus on an additional trajectory also potentially shaping these wage employment outcomes: transitions to formal self-employment following a job loss. More specifically, I estimate the causal effect of job loss on self-employment decisions and its correlation with observed employment outcomes after reentry into wage employment. My analysis is focused on Brazil, a country which implemented a legislation change in 2009 that created a new business registration format for self-employed workers, reducing the paperwork associated with opening a new firm and providing business owners with some social security benefits. It led to the creation of 23 million registered self-employed businesses between 2009 and 2023. Hence, in this paper, I also aim to explore the differences between the periods before and after the 2009 legislation change, shedding light upon the effects of reduced barriers to formalization on wage employment and self-employment dynamics.

I combine administrative data on the universe of job contracts in Brazil with identified data on business ownership (including formal self-employed workers), constructing a panel that allows me to track individuals through transitions to different occupational statuses. To identify the effects of job displacement on self-employment decisions, I leverage mass displacement events, which I define as establishment-level employment changes due to firings of at least 30 percent between two consecutive years. To ensure an appropriate comparison group to mass displaced workers, I match them with non-displaced individuals using observed covariates from the year immediately before the mass displacement event.

Two results emerge when exploring event study specifications around mass displacement events, comparing workers who face a job separation to those who do not. First, for workers displaced in 2007 and 2008 (prior to the 2009 policy change), I report a .31 percentage-point increase in the probability that workers transition to formal self-employment in the year of job separation. However, upon comparing the effects across quartiles of the pre-displacement wage distribution, I show a .79p.p. displacement effect for high-income workers, while point estimates for low-income workers are small and statistically not significant. Second, for workers displaced in 2012 and 2013 (after the 2009 policy change and excluding an implementation period), the displacement effect amounts to .67p.p. This rise in formal self-employment after job loss is primarily attributed to firm ownership under the format introduced by the 2009 legislation change. Furthermore, the displacement effect is now of .57p.p. for low-income workers, compared to 1.54p.p. for high-income workers. Taken together, these results indicate that formal self-employment is a relevant option for displaced workers, but it was only after the 2009 policy change that low-income individuals also started to follow this path.

Motivated by the finding that the reform had heterogeneous impacts across the wage distribution, I proceed to understand the differential consequences of formal self-employment spells. I show that workers who transition to formal self-employment following a job loss are around 66 to 68p.p. less likely to return to wage employment (on top of a 82 percent probability for workers who do not open any firm), with small differences between high- and low-income workers, self-employment formats, and across periods.

I then evaluate wages at reentry, conditional on workers returning to wage employment. Using a wage change measure that takes into account the trajectory of non-displaced workers, I reveal that high-income workers who take the self-employment path face a wage penalty of 12 log points. In contrast, for low-income workers, the correlation between self-employment and reemployment wages is marginal and often statistically non-significant. I provide suggestive evidence that the existence of minimum wage regulations greatly reduces the extent to which low-income workers can be penalized following a job loss. I also show that, although the 2009 reform increased the attractiveness of formal self-employment, it does not appear to have altered these patterns.

Lastly, I show that the negative correlation between self-employment and reemployment wages for high-income workers appears to be associated with individuals who, based on observed covariates, would typically be expected to be successful self-employed workers (those with higher education, managerial experience, and available resources). I also report that, among these workers, self-employment spells lead to reentry into occupations with lower skill demands. This finding is consistent with the erosion of human capital during the time high-income workers spend in self-employment. Other potential mechanisms are: (i) a negative selection of MEI owners based on unobservable characteristics; and (ii) a negative signaling effect upon returning to wage employment. I leave it to future versions of this paper to further explore these potential explanations.

I relate my work to two main areas of research. First, I contribute directly to the extensive literature exploring the consequences of job displacement. The previously cited papers by Topel (1990), Gibbons and Katz (1991), Jacobson et al. (1993), Lachowska et al. (2020), Bertheau et al. (2022), Schmieder et al. (2023), and Schmieder et al. (2016) are complemented by Menezes-Filho and Fernandes (2004), who report similarly adverse effects of job loss on labor market outcomes in Brazil. The negative outlooks also extend to dimensions such as domestic violence (Bhalotra et al. 2021), criminality (Britto et al. 2022), and health (Amorim et al. 2023, Fontes et al. 2023), in all cases affirming the detrimental effects of job loss in the Brazilian context.

Second, I add to the literature on the consequences of self-employment spells for workers' labor market outcomes. While most papers indicate that self-employed workers face negative outcomes in wage employment (Failla et al. 2017, in Denmark; Bruce and Schuetze 2004, in the US; Koellinger et al. 2015, in the UK), a more nuanced result is found in other contexts. Kaiser and Malchow-Møller (2011) show that the lower wages for Danish ex-entrepreneurs is attributable to their higher likelihood of switching sectors. Hyytinen and Rouvinen (2008) reveal that lower wages are driven by negative selection into and out of self-employment in Europe. Baptista et al. (2012), while also stressing a negative wage effect for entrepreneurs transitioning to wage employment in the context of Portugal, show that they tend to hold positions higher up the job ladder in the wage sector. The positive effects seem to be concentrated in high-skilled entrepreneurs, such as those in the semiconductor industry in the US (Campbell 2013), in more broadly defined innovative sectors (Luzzi and Sasson 2016), or in technical and professional activities (Daly 2015).

My work lies at the intersection of these two strands of the literature. I refocus the discussion on the consequences of job loss to an additional and often overlooked dimension: self-employment spells. This paper highlights both the mediating effects of the self-employment trajectory in shaping the well-documented negative consequences of job loss and the changes brought about by a massive policy change that reduced the costs associated with opening and running self-employment businesses. Additionally, in the literature on the consequences of self-employment spells, to the best of my knowledge, there are no papers exploring the consequences of displacement-driven self-employment spells on wage employment outcomes. Most similar to my paper is Mahieu et al. (2022), who show that Norwegian self-employed workers returning to the labor market earn 27% less than their matched counterparts. The data sets I use in this paper allow me to focus on job loss (instead of job separations more broadly) and leverage mass displacement events for identification.

I also speak to papers exploring workers' coping strategies after job loss. Gerard and Naritomi (2021) show that laid off Brazilian workers rapidly tap into their severance pay accounts, while Andersen et al. (2023) reveal that reduced consumption and lowered accumulation of liquid assets account for 80% of workers' adjustment to the negative income shock among households in Denmark. The role of private savings after a job loss is also stressed by Basten et al. (2016) in the case of Norway. My paper highlights self-employment as an additional channel through which workers might buffer the displacement shock, while at the same time exploring its consequences on wage employment outcomes.

Next, I contribute to the literature on the effects of policies targeted at business formalization. While a meta-analysis in Floridi et al. (2020) points towards interventions being mostly ineffective at promoting increased registration, Jessen and Kluve (2021) combine 170 impact estimates to argue that such policies can be successful. These two papers find common ground when indicating that large-scale policies coupled with clear benefits to formalization tend to be more successful. My paper not only highlights a legislation change that falls along such lines and led to a sharp increase in formal business registration in Brazil, but also extends the analysis to explore potential unintended consequences of such policies in the labor market.

Finally, this paper adds to the growing literature that explores entrepreneurship, self-employment, and the 2009 business registration reform in Brazil. Nunes (2023) employs the same data sets and empirical strategy. However, it does not evaluate formal self-employment but focuses solely on the creation of larger firms, observing an increase in entrepreneurship following displacement events. The consequences of displacement-driven self-employment spells to workers' career trajectories are also unaddressed. Another pertinent study is Rocha and de Farias (2022), revealing that the 2009 policy change promoted the formalization of self-employed workers but did not increase their aggregate number (that is, combining formal and informal businesses). In the same context, Alvarez (2023) shows a decrease in formal wage employment contracts in regions with a higher number of new firms created under the format introduced in 2009. Her findings are backed by both an instrumental variable approach and a structural heterogeneous agents model.

This paper proceeds as follows. In Section 2, I characterize self-employment in Brazil and the 2009 reform that led to changes in firm creation for self-employed workers. In Section 3, I first present the two main data sets used in this paper and then outline the sample derived from the mass displacement design and summarize its main characteristics. In Section 4, I outline the paper's empirical strategy and, in Section 5, I discuss its findings. Finally, Section 6 concludes.

2 Self-Employment and Firm Ownership in Brazil

Self-employed individuals represent an important fraction of the workforce in many countries, having become a focal policy topic. Boeri et al. (2020) report an increase in self-employment in OECD countries, which now accounts for a substantial proportion of total employment (ranging from 4 to 22 percent). Fields (2019) also show that self-employed workers are a large share of the workforce in emerging economics, ranging from over 70 percent in Sub-Saharan Africa to approximately 30 percent in the Latin American and the Caribbean. In Brazil, between 2003 and 2009, self-employed workers and employers constituted approximately 23% and 4% of the active workforce, respectively. However, due to Brazil's pervasive informality, many of these individuals never formalized their businesses. To address this issue, Brazil enacted new legislation in 2009 allowing businesses with at most one employee to be constituted under a format called *Micro-Empreendedor Individual* (MEI) or *Individual Micro-Entrepreneur*. This change aimed to reduce the burden associated with formal business ownership and extend certain social security benefits to business owners.

The attractiveness of the MEI model rests on three main differentials. Firstly, registering a MEI firm is a straightforward online process, often requiring a single form to be completed. By contrast, in 2013, the typical time to start a business in Brazil stood at 83 days, according to the World Bank. Secondly, operating a MEI firm does not necessitate the involvement of an accountant for tax compliance, as the firm is subject to a fixed monthly tax of approximately R$50, regardless of revenue.[1] Thirdly, MEI owners enjoy social security benefits, including maternity leave, sickness benefits, and retirement benefits.[2] A 2019 survey revealed that access to social security benefits ranked as the most commonly cited motivation to open a MEI firm. Additionally, complying with regulations, issuing invoices, and accessing the banking system were also cited as incentives for individuals (Sebrae 2019).[3]

[1]The monthly tax is equivalent to 5% of the national minimum wage plus an additional fee from R$1 to R$6 depending on the nature of thhe business activity. The minimum wage is adjusted annually.

[2]MEI owners enjoy social security benefits after a waiting period (10 months for maternity leave; 12 months for sickness benefits and ill-health retirement benefits; and 180 months for general retirement benefits), discouraging workers to strategically open a MEI firm to claim benefits for pre-existing or anticipated conditions.

[3]MEI firms have also been used as an alternative method of hiring employees in Brazil. In such cases, individuals who would otherwise be formal employees establish MEI firm and work as contractors, avoiding certain taxes and labor protection regulations. This phenomenon was less significant in the period I evaluate in this paper, since outsourcing many activities was not allowed before a labor reform in 2017. After the reform, although employment relationships satisfying some criteria (e.g., being under the control of another party, being carried out personally by the worker, requiring the payment of remuneration to the worker, and having a certain continuity) mandate the hiring of a formal employee, a legal grey area has led to the widespread use of MEI firms as a hiring tool in Brazil.

MEI firms are limited to specific sectors listed by the national tax authority, primarily encompassing activities that do not require formal education (that is, do not require a college degree) and rely heavily on manual skills. Examples include hairdressers, construction workers, administrative assistants, advertisers, photographers, and gardeners. MEI owners are not allowed to own other firms (whether MEI or not), but they can simultaneously hold a formal job as an employee in another organization. To maintain the MEI status, firms' annual revenues were capped at R$36,000 from 2009 to 2011 and subsequently raised to R$ 60,000 from 2011 to 2017.[4] Businesses which do not meet these conditions have the option to be established under alternative legal formats.

Since their introduction in 2009, MEI firms have gained widespread adoption. In particular, they have been largely used as the registration format for self-employed workers, since as of 2017, a remarkable 98.6% of MEI firms had no employees. Figure 1 shows an important shift in the number of firm openings in Brazil. From 2003 until 2009, it ranged between 500,000 and 1 million new businesses each year. However, this figure increased sharply after 2009, peaking at more than 2.5 million new firms in 2016. This surge was driven by MEI firms, which now account for three out of four new firm openings in Brazil. The number of firm openings under alternative legal formats has remained relatively stable.

Figure 2 displays the geographical distribution of different types of firms in Brazil before and after the policy introducing MEI firms. For each microregion, I calculate the per capita number of firms (either large, self-employed non-MEI, or self-employed MEI) using firm ownership data from the Receita Federal Firm Registry (see Section 3 below) and population data from IBGE (*Instituto Brasileiro de Geografia e Estatística*), the official statistics agency in Brazil. I categorize microregions into quartiles based on the per capita firm distribution. Panels A and B show that, in 2008, formal businesses were concentrated in the southern part of the country, while Panels C and D indicate that this distribution remained largely unchanged from 2008 to 2017. Panel E also reveals that in 2017, self-employed MEI business were concentrated in the same area. However, the microregions where self-employed MEI businesses represent a more significant proportion of self-employed businesses are those where other non-MEI self-employed businesses were not prevalent (Panel F), indicating that the relative impact of the MEI policy was more substantial in less developed regions.

Figure 3 confirms these findings. It presents municipality-level scatter plots, with

[4] In 2018, the limit was increased again to R$ 81,000. It is important to note that exchange rate fluctuations should be considered when comparing these limits to USD values (for example, R$60,000 was equivalent to approximately $ 32,258 USD in 2011 and $ 18,126 USD in 2017.

the number of firms per 1,000 people on the y-axis and average income on the x-axis. Panels A through D reveal a positive correlation between firm ownership (large or self-employed non-MEI) and income levels in both 2008 and 2017, as well as between self-employed MEI business ownership and average income in 2017 (Panel E). Panel F then shows that the relative number of self-employed MEI businesses follows an inverted U-shaped pattern and is higher in middle-income municipalities.

In summary, the findings from this section underscore that the 2009 policy reform made formal self-employment more appealing, triggering an increase in its adoption across microregions (although, in relative terms, the policy's impact was more pronounced in less developed areas). This result indirectly indicates potential differences across low- and high-income workers' responses. However, as highlighted in the introduction of this paper, the implications of these changes in terms of wage employment outcomes are uncertain. The subsequent sections of this paper explore this question in the context of distressed workers following job loss.

3 Data and Sample Construction

In this paper, I combine two main data sets for analysis. The first source of data is Rais (*Relação Anual de Informações Sociais*), an administrative employer-employee data set covering the universe of formal job contracts in Brazil. Workers are uniquely identified by their CPF (*Cadastro de Pessoas Físicas*), an individual tax identifier. In contrast, establishments are identified through their CNPJ (*Cadastro Nacional de Pessoas Jurídicas*), a unique tax identifier for legal entities. I observe 97.8 million workers and 7.6 million establishments from 5.9 million firms from 2003 to 2017. Available information includes job-related attributes (such as wages, occupation, industry, hire date, and separation date) and worker characteristics (such as age, gender, race, and education).[5] Contrary to most similar data sets in other countries, Rais also reports the cause of separation when job contracts cease to exist, allowing me to differentiate between workers who quit and those whose contracts were terminated.

The second data set employed in this paper is the firm registry maintained by *Receita Federal*, the Brazilian tax revenue agency, encompassing information such as sector,

[5]Rais is reported by firms, with minimal direct input from workers themselves. Consequently, worker characteristics may not remain consistent over time and across different contracts. To address this, I assign workers their race classification, birth year, gender, and educational level as reported in the year before the mass displacement event. For non-displaced workers, the year before the displacement is determined based on the displacement year of the matched displaced worker.

location, open date, changes to the registry, and tax classifications for the universe of formal firms across the country. From 2003 to 2017, the data set features 31.8 million businesses, including 21.4 million business which started operating during this period.

I classify firms in this data set into four groups: (i) large businesses; (ii) self-employed businesses not operating as MEI firms; (iii) self-employed businesses operating as MEI firms; and (iv) solo proprietors. Table 1 displays the key differences. The group of large businesses comprises 1.6 million firms (among which 0.7 million started their operation between 2003 and 2017) with at least two employees, owned by one or more individuals. The group of self-employed businesses operating as MEI firms includes 9.7 million firms (all of which started to operate after 2003, as this legal format was only introduced in 2009) limited to one employee. The group of non-MEI self-employed business consists of 12.6 million firms (7.4 million operating after 2003), allowing multiple owners but restricted to at most one employee (for comparison with MEI businesses). Lastly, solo proprietors represent a legal format for single-owner businesses. In this case, however, there are no employee constraints.[6]

In order to merge the firm registry with Rais data, I leverage the fact that ownership information is available for large businesses, self-employed non-MEI businesses, and self-employed MEI businesses. For large business and self-employed non-MEI businesses, partial CPFs (six out of eleven digits) and owner names are disclosed. In the case of self-employed MEI owners, both owner names and complete CPFs can be extracted from the firm registry, enabling exact matching. I use these observations to calibrate a probabilistic matching algorithm that utilizes only owner names and partial CPFs. This exercise yields a procedure where 99.72% of MEI owners are correctly matched with their observations in Rais. I then apply this same algorithm for large businesses and self-employed non-MEI business, allowing me to complete the merge between Rais and the firm registry. The only limitation arises from solo proprietor businesses, where ownership information is not observed. Yet, Figure 1 shows a constant share of new businesses under this format from 2003 to 2017. Hence, comparisons across time should remain possible. Moreover, I emphasize that I observe ownership data from 86% of all businesses, signifying extensive coverage.

[6]Firms are categorized into these four groups based on their legal status and size on December 31st of their first year of operation. Firms that started operating before 2003 are classified according to their legal status and size on December 31st, 2003. In this version of the paper, I do not allow firms to transition between groups.

3.1 Mass Displacement Events

To identify mass displacement events, I first create a yearly employment panel at the establishment level, focusing on employee counts as of December 31st each year. Similar to Schmieder et al. (2023), a given establishment is classified as having undergone a mass displacement in year t based on the following criteria. Firstly, the establishment must have employed a minimum of 50 workers in year $t-1$ prior to the displacement, ensuring a substantial number of employees were affected. Secondly, employment must drop at least 30 percent between years $t-1$ and t. Thirdly, the establishment's employment must have increased at most 30 percent between $t-3$ and $t-2$, as well as between $t-2$ and $t-1$. These criteria guarantee that mass displacement events occur in relatively stable establishments with limited employment fluctuations leading up to the event, making them less likely to have been anticipated. Fourthly, to avoid cases where employment quickly rebounded in the following years, I also require that employment does not increase by more than 30 percent between years t and $t+1$, $t+1$ and $t+2$, and well as between t and $t+2$. Adhering to these criteria, I identify 25,917 mass displacement events between 2006 and 2015.[7]

Using the same data set, I construct a yearly panel of workers from 2003 to 2017, tracking their employment status as of December 31st each year. When a worker holds multiple job contracts on these dates, I select a primary contract by successively applying the following criteria until only one contract remains for each worker. I prioritize the contract with the most contracted hours, followed by the contract with higher tenure and, subsequently, higher wages. In cases of persistent ties, a contract is randomly selected from the remaining options.

The next step entails identifying the mass displaced workers. A worker is classified as mass displaced in year t under the following conditions. Firstly, the establishment employing the worker in year t must have experienced a mass displacement event in the same year t. Secondly, the worker must have undergone a job separation during year t. Since the data allows me to distinguish between firings and quits, I exclude from the analysis workers who voluntarily quit their jobs in year t. I then focus on workers between the ages of 24 and 50 in the pre-displacement year $t-1$, excluding workers in college or nearing

[7] Even though my data set covers employment information from 2003 to 2017, I can only identify mass displacement events between 2006 and 2015 due to the requirement that establishments be observed three years before and two years after the potential displacement year. Appendix Figure A.1, Panel A, provides a yearly breakdown of mass displacement events and also reports the number of establishment closure events using a more restrictive criterion where at least 80 percent of workers are fired. Panel B shows the distribution of the employment loss during the displacement year, along with the cutoffs which were used to define mass displacement events and plant closures.

retirement. Additionally, I require that workers have at least three years of tenure by the end of year $t-1$, thus concentrating on workers who are strongly attached to their jobs and for whom the displacement event was more unexpected.[8] Lastly, to prevent overlaps between displacement events, workers experiencing more than one mass displacement event are omitted from the sample. Consequently, each displaced worker is associated with a specific displacement cohort identified by year t. Following this procedure, I identify 929,392 displaced workers between 2007 and 2015.[9]

Having established the sample of displaced workers, I select a counterpart sample of non-displaced workers based on observed covariates, proceeding in two steps. Initially, I define the pool of potential non-displaced workers for each displacement cohort t as all workers not in the sample of mass displaced workers. These potential non-displaced workers adhere to the same criteria as displaced workers: (i) employment in establishments with more than 50 employees in year $t-1$; (ii) age between 24 and 50 during $t-1$; and (iii) at least three years of tenure in $t-1$. Subsequently, displaced workers from cohort t are categorized into cells defined by key dimensions from year $t-1$: birth cohort, job tenure in years, earnings (in R$ 250 bins), 2-digit industry, and state. Non-displaced workers with the same characteristics are also categorized into these same cells. Within each cell, I ensure that the number of non-displaced workers matches that of displaced workers. In the rare event of a cell having only displaced workers, I exclude the entire cell from the sample. If there are more displaced workers than non-displaced workers, I randomly choose some displaced workers to ensure that their number matches that of non-displaced workers. I then construct my final panel by stacking the panels of displaced and non-displaced workers for each cohort t. Importantly, my approach does not require non-displaced workers to continuously hold the same contract or be in firms unaffected by mass displacement events. It also allows a single worker to serve as the non-displaced counterpart for displaced workers in various cohorts.

3.2 Sample Characteristics

Table 2 reports the summary statistics for the matched sample. I provide separate statistics for workers displaced in two distinct periods. The first period encompasses workers who were

[8] In Brazil, employment spells are characterized by high turnover rates. By the end of 2017, for example, only 39.6% of job contracts had tenure over three years. 25% of the contracts had tenure smaller than nine months, and 50% had tenure smaller than 26 months. Only 10% of the contracts had been continuously active for the past ten years.

[9] Appendix Figure A.2 provides a yearly breakdown of mass displaced workers in each year. Due to the matching algorithm, the number of non-displaced workers in each cohort is identical. The 2006 cohort is excluded from the analysis, because industry information is not available in 2005 (the pre-displacement year for the 2006 cohort).

mass displaced between 2007 and 2008 and their non-displaced counterparts. This period predates the 2009 law that introduced MEI firms; thus, opening a MEI firm was not an alternative for these workers immediately after the job loss. Conversely, the second period comprises workers who were mass displaced between 2012 and 2013. This latter period occurred after the 2009 reform and a transition period from 2009 to 2011 when the number of MEI firm openings increased exponentially. In both cases, the selection of displacement years ensures that workers are observed at least four years before and after the job loss. Since I required the number of displaced and non-displaced workers to be the same within each matching cell, both groups consist of an equal number of individuals. In total, I follow 78,704 workers displaced in 2007 or 2009 and 109,612 workers displaced in 2012 or 2013.

Displaced and non-displaced workers are similar across the dimensions defining the matching cells (age, tenure, wage, industry, and region). Appendix Table A.1 reports the difference in means between the two groups, and none of these differences are statistically significant. This finding holds true regardless of the period under consideration. The remaining variables are categorized into worker and occupational characteristics. Importantly, although Appendix Table A.1 indicates statistically significant differences between displaced and non-displaced workers across these dimensions, Table 2 reveals that such differences are generally small in magnitude, suggesting limited economic significance. Nevertheless, it is worth noting that non-displaced workers tend to be employed in larger firms, especially among the 2007-2008 cohorts, while for the 2012-2013 cohorts, the difference is notably less pronounced.

4 Empirical Strategy

In this paper, I leverage mass layoffs to identify the link between job loss, self-employment, and reentry into wage employment within the formal sector in Brazil. I first employ an event study specification to identify the causal effect of job separations on self-employment decisions. I also use a similar model to characterize employment probabilities depending on workers' decision to become self-employed following a job loss. I then focus on displaced workers and report on the correlation between self-employment and wage reemployment, including reentry wages.

4.1 The Effect of Job Loss on Self-Employment Decisions

I employ an event study design to identify job separations' effect on transitions to formal self-employment and to characterize its main determinants. To do this, I estimate the following regression model:

$$Open_{it} = \alpha + \beta \cdot MassDisp_i + \sum_{\ell=-4}^{4} \mu_\ell 1 \cdot \{t - E_i = \ell\} \cdot MassDisp_i + \phi_t + \varepsilon_{it} \tag{1}$$

In this equation, the outcome variable $Open_{it}$ is a binary indicator equal to 1 if worker i opens a formal business in year t. I present results for the opening of any self-employment businesses and, for the cohorts 2012-2013, I disaggregate the opening of MEI and non-MEI self-employment business. I also show the results for the opening of large businesses for benchmarking. $MassDisp_i$ is a dummy variable equal to 1 if worker i is mass displaced in any year during the analysis period. I define E_i as the year t when worker i is mass displaced or, in the case of non-displaced workers, the year when their displaced counterpart is laid off. Hence, ℓ measures the temporal gap (in years) between year t and displacement year E_i, with μ_ℓ representing the coefficients of interest. These coefficients capture the differential effect of a mass displacement event between displaced and non-displaced workers. Although omitted in Equation 1, I included binned dummy variables for the relative years before $\ell = -4$ and after $\ell = 4$. Finally, ϕ_t denotes the year fixed effects, and ℓ_{it} is the error term.

In line with Sun and Abraham (2021), my specification is designed to identify the treatment effect of job separations on self-employment transitions under three key assumptions: (i) parallel trends in baseline outcomes; (ii) no anticipatory behavior before treatment; and (iii) treatment effect homogeneity.

Concerns related to the potential violation of hypothesis (i) are addressed through the matching procedure. This procedure generates comparisons between workers who share similar observed characteristics, thereby increasing the likelihood of a parallel trajectory in the absence of the mass displacement event (Bhalotra et al. 2021, Schmieder et al. 2023). Additionally, it is reassuring that the results in the subsequent section will underscore that a parallel trend in outcomes appears to hold during the pre-displacement period as well.

Regarding hypothesis (ii), in my setting, it is plausible to expect that some workers might anticipate a forthcoming mass displacement based on certain conditions observed by the worker (although not observed by me) at the firm.[10] In this case, the trajectory of

[10] It is also possible that workers receive advance notice of their dismissal. However, workers in Brazil are typically informed of their dismissal no more than 30 days before the actual contract termination. Given that I work with a yearly panel, this should have limited impact on the estimates.

displaced and non-displaced workers could start drifting apart before the mass displacement year. I consider this possibility in the main specification and omit the dynamic treatment effect for $\ell = -2$ instead of $\ell = -1$. Consequently, hypothesis (ii) of no anticipatory behavior before treatment is required to hold before $\ell = -2$ only, and all regression estimates should be interpreted relative to this period.

Lastly, following the 2009 policy change and the subsequent exponential surge in the number of MEI firm openings (as illustrated in Figure 1), it is expected that the probability that any individual open a MEI firm over time increased during the period of interest. Regression estimates will incorporate this variation across cohorts, potentially violating hypothesis (iii) of treatment effect homogeneity. However, my sample construction and analysis strategy mitigate this concern. First, I conduct separate analyses before and after the 2009 policy change, using the 2007-2008 and 2012-2013 cohorts. This ensures that within each period, there are only two closely spaced cohorts, limiting the room for substantial heterogeneous treatment effects to emerge. Second, in line with the approach in Schmieder et al. (2023), by matching displaced and non-displaced workers and stacking different panels for each cohort, displaced workers are assigned a specific comparison counterpart. Along with the fact that the matching procedure also generates a large "never-treated" group, this helps mitigate concerns that the forbidden comparisons in Goodman-Bacon (2021) and Callaway and Sant'Anna (2021) are driving the results. Nevertheless, in the Appendix, I also estimate my main analyses separately for each of the four displacement cohorts and implement the estimation procedure proposed by Sun and Abraham (2021). In both cases, the results are identical to those in the main analysis.[11]

4.2 Wage Employment After Job Loss

In this analysis, I examine the reentry into wage employment following a job loss and its connection with self-employment. First, to assess the employment status of workers, I employ an event study specification similar to Equation 1, but now the the outcome variable Emp_{it} is a binary indicator equal to 1 if worker i is employed by the end of year t.

$$Emp_{it} = \alpha + \beta \cdot MassDisp_i + \sum_{\ell=-4}^{4} \mu_\ell 1 \cdot \{t - E_i = \ell\} \cdot MassDisp_i + \phi_t + \varepsilon_{it} \qquad (2)$$

I estimate this equation for different groups of displaced workers: (i) those who become self-employed workers, combining both MEI and non-MEI firms; (ii) those who open a large

[11] Appendix Figures A.5, A.6, A.7, and A.8.

firm; and (iii) those who do not open any firm after a job loss. For the 2012-2013 cohorts, I also separate self-employed MEI owners from non-MEI owners. To classify workers, I only consider businesses that begin to operate before their owners' reentry into wage employment. Additionally, I exclude from the analysis workers who opened a firm before the displacement event (before or at $\ell = -1$). Similar to the previous analyses, displaced workers are assigned their non-displaced counterparts within their matching cells, thus guaranteeing a comparison between similar workers.

An important caveat is that, from this analysis alone, it is not possible to derive a causal relationship between self-employment and wage employment after a job loss. Displaced workers select themselves into these four groups based on their observed and unobserved characteristics, as well as other conditions at the time of displacement. When comparing the results for the first and second periods (2007-2008 and 2012-2013), it is also important to note that causal conclusions regarding the impact of the MEI policy change on firm ownership and wage reemployment cannot be drawn.

To further evaluate the connection between workers' condition upon reentry into wage employment and self-employment, along with differences across the periods before and after the introduction of MEI firms in 2009, I then estimate linear regression models at the individual level using the sample of displaced workers only:

$$Y_{icf} = \alpha + \phi_f + \theta_c + \phi_f \cdot \theta_c + X_i\beta + \varepsilon_{icf} \tag{3}$$

In this equation, ϕ_f is a vector of employment status after the job loss, including self-employment and ownership of a large firm, with the omitted category being not opening any business. θ_c indicates the cohort fixed effects (in this specification, a binary indicator equal to 1 for workers displaced in 2012 or 2013). X_i is a vector of control variables, which includes the same covariates that characterize the matching cells, and ε_{if} is the error term. The first outcome variable Y_{icf} is $Reentry_{icf}$, a binary indicator equal to 1 if worker i from cohort c who follows trajectory f after a job loss reenters wage employment. I estimate this model using all displaced workers. The second outcome variable is $TimeReentry_{icf}$, the temporal gap (in years) between job loss and reentry into wage employment. Given that I use a yearly panel where workers' employment status is assessed on December 31st of every year, workers can take $0, 1, \cdots, 4$ years to reentry.[12] At last, the third outcome variable is $\Delta WageDiff_{icf}$, the difference between log wages in $\ell = -1$ and in $\ell = R_{if}$, where R_{if} is

[12]Workers who take 0 years to reentry are those who suffer a job loss in $\ell = 0$ but are reemployment by the end of the same year $\ell = 0$

the first period when the worker is reemployed after the wage loss. Similar in spirit to the difference-in-differences equation, my measure of changes in log wages takes into account the path of the non-displaced workers:

$$\Delta WageDiff_{icf} = (Wage_{icf,\ell=R_{if}} - Wage_{icf,\ell=-1}) - (Wage_{c(ic)f,\ell=R_{if}} - Wage_{c(ic)f,\ell=-1}),$$

where $c(ic)$ is the non-displaced counterpart to displaced worker i from cohort c.

Note that $TimeReentry_{icf}$ and $\Delta WageDiff_{icf}$ are only defined for the subset of displaced workers who reentry wage employment. Hence, the results for these outcome variables should be interpreted as conditional on reentry. $\Delta WageDiff_{icf}$ also requires that the counterpart non-displaced worker is employed in the year when the displaced worker reenters wage employment.

I also estimate a simpler version of Equation 3 for the subset of workers displaced in 2012 or 2013:

$$Y_{i,c=2012|2013,f} = \alpha + \phi_f + X_i\beta + \varepsilon_{i,c=2012|2013,f} \tag{4}$$

In Equation 4, ϕ_f is extended to allow for the separation of self-employed MEI owners from non-MEI owners.

5 Results

The Effect of Job Loss on Self-Employment Decisions

Figure 4 presents the main results from the estimation of Equation 1. Panel A shows the displacement effect on firm ownership for workers displaced in 2007 and 2008. I report a .31p.p. increase in the probability that workers transition to self-employment in the year of job separation. At only .06p.p., the effect on large firm ownership is comparatively smaller but still statistically significant. The results for workers displaced in 2012 and 2013 (after the 2009 policy change and excluding an implementation period) are reported in Panel B. I observe an increase of .67p.p. in the probability that workers open a formal self-employment business in this second period during the year of the displacement, then further increasing to .91p.p. in the following year, whereas large firm ownership remains less likely at only .06p.p. Panel C breaks down the effect on self-employment into MEI ownership and non-MEI ownership. It is evident that the surge in self-employment after job loss is primarily attributed to MEI ownership. The transition to non-MEI self-employment, which is directly comparable to the overall self-employment curve in the first period, remains largely unchanged.

In Panels D through F, I repeat the analysis for workers at the bottom quartile of the pre-displacement wage distribution, while Panels G through I display the results for high-income workers. The findings indicate that in the first period, high-income workers were .79 p.p. more likely to transition to self-employment in the year of the mass displacement event. For low-income workers, however, there were no statistically significant displacement effects. The results for the second period are starkly different, since low-income workers begin to follow the formal self-employment trajectory after a job loss. The displacement effect reaches .57p.p. for low-income workers in the year after the job loss, once again entirely driven by MEI firms. This effect, when compared to the 1.54p.p. increase for high-income workers in the second period (also largely driven by MEI ownership), indicates that low-income workers are able to close about one-third of the self-employment gap. Taken together, these results underscore that the 2009 policy change successfully included displaced low-income workers into formal self-employment, while at the same time also improving the attractiveness of this path for high-income workers.[13]

The selection of displaced workers into self-employment is further explored in Table 3, where I report the estimates from a linear probability model where the outcome variable is a binary indicator equal to 1 for workers who open a formal self-employment business. I separate the analysis by displacement cohort (2007-2008 and 2012-2013). In all columns I include industry and state fixed effects. The results fall largely in line with those discussed above, with pre-displacement wages being positively associated with transitions into self-employment in both periods. A similar result is found for managerial experience and educational achievement. However, for these two correlates, comparing the estimates for the two periods yields contrasting results. First, the coefficient for managerial experience increases from .008 in the first period to .014 in the second period, indicating that managers are more likely (relative to non-managers) to move into self-employment in the second period. Second, the coefficient for having a college degree decreases from .026 to .011. It indicates that while highly-educated workers remain more likely to become self-employed, the gap relative to workers without a high school degree shrank.

[13] Appendix Figures A.3 and A.4 show that the results reported in Figure 4 are aligned with alternative sample divisions focusing on educational level (primary or less, high school, college or more) and managerial experience.

Wage Employment After Job Loss

Motivated by the finding that the reform had heterogeneous impacts across the wage distribution, I proceed to understand the differential consequences of self-employment spells. My analysis focuses of three dimensions: (i) whether self-employed workers reentry into wage employment; (ii) conditional on reentry, how long the period between job loss and reemployment is; and (iii) also conditional on reentry, how reentry wages compare to pre-displacement wages. As argued in Section 4, it is important to note that these results should not be interpreted as causal. Future versions of this project will delve into this issue and attempt to establish a causal connection between self-employment and wage employment outcomes.

Figure 5 displays the results from estimating Equation 2, with Panels A through I following the pattern from Figure 4. I show that, by the end of the year of the displacement event, workers who do not open any business are 50p.p. (cohorts 2007-2008) and 47p.p (cohorts 2012-2013) less likely to be employed. This disemployment effect of job loss is larger among workers who transition to firm ownership (either self-employment or large business), with employment probabilities decreasing more than 80p.p. in the displacement year regardless of the cohort. In the year following the displacement event, I observe a recovery in employment probability for workers who did not open any firm, while such recovery is more sluggish for business owners. This pattern persists in the subsequent years. By the fourth year following displacement, employment probability for displaced workers who do not open any firm is only 11p.p. (cohorts 2007-2008) and 12p.p. (cohorts 2012-2013) below non-displaced workers. However, workers who open a firm remain at least 45p.p. less likely to be employed, once again regardless of the cohort I evaluate. Besides the lack of large changes from 2007-2008 to 2012-2013, self-employed MEI owners and non-MEI owners also appear to behave similarly in this dimension.

Across the wage distribution, both low- and high-income workers repeat the pattern outlined in the previous paragraph. However, firm ownership is a more absorbing state for high-income workers (Panels G and H vs. Panels D and E). Moreover, Panels C, F, and I indicate that among business formats, those requiring more commitment tend to correlate with lower rates of reentry into wage employment.

The findings from Figure 5 are largely consistent with those in Tables 4 and 5, in which I report the coefficients from estimating Equation 3 with reentry into wage employment and, conditional on reentry, years to reentry as outcome variables. In both tables, Panel A follows Equation 3 and presents the estimates combining cohorts 2007-2008 and 2012-2013, while Panel B zooms into the second period, showing the results from estimating Equation 4.

In Table 4, Panel A, columns 1 and 2 indicate that workers who transition into self-employment are 66-68p.p. less likely to return to wage employment compared to workers who did not open any business after the job loss. Coefficients are remarkably similar for low- and high-income workers (columns 3-4 and 5-6, respectively). The coefficients for the interaction between owning a self-employment business and being displaced in 2012-2013 indicate that, in this second period, self-employed business owners were more likely to reentry wage employment following a displacement-driven self-employment spell. Panel B then reports that in this second period, among self-employed workers, there does not appear to be a large difference in reentry probabilities across individuals who own a MEI (-.516) or a non-MEI business (-.560). This result holds for both low- (-.507 and -.519, respectively) and high-income individuals (-.489 and -.557, respectively).

In Table 5, I evaluate how long it takes workers to reentry into wage employment following a job loss. This analysis is conditional on workers returning to wage employment at some point in my period of analysis. Panel A shows that, compared to workers who do not open any firm, self-employed workers take 1.348 (column 1) to 1.415 (column 2) years longer to reenter. The coefficients are similar for low- and high-income workers (columns 3-4 and 5-6, respectively). However, the coefficient for the interaction with the second period indicates that after 2009, low-income workers who resort to self-employment spend less time away from wage employment. This is reflected in Panel B, where low-income self-employed MEI owners spend a shorter period away from wage employment than high-income workers. It is worth noting that these results are relative to workers who do not become business owners following job loss.

Table 6 sheds light upon the workers who are reentering wage employment after a self-employment spell. Both before and after 2009, workers with larger pre-displacement wages are more likely to find a new wage job. However, workers who reentry are different across other dimensions and potentially less skilled in the second period. I report that in 2012-2013, the reentry probability is negatively correlated with tenure in the pre-displacement job and, compared to the first period, less likely to have a high school diploma or a college degree (*vis-à-vis* the omitted category of workers who did not complete high school). Also, in this period, reentry is more associated with workers employed in larger firms before the displacement. They are also more likely to be non-white and less likely to be female.

I then evaluate wages at reentry, conditional on workers returning to wage employment. Using the wage measure defined in Section 4, Table 7 reveals that transitions to self-employment after job loss are associated with a 5.9 log points wage penalty (column

2) on top of a wage loss of 14 log points for workers who do not open any firm. The comparison between low- and high-income workers reveals a stark difference. While the self-employment effect on reentry wages is statistically non-significant for low-income workers (column 4), high-income individuals face a wage penalty of 12 log points (column 6). I also note that the wage effect for those who do not open any firm is also very different across the wage distribution, with a null effect for low-income worker (0.007) and a large penalty for high-income workers (-.288), who appear to face large income losses regardless of their trajectory after the job loss. Remarkably, the effect of self-employment on reentry wages does not appear to be different for the cohorts 2012-2013, since the coefficients for the interaction of business ownership and cohort is not significant for workers who transitioned to self-employment. Panel B complements these results by showing that, among high-income workers, the wage penalty is larger for self-employed MEI owners (-.221) than for non-MEI owners (-.126).

Next, in Table 8, I evaluate how minimum wage regulations affect the extent of wage losses after a displacement event. Columns 1, 3, and 5 replicate the results in columns 2, 4, and 6 from Table 7, while columns 2, 4, and 6 display the results using a hypothetical wage difference measure where I assume that all displaced workers earn the the national minimum wage when reentering wage employment. Hence, the results in these columns present an upper bound for wage losses. I highlight three results. First, for both low- and high-income workers who do not open any business, actual wage effects (.007 and -.288 log points, respectively) are much smaller than maximum wage losses (-.316 and -1.466, respectively). Second, the upper bound on wage losses for low-income workers (-.316) is not much larger than the actual losses for high-income workers (-.288), indicating that the existence of the minimum wage greatly reduces the extent to which low-income workers can be penalized following a job loss. Third, using this hypothetical wage measure, both high-income and low-income workers who move into self-employment do not face the extra wage penalty on top of the one for workers who did not open any business. Since the only source of variation across workers in this column is pre-displacement wages, it indicates that, in this dimension, workers who move into self-employment are not much different from those who choose not to.

Extensions

In this section, I explore other mechanisms potentially explaining the self-employment effects on reentry wages and the heterogeneous results we observe between low- and high-income workers.

First, in Table 9 I evaluate the existence of heterogeneous responses to self-employment decisions across a series of observed covariates, aiming to understand the drivers behind the differences between low- and high-income workers. I find that wage differences are small (and in most cases positive) for low-income workers across all heterogeneous groups. I also do not observe a correlation between self-employment spells and reentry wages in all columns 1 through 6. For high-income workers, on the contrary, wage losses are large across the board and the coefficients for self-employed business ownership are particularly large for college-educated individuals (column 8), those who have access to a large severance payment (column 9)[14], and among younger workers (columns 10 and 11). For managers who resort to self-employment, column 7 indicates a significantly larger wage loss in the second period. Panel B then shows that the wage losses for high-income self-employed workers who attempted self-employment are larger for the individuals who opened their businesses as a MEI firm and, in particular, among workers who would typically be expected to be successful self-employed workers: workers who held a managerial position before the displacement (column 7); college-educated workers (column 8); and those who have access to a large severance payment (column 9).

Next, I focus on the difference between pre-displacement and reentry occupations. I proxy the skill content of each 3-digit occupation in every year by the average years of schooling of workers employed in those occupations.[15] To create this measure, I use a larger sample that includes all observations in Rais. I then create a new outcome variable $\Delta SkillDiff_{icf}$, the difference between the skill content in the pre-displacement occupation and in the reentry occupation.[16] It is analogous to the measure of changes in log wages:

$$\Delta SkillDiff_{icf} = (Skill_{icf,\ell=R_{if}} - Skill_{icf,\ell=-1}) - (Skill_{c(ic)f,\ell=R_{if}} - Skill_{c(ic)f,\ell=-1}),$$

The results using this outcome variable are displayed in Table 10. Since the results combining cohorts 2007-2008 and 2012-2013 are mostly non-significant in Panel A, I focus on the second period in Panel B. Column 1 presents the results using all workers, while the remaining columns focus on heterogeneous responses between low- and high-income workers (columns 2 and 3, respectively) and non-managers and managers (columns 4 and 5, respectively). Both low-income workers and those without managerial experience appear to benefit from the spell as owners of a self-employed MEI business, as they move to occupations

[14]Dismissed workers are entitled to access funds from a severance account, called FGTS. The size of this payment can be approximated using workers' employment trajectory, which I observe in Rais.

[15]In Appendix Table A.2, I present simiar results using a skill content measure at the 2-digit level.

[16]Appendix Figure A.9 shows how the skill content measure correlates with pre-displacement wages.

requiring more skills when reentering wage employment. For high-income workers and managers, I report opposite results. Although the coefficients are not always statistically significant, these workers appear to benefit more from owning large businesses. This finding is consistent with the (relative) erosion of human capital during the time high-income workers spend as self-employed MEI owners. This hypothesis is also supported by the fact that MEI businesses are allowed to operate in sectors requiring mostly manual skills, thus largely excluding activities requiring a college degree. For high-income workers and managers, this restriction indicates that MEI ownership potentially leads to activities less aligned with their pre-existing skills.

Lastly, I focus on the trajectory of the displacement-driven new business. For this analysis, I report the results for the second period only (cohorts 2012-2013). Figure 6, Panel A, shows the survival probability of these businesses in the years since their opening. The results indicate that self-employed businesses (and in particular those operating under the MEI format) are more short-lived than larger businesses. This result complements those from Figure 5, which shows that owners of larger firms are less likely to return to wage employment following a job loss, potentially due to the their businesses being less likely to stop operating. Then, in Panel B, I correlate the timing of firm closure (before reentry into wage employment, after reentry into wage employment, and a third group for business that are not closed in the period I evaluate) with wage changes between displacement and reentry, focusing on MEI ownership. For both low- and high-income workers, there does not appear to be any correlation. However, it is important to note that MEI owners do not have large incentives to officially close their businesses, since the cost of keeping them operating is small. Hence, the firm closure measure for this analysis is likely to be noisy.

6 Concluding Remarks

In this paper, I examine the mediating effect of formal self-employment spells on workers' trajectories following job loss. Combining administrative data on the universe of job contracts in Brazil with identified data on firm ownership, I first explore an event study design that compares mass displaced workers to a comparable group of non-displaced workers. Then, I focus on displaced individuals and report on the dynamics between wage employment and self-employment.

I find an increase in the probability that workers transition to formal self-employment following job loss, particularly after a legislation change in 2009 that significantly reduced the barriers to firm ownership among self-employed workers. Next, I show that individuals who follow the self-employment path are less likely to return to wage employment, but for those who eventually do return, there is a significant distributional effect. High-income workers face a wage penalty, while the consequences for low-income workers are muted, partially due to the existence of minimum wage regulations that greatly reduce the extent to which low-income workers can be penalized. I provide suggestive evidence that the negative correlation between self-employment and reemployment wages for high-income workers appears to be associated with individuals who, based on observed covariates, would typically be expected to be successful self-employed workers. Future versions of this paper will continue to explore potential mechanisms behind the wage effect results for high-income workers. Lastly, the results from this paper indicate that, while the 2009 legislation change has had a positive effect on entry into self-employment, the consequences for workers' wage employment outcomes are much more limited.

Importantly, while I can causally estimate the effect of job loss on self-employment decisions, the results regarding workers' reemployment outcomes and the effects of the 2009 legislation change are largely correlational. Hence, future versions of this work will attempt to overcome this limitation. In this dimension, exciting future research avenues include: (i) leveraging regional labor market heterogeneity to construct instruments for self-employment decisions; (ii) exploring the staggered expansion across Brazilian municipalities of a public agency supporting self-employed workers and small business owners; and (iii) investigating how the sectorial restrictions to MEI ownership shape workers decisions. I also intend to guide future analyses through the lens of a theoretical model. Finally, this project is part of a research agenda aiming to not only evaluate self-employment post job loss but also elucidate its causal effects on workers' labor market trajectories more broadly.

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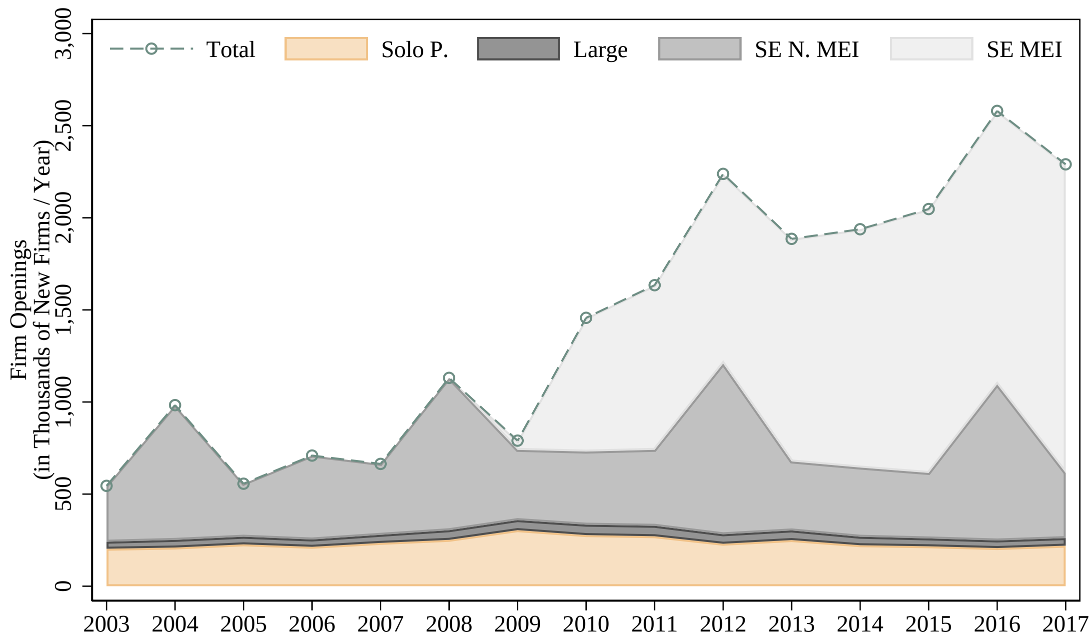
Figures and Tables

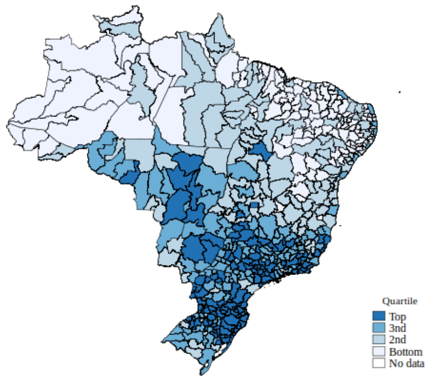
Figure 1: Firm Openings in Brazil



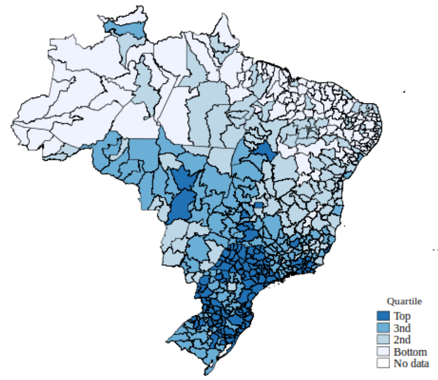
Note: Figure 1 shows the number of new formal firm openings in Brazil. Firms are classified according to their legal status and size as of December 31 of their opening year. Data from the Receita Federal Firm Registry, years 2003-2017.

Figure 2: Geographical Distribution

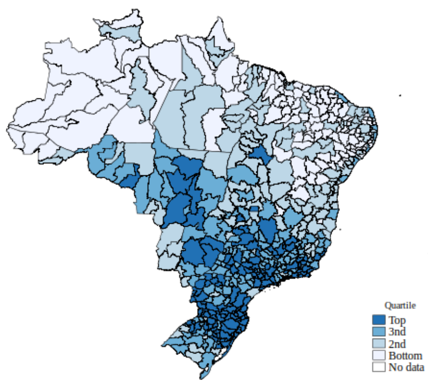
(a) Large (2008)



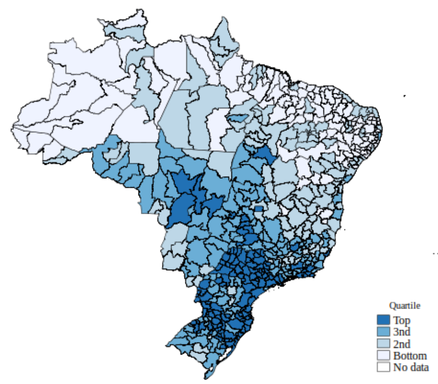
(b) SE: Not MEI (2008)



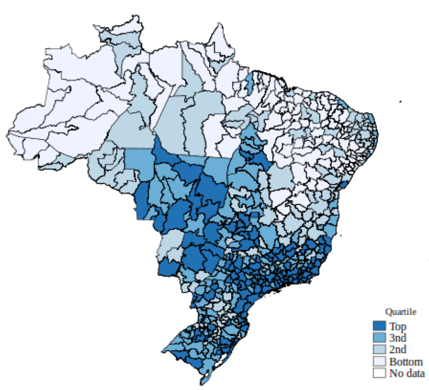
(c) Large (2017)



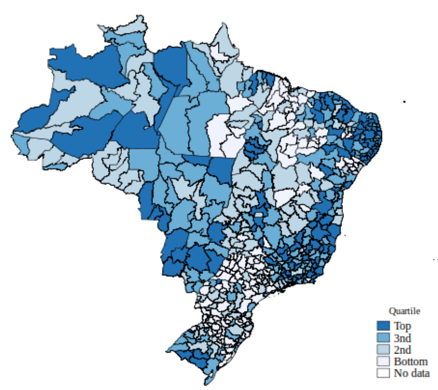
(d) SE: Not MEI (2017)



(e) SE: MEI (2017)



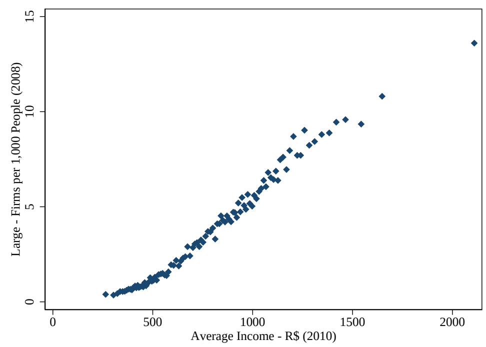
(f) SE: MEI / Not MEI (2017)



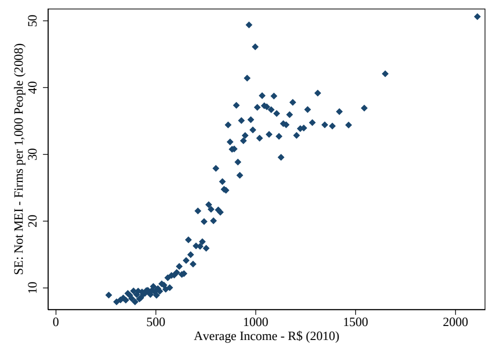
Note: Figure 2 show the distribution of formal businesses across microregions. The per capita number of firms is calculated using firm ownership data from Receita Federal and 2010 population data from IBGE.

Figure 3: Municipality Characteristics and Firms

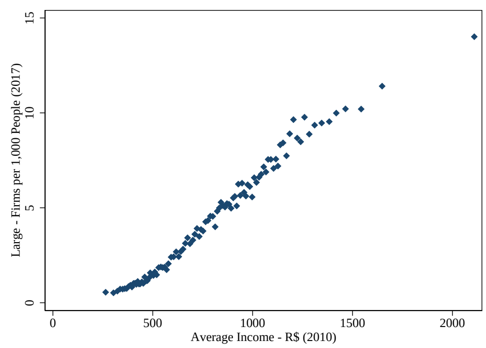
(a) Large (2008)



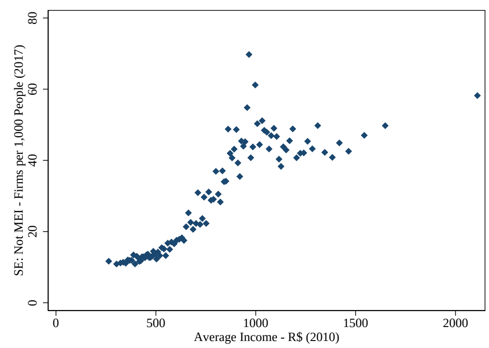
(b) SE: Not MEI (2008)



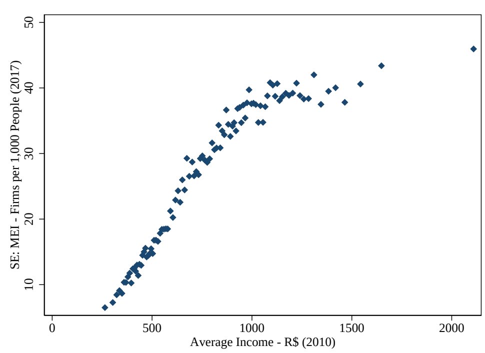
(c) Large (2017)



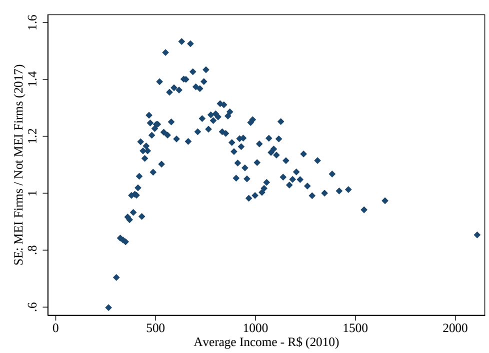
(d) SE: Not MEI (2017)



(e) SE: MEI (2017)

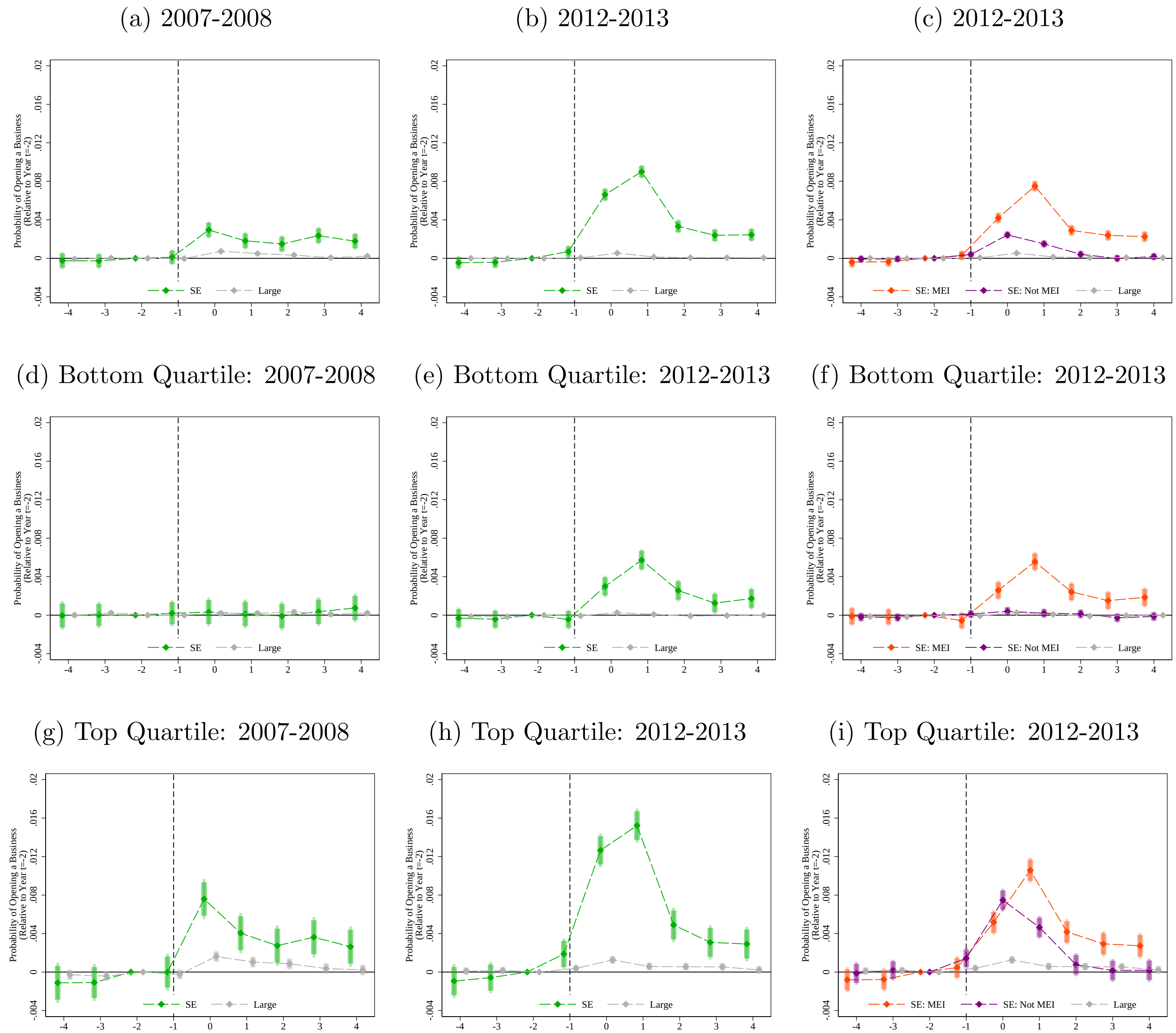


(f) SE: MEI / Not MEI (2017)



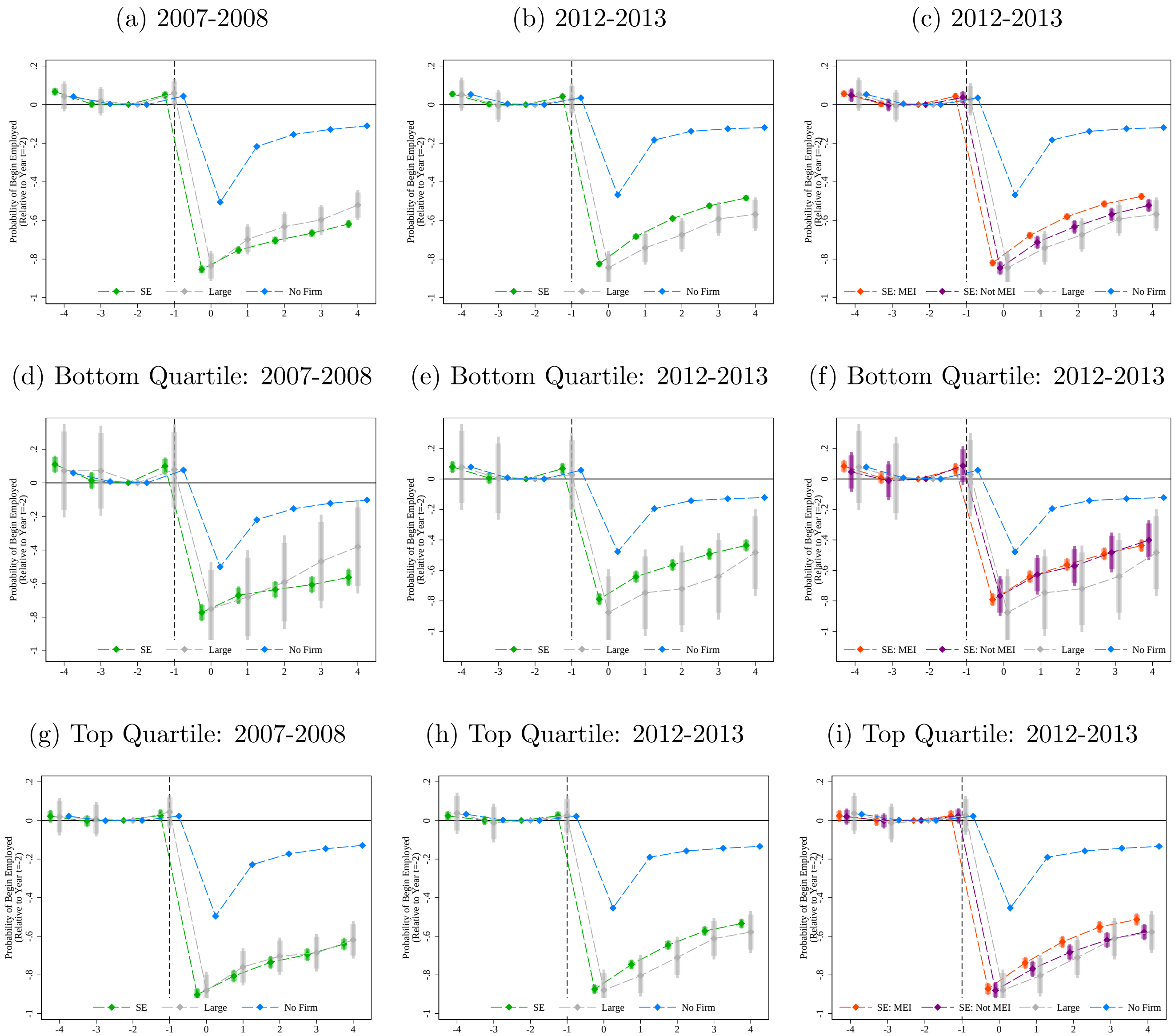
Note: Figure 3 shows municipality-level scatter plots with the number of firms per 1,000 people on the y-axis and average income in the x-axis. 2010 income data from IBGE. Firm registry data from Receita Federal.

Figure 4: Job Loss and Firm Ownership



Note: Figure 4 shows the results from estimating Equation 1. Outcome variable is a binary indicator for new firm openings. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

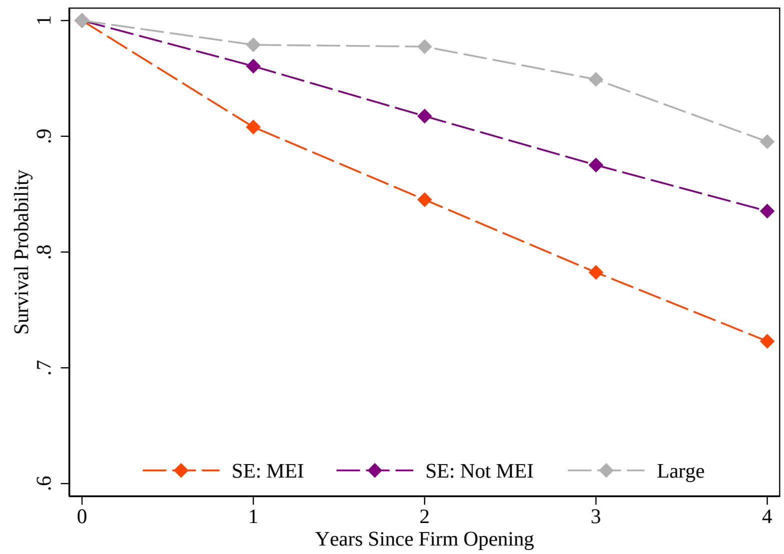
Figure 5: Job Loss and Employment



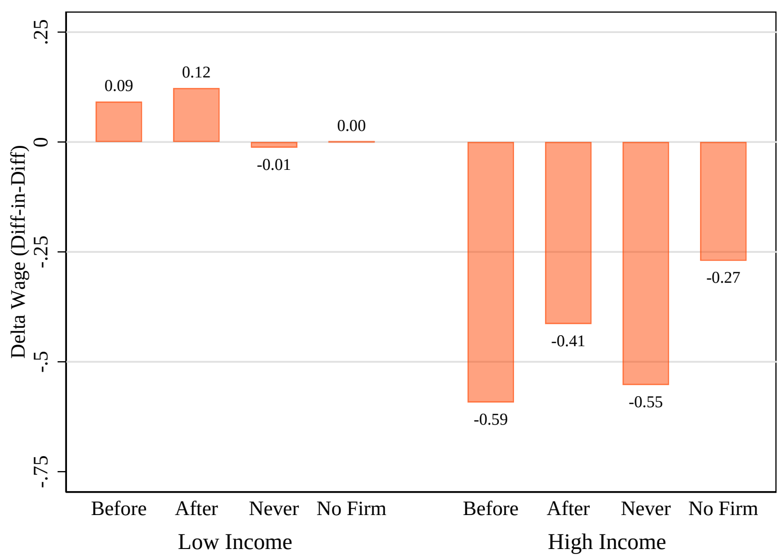
Note: Figure 5 shows the results from estimating Equation 2. Outcome variable is a binary indicator for worker-level employment. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure 6: Firm Survival and Wage at Reentry

(a) Firm Survival Probability



(b) Wage Loss (Only SE MEI)



Note: Cohorts 2012-2013 only. Figure 6, Panel A, shows the survival probability of firms. Panel B shows the average difference between reentry and pre-displacement wages. Before: workers who open a SE MEI business but close it before reentering wage employment. After: workers who open a SE MEI business but close it after reentering wage employment. Never: workers who open a SE MEI business but never close it during my period of analysis. No firm: workers who do not open any firm after job loss.

Table 1: Firm Classification

	Owners	Employees	Lim. Liability	Own. Data	2003-2017	
					Total	Openings
Large Firms	1+	2+	Depends	Yes	1.6 million	0.7 million
Self-Employed: Not MEI	1+	0-1	Depends	Yes	12.6 million	7.4 million
Self-Employed: MEI	1	0-1	No	Yes	9.7 million	9.7 million
Solo Proprietor	1	0+	No	No	7.8 million	3.5 million

Note: Table 1 classifies firms into four groups. Total number of firms and number of firms openings: data from Receita Federal.

Table 2: Summary Statistics: Matched Sample

	2007-2008		**2012-2013**	
	Non-Disp.	Displaced	Non-Disp.	Displaced
Matching Variables				
Age	35.47	35.47	35.94	35.94
Age: 29-	0.45	0.45	0.44	0.44
Age: 30-39	0.36	0.36	0.37	0.37
Age: 40+	0.15	0.15	0.16	0.16
Years of Tenure	5.93	5.93	5.49	5.49
Monthly Wage	1818.04	1809.65	2179.26	2174.61
Industry: Manufacturing	0.43	0.43	0.37	0.37
Industry: Retail and Services	0.43	0.43	0.46	0.46
Industry: Health and Education	0.03	0.03	0.02	0.02
Industry: Public Sector	0.00	0.00	0.00	0.00
Industry: Other	0.11	0.11	0.14	0.14
Region: North	0.06	0.06	0.05	0.05
Region: Northeast	0.15	0.15	0.23	0.23
Region: Southeast	0.57	0.57	0.52	0.52
Region: South	0.19	0.19	0.15	0.15
Region: Center-West	0.03	0.03	0.05	0.05
Worker Characteristics				
Race: Non-White	0.38	0.40	0.47	0.48
Gender: Female	0.34	0.34	0.34	0.33
Education: Primary or Less	0.61	0.63	0.44	0.47
Education: High School	0.35	0.33	0.48	0.46
Education: College or More	0.04	0.04	0.08	0.07
Occupational Characteristics				
Firm Size	972.31	671.10	1351.48	1215.80
Manager	0.04	0.05	0.05	0.06
Firm Owner	0.02	0.02	0.02	0.02
MEI Owner	0.00	0.00	0.00	0.01
Observations	78704	78704	109612	109612

Note: Table 2 displays the sample characteristics of workers included in the main sample. Non-displaced and displaced workers are matched using the matching variables listed in this table.

Table 3: Selection into Self-Employment

	2007-2008			2012-2013		
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly Wage (Ln)	0.021***	0.020***	0.017***	0.030***	0.029***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Years of Tenure		-0.000**	0.000		-0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
		[0.028]	[0.974]		[0.130]	[0.537]
Manager		0.010**	0.008**		0.015***	0.014***
		(0.004)	(0.004)		(0.003)	(0.003)
		[0.010]	[0.034]		[0.000]	[0.000]
Firm Size (Ln)		0.000	0.000		-0.001	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
		[0.631]	[0.908]		[0.308]	[0.305]
Age			0.003***			0.004***
			(0.001)			(0.001)
			[0.001]			[0.000]
Age*Age			-0.000***			-0.000***
			(0.000)			(0.000)
			[0.000]			[0.000]
Race: Non-White			-0.004**			-0.004***
			(0.001)			(0.001)
			[0.011]			[0.005]
Gender: Female			0.007***			0.004***
			(0.002)			(0.002)
			[0.000]			[0.006]
Education: High School			0.008***			0.009***
			(0.002)			(0.001)
			[0.000]			[0.000]
Education: College or More			0.026***			0.011***
			(0.005)			(0.004)
			[0.000]			[0.004]
Average LHS	0.034	0.034	0.034	0.045	0.045	0.045
Observations	78704	78704	78704	109612	109612	109612
R-Squared	0.008	0.008	0.010	0.012	0.012	0.014
Industry FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES

Note: Table 3 reports the estimates from a linear probability model where the outcome variable is a binary indicator equal to 1 for workers who open a formal self-employment business following a job loss. Analysis restricted to displaced workers. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table 4: Reentry into Wage Employment

	All Workers		Low-Income		High-Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort: 2007-2008, 2012-2013						
Business Owner: SE	-0.667***	-0.680***	-0.657***	-0.650***	-0.639***	-0.634***
	(0.007)	(0.007)	(0.014)	(0.014)	(0.013)	(0.013)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SE # Cohort: 2012-2013	0.154***	0.152***	0.145***	0.139***	0.119***	0.118***
	(0.010)	(0.010)	(0.021)	(0.021)	(0.017)	(0.017)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Business Owner: Large	-0.614***	-0.628***	-0.605***	-0.603***	-0.659***	-0.642***
	(0.028)	(0.029)	(0.080)	(0.086)	(0.035)	(0.036)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Large # Cohort: 2012-2013	0.019	-0.010	0.044	0.061	-0.008	-0.036
	(0.044)	(0.045)	(0.131)	(0.148)	(0.053)	(0.054)
	[0.670]	[0.824]	[0.736]	[0.679]	[0.886]	[0.502]
Cohort: 2012-2013	0.000	-0.022***	0.006	-0.085***	-0.004	-0.017***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)
	[0.828]	[0.000]	[0.131]	[0.000]	[0.298]	[0.000]
Mean: Not A Business Owner	0.820	0.820	0.759	0.759	0.841	0.841
Observations	188208	188208	48491	48491	46739	46739
R-Squared	0.081	0.126	0.046	0.111	0.125	0.172
Cohorts: 2012-2013						
Business Owner: SE MEI	-0.511***	-0.516***	-0.512***	-0.507***	-0.497***	-0.489***
	(0.008)	(0.007)	(0.016)	(0.016)	(0.014)	(0.014)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Business Owner: SE Not MEI	-0.524***	-0.560***	-0.515***	-0.519***	-0.564***	-0.557***
	(0.014)	(0.015)	(0.051)	(0.050)	(0.018)	(0.018)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Business Owner: Large	-0.595***	-0.631***	-0.562***	-0.531***	-0.667***	-0.676***
	(0.034)	(0.035)	(0.103)	(0.119)	(0.039)	(0.040)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Mean: Not A Business Owner	0.820	0.820	0.762	0.762	0.839	0.839
Observations	109561	109561	28093	28093	27170	27170
R-Squared	0.072	0.111	0.041	0.097	0.116	0.155
Controls		YES		YES		YES
Industry FE		YES		YES		YES

Note: Table 4 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Outcome variable is a binary indicator equal to 1 for workers who reentry wage employment. Analysis restricted to displaced workers. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value $< .1$; ** p-value $< .05$; *** p-value $< .01$.

Table 5: Years to Reentry

	All Workers		Low-Income		High-Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort: 2007-2008, 2012-2013						
Business Owner: SE	1.348***	1.415***	1.537***	1.582***	1.278***	1.318***
	(0.069)	(0.068)	(0.208)	(0.218)	(0.097)	(0.097)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SE # Cohort: 2012-2013	-0.239***	-0.272***	-0.512**	-0.566**	-0.041	-0.074
	(0.077)	(0.075)	(0.225)	(0.233)	(0.111)	(0.111)
	[0.002]	[0.000]	[0.023]	[0.015]	[0.714]	[0.504]
Business Owner: Large	1.174***	1.198***	1.402	1.365*	1.202***	1.186***
	(0.217)	(0.217)	(0.981)	(0.818)	(0.298)	(0.298)
	[0.000]	[0.000]	[0.153]	[0.095]	[0.000]	[0.000]
Large # Cohort: 2012-2013	-0.241	-0.232	0.853	0.616	-0.008	0.024
	(0.306)	(0.303)	(1.277)	(1.110)	(0.420)	(0.420)
	[0.431]	[0.443]	[0.504]	[0.579]	[0.984]	[0.955]
Cohort: 2012-2013	-0.165***	-0.092***	-0.186***	-0.056***	-0.134***	-0.083***
	(0.005)	(0.005)	(0.011)	(0.015)	(0.010)	(0.011)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Mean: Not A Business Owner	0.754	0.754	0.823	0.823	0.675	0.675
Observations	149849	149849	36040	36040	37582	37582
R-Squared	0.025	0.070	0.017	0.079	0.041	0.076
Cohorts: 2012-2013						
Business Owner: SE MEI	1.105***	1.127***	1.020***	1.000***	1.259***	1.250***
	(0.038)	(0.037)	(0.089)	(0.084)	(0.065)	(0.064)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Business Owner: SE Not MEI	1.127***	1.166***	1.088***	0.996***	1.186***	1.197***
	(0.074)	(0.074)	(0.317)	(0.311)	(0.099)	(0.098)
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
Business Owner: Large	0.933***	0.960***	2.255***	1.963**	1.194***	1.197***
	(0.216)	(0.211)	(0.817)	(0.799)	(0.296)	(0.294)
	[0.000]	[0.000]	[0.006]	[0.014]	[0.000]	[0.000]
Mean: Not A Business Owner	0.685	0.685	0.745	0.745	0.619	0.619
Observations	87257	87257	20955	20955	21787	21787
R-Squared	0.025	0.080	0.012	0.089	0.049	0.088
Controls		YES		YES		YES
Industry FE		YES		YES		YES

Note: Table 5 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Outcome variable is the temporal gap (in years) between job loss and reentry into wage employment. Analysis restricted to displaced workers who reentry wage employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table 6: Selection into Reentry (Conditional on Self-Employment)

	2007-2008			2012-2013		
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly Wage (Ln)	0.085***	0.085***	0.064***	0.035***	0.052***	0.035**
	(0.013)	(0.014)	(0.015)	(0.012)	(0.013)	(0.015)
	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]	[0.019]
Years of Tenure		-0.003*	-0.001		-0.010***	-0.007***
		(0.002)	(0.002)		(0.002)	(0.002)
		[0.089]	[0.687]		[0.000]	[0.000]
Manager		0.034	0.030		-0.028	-0.021
		(0.030)	(0.030)		(0.022)	(0.022)
		[0.255]	[0.313]		[0.215]	[0.347]
Firm Size (Ln)		0.009	0.009		0.015***	0.013**
		(0.006)	(0.006)		(0.005)	(0.005)
		[0.130]	[0.139]		[0.005]	[0.014]
Age			-0.015			-0.010
			(0.010)			(0.010)
			[0.142]			[0.325]
Age*Age			0.000			0.000
			(0.000)			(0.000)
			[0.229]			[0.582]
Race: Non-White			-0.027*			0.028*
			(0.016)			(0.015)
			[0.093]			[0.060]
Gender: Female			-0.039***			-0.059***
			(0.015)			(0.015)
			[0.009]			[0.000]
Education: High School			0.050***			0.039**
			(0.016)			(0.015)
			[0.002]			[0.011]
Education: College or More			0.060*			0.035
			(0.032)			(0.027)
			[0.060]			[0.185]
Average LHS	0.150	0.150	0.150	0.304	0.304	0.304
Observations	2676	2676	2676	4919	4919	4919
R-Squared	0.045	0.047	0.058	0.032	0.039	0.048
Industry FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES

Note: Table 3 reports the estimates from a linear probability model where the outcome variable is a binary indicator equal to 1 for workers who reentry wage employment following job loss. Analysis restricted to displaced workers who transitioned to formal self-employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table 7: Δ Wage (Diff-in-Diff)

	All Workers		Low-Income		High-Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort: 2007-2008, 2012-2013						
Business Owner: SE	-0.148***	-0.059**	0.051	0.055	-0.163***	-0.120***
	(0.030)	(0.027)	(0.054)	(0.054)	(0.046)	(0.045)
	[0.000]	[0.032]	[0.342]	[0.308]	[0.000]	[0.008]
SE # Cohort: 2012-2013	0.000	-0.033	-0.026	-0.027	-0.064	-0.072
	(0.033)	(0.030)	(0.060)	(0.060)	(0.053)	(0.052)
	[0.994]	[0.273]	[0.667]	[0.654]	[0.223]	[0.161]
Business Owner: Large	0.065	0.188*	-0.056	-0.021	0.159	0.236
	(0.107)	(0.101)	(0.036)	(0.059)	(0.193)	(0.178)
	[0.545]	[0.064]	[0.117]	[0.722]	[0.410]	[0.184]
Large # Cohort: 2012-2013	-0.204	-0.232*	-0.270***	-0.338***	-0.407	-0.416*
	(0.148)	(0.137)	(0.036)	(0.061)	(0.255)	(0.243)
	[0.166]	[0.091]	[0.000]	[0.000]	[0.110]	[0.087]
Cohort: 2012-2013	0.009***	0.039***	-0.016***	0.073***	0.041***	0.028***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)	(0.006)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Mean: Not A Business Owner	-0.140	-0.140	0.007	0.007	-0.288	-0.288
Observations	140620	140620	33713	33713	34821	34821
R-Squared	0.002	0.116	0.001	0.048	0.005	0.063
Cohorts: 2012-2013						
Business Owner: SE MEI	-0.140***	-0.104***	0.033	0.037	-0.247***	-0.221***
	(0.016)	(0.014)	(0.029)	(0.029)	(0.030)	(0.029)
	[0.000]	[0.000]	[0.258]	[0.195]	[0.000]	[0.000]
Business Owner: SE Not MEI	-0.176***	-0.056*	-0.055	-0.042	-0.182***	-0.126***
	(0.034)	(0.032)	(0.060)	(0.057)	(0.049)	(0.048)
	[0.000]	[0.074]	[0.355]	[0.454]	[0.000]	[0.009]
Business Owner: Large	-0.140	-0.048	-0.327***	-0.382***	-0.248	-0.175
	(0.102)	(0.093)	(0.002)	(0.019)	(0.167)	(0.166)
	[0.170]	[0.602]	[0.000]	[0.000]	[0.136]	[0.291]
Mean: Not A Business Owner	-0.136	-0.136	0.001	0.001	-0.270	-0.270
Observations	81779	81779	19592	19592	20138	20138
R-Squared	0.003	0.109	0.000	0.048	0.006	0.060
Controls		YES		YES		YES
Industry FE		YES		YES		YES

Note: Table 7 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Outcome variable is the measure of wage difference between pre-displacement and reentry. Analysis restricted to displaced workers who reentry wage employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table 8: Δ Wage (Diff-in-Diff): Minimum Wage

	All Workers		Low-Income		High-Income	
	(1) Actual	(2) MW	(3) Actual	(4) MW	(5) Actual	(6) MW
Cohort: 2007-2008, 2012-2013						
Business Owner: SE	-0.059**	-0.012	0.055	0.001	-0.120***	-0.004
	(0.027)	(0.013)	(0.054)	(0.024)	(0.045)	(0.023)
	[0.032]	[0.336]	[0.308]	[0.963]	[0.008]	[0.863]
SE # Cohort: 2012-2013	-0.033	0.002	-0.027	-0.011	-0.072	-0.008
	(0.030)	(0.014)	(0.060)	(0.028)	(0.052)	(0.025)
	[0.273]	[0.863]	[0.654]	[0.706]	[0.161]	[0.746]
Business Owner: Large	0.188*	0.053	-0.021	-0.052	0.236	0.167*
	(0.101)	(0.055)	(0.059)	(0.084)	(0.178)	(0.096)
	[0.064]	[0.338]	[0.722]	[0.538]	[0.184]	[0.083]
Large # Cohort: 2012-2013	-0.232*	-0.067	-0.338***	-0.136	-0.416*	-0.197*
	(0.137)	(0.065)	(0.061)	(0.084)	(0.243)	(0.113)
	[0.091]	[0.300]	[0.000]	[0.109]	[0.087]	[0.079]
Cohort: 2012-2013	0.039***	0.183***	0.073***	0.165***	0.028***	0.180***
	(0.002)	(0.001)	(0.005)	(0.003)	(0.006)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Mean: Not A Business Owner	-0.140	-0.833	0.007	-0.316	-0.288	-1.466
Observations	140620	140620	33713	33713	34821	34821
R-Squared	0.116	0.893	0.048	0.550	0.063	0.819
Cohorts: 2012-2013						
Business Owner: SE MEI	-0.104***	-0.012*	0.037	-0.006	-0.221***	-0.026*
	(0.014)	(0.007)	(0.029)	(0.015)	(0.029)	(0.013)
	[0.000]	[0.098]	[0.195]	[0.707]	[0.000]	[0.057]
Business Owner: SE Not MEI	-0.056*	0.000	-0.042	-0.045*	-0.126***	0.017
	(0.032)	(0.013)	(0.057)	(0.026)	(0.048)	(0.019)
	[0.074]	[0.973]	[0.454]	[0.088]	[0.009]	[0.360]
Business Owner: Large	-0.048	-0.012	-0.382***	-0.190***	-0.175	-0.030
	(0.093)	(0.034)	(0.019)	(0.010)	(0.166)	(0.059)
	[0.602]	[0.721]	[0.000]	[0.000]	[0.291]	[0.610]
Mean: Not A Business Owner	-0.136	-0.832	0.001	-0.317	-0.270	-1.457
Observations	81779	81779	19592	19592	20138	20138
R-Squared	0.109	0.897	0.048	0.586	0.060	0.820
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Note: Table 8 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Columns 1, 3, and 5: outcome variable is the measure of wage difference between pre-displacement and reentry. Columns 2, 4, and 6: outcome variable is the measure of hypothetical wage measure in the case when all reentry wages are at minimum-wage levels. Analysis restricted to displaced workers who reentry wage employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table 9: Δ Wage (Diff-in-Diff)

	Low-Income						High-Income					
	(1) Mgr.	(2) Coll.	(3) FGTS	(4) 24-29	(5) 30-39	(6) 40-50	(7) Mgr.	(8) Coll.	(9) FGTS	(10) 24-29	(11) 30-39	(12) 40-50
Cohort: 2007-2008, 2012-2013												
Business Owner: SE	-0.025	0.059	-0.096	0.031	0.048	0.108	-0.067	-0.162	-0.230**	-0.149*	-0.121*	-0.078
	(0.092)	(0.080)	(0.203)	(0.108)	(0.069)	(0.090)	(0.066)	(0.106)	(0.109)	(0.087)	(0.063)	(0.094)
	[0.785]	[0.464]	[0.635]	[0.777]	[0.488]	[0.231]	[0.311]	[0.129]	[0.036]	[0.088]	[0.057]	[0.407]
SE # Cohort: 2012-2013	0.139	-0.310***		-0.039	-0.011	-0.040	-0.171**	-0.152	0.018	-0.034	-0.057	-0.155
	(0.115)	(0.117)		(0.116)	(0.082)	(0.104)	(0.083)	(0.125)	(0.122)	(0.104)	(0.071)	(0.108)
	[0.230]	[0.009]		[0.737]	[0.897]	[0.703]	[0.039]	[0.224]	[0.879]	[0.745]	[0.424]	[0.153]
Business Owner: Large	0.042			0.034***		-0.042	-0.006	-0.126	-0.116	1.293***	0.231	-0.029
	(0.026)			(0.009)		(0.083)	(0.174)	(0.271)	(0.201)	(0.496)	(0.248)	(0.141)
	[0.104]			[0.000]		[0.612]	[0.972]	[0.643]	[0.566]	[0.009]	[0.351]	[0.837]
Large # Cohort: 2012-2013	-0.389***					-0.316***	-0.199	-0.199	-0.068	-1.228**	-0.540	-0.560***
	(0.044)					(0.087)	(0.426)	(0.433)	(0.376)	(0.550)	(0.341)	(0.142)
	[0.000]					[0.000]	[0.641]	[0.645]	[0.856]	[0.026]	[0.113]	[0.000]
Cohort: 2012-2013	0.077***	0.162***	-0.005	0.069***	0.077***	0.073***	0.036**	0.033*	-0.004	0.004	0.018**	0.053***
	(0.012)	(0.058)	(0.108)	(0.010)	(0.008)	(0.009)	(0.014)	(0.018)	(0.017)	(0.013)	(0.009)	(0.010)
	[0.000]	[0.006]	[0.967]	[0.000]	[0.000]	[0.000]	[0.011]	[0.064]	[0.811]	[0.728]	[0.040]	[0.000]
Mean: Not A Business Owner	-0.000	0.095	0.156	0.003	0.014	0.003	-0.373	-0.286	-0.210	-0.276	-0.282	-0.306
Observations	7209	408	270	9262	13538	10913	7354	4543	5471	7403	16642	10776
R-Squared	0.066	0.187	0.145	0.044	0.051	0.062	0.048	0.076	0.058	0.047	0.052	0.110
Cohorts: 2012-2013												
Business Owner: SE MEI	0.136*	-0.118	-0.104	0.002	0.035	0.089	-0.253***	-0.408***	-0.279***	-0.260***	-0.199***	-0.238***
	(0.079)	(0.115)	(0.217)	(0.048)	(0.046)	(0.056)	(0.063)	(0.076)	(0.071)	(0.065)	(0.039)	(0.058)
	[0.084]	[0.305]	[0.631]	[0.967]	[0.449]	[0.109]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Business Owner: SE Not MEI	-0.154***		-0.406	-0.107**	0.061	-0.101	-0.211**	-0.159	-0.133*	-0.028	-0.128**	-0.226*
	(0.038)		(0.327)	(0.053)	(0.111)	(0.092)	(0.085)	(0.114)	(0.080)	(0.101)	(0.058)	(0.126)
	[0.000]		[0.216]	[0.046]	[0.582]	[0.272]	[0.013]	[0.163]	[0.096]	[0.777]	[0.027]	[0.074]
Business Owner: Large	-0.335***					-0.349***	-0.207	-0.372	-0.228	0.087	-0.309	-0.568***
	(0.049)					(0.031)	(0.402)	(0.305)	(0.326)	(0.239)	(0.232)	(0.029)
	[0.000]					[0.000]	[0.607]	[0.223]	[0.484]	[0.715]	[0.182]	[0.000]
Mean: Not A Business Owner	-0.006	0.088	0.120	-0.005	0.008	-0.004	-0.359	-0.265	-0.203	-0.268	-0.267	-0.277
Observations	3994	236	205	5018	7811	6763	4203	2814	3824	4225	9834	6079
R-Squared	0.050	0.281	0.184	0.058	0.052	0.053	0.054	0.088	0.052	0.054	0.054	0.101
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Table 9 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Outcome variable is the measure of wage difference between pre-displacement and reentry. Analysis restricted to displaced workers who reentry wage employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value $<$ .1; ** p-value $<$ .05; *** p-value $<$ .01.

Table 10: Δ Skill Content

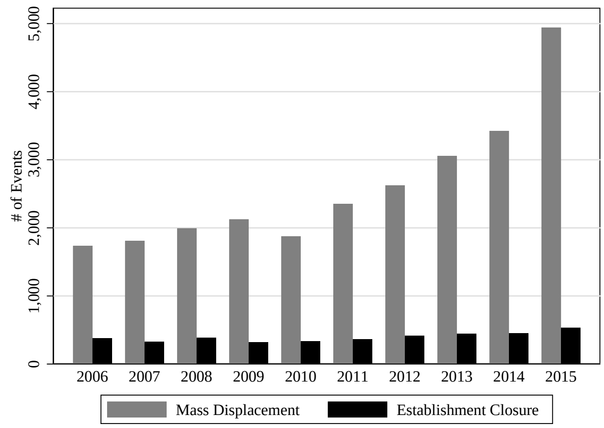
	All	Low	High	Non-Mgr	Mgr
	(1)	(2)	(3)	(4)	(5)
Cohort: 2007-2008, 2012-2013					
Business Owner: SE	0.151*	0.294	0.034	0.144	0.273
	(0.082)	(0.182)	(0.120)	(0.088)	(0.218)
	[0.066]	[0.105]	[0.774]	[0.102]	[0.212]
SE # Cohort: 2012-2013	-0.060	-0.071	0.019	-0.079	-0.006
	(0.091)	(0.210)	(0.136)	(0.097)	(0.250)
	[0.506]	[0.735]	[0.890]	[0.416]	[0.981]
Business Owner: Large	0.381*	-1.126*	0.317	0.334	0.486
	(0.219)	(0.607)	(0.322)	(0.248)	(0.495)
	[0.082]	[0.064]	[0.325]	[0.177]	[0.326]
Large # Cohort: 2012-2013	-0.216	0.606	0.102	-0.395	0.855
	(0.346)	(1.134)	(0.530)	(0.374)	(0.801)
	[0.533]	[0.593]	[0.847]	[0.291]	[0.285]
Cohort: 2012-2013	-0.037***	-0.016	-0.055***	-0.041***	0.022
	(0.007)	(0.019)	(0.016)	(0.008)	(0.037)
	[0.000]	[0.402]	[0.000]	[0.000]	[0.554]
Mean: Not A Business Owner	0.257	0.392	0.165	0.284	-0.205
Observations	149849	36040	37582	141562	8287
R-Squared	0.020	0.041	0.008	0.021	0.084
Cohorts: 2012-2013					
Business Owner: SE MEI	0.088**	0.272**	0.042	0.078*	0.198
	(0.043)	(0.111)	(0.077)	(0.045)	(0.157)
	[0.040]	[0.014]	[0.591]	[0.081]	[0.207]
Business Owner: SE Not MEI	0.143*	-0.227	0.106	0.071	0.339*
	(0.084)	(0.252)	(0.118)	(0.093)	(0.190)
	[0.088]	[0.367]	[0.368]	[0.447]	[0.074]
Business Owner: Large	0.173	-0.549	0.401	-0.046	1.274**
	(0.267)	(1.031)	(0.420)	(0.279)	(0.624)
	[0.516]	[0.594]	[0.339]	[0.869]	[0.041]
Mean: Not A Business Owner	0.233	0.358	0.148	0.257	-0.149
Observations	87257	20955	21787	82111	5146
R-Squared	0.023	0.050	0.011	0.026	0.099
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Note: Table 10 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Outcome variable is the measure of changes in skill content. Skill content is proxied by the average years of schooling of workers employed in each 3-digit occupation. Analysis restricted to displaced workers who reentry wage employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

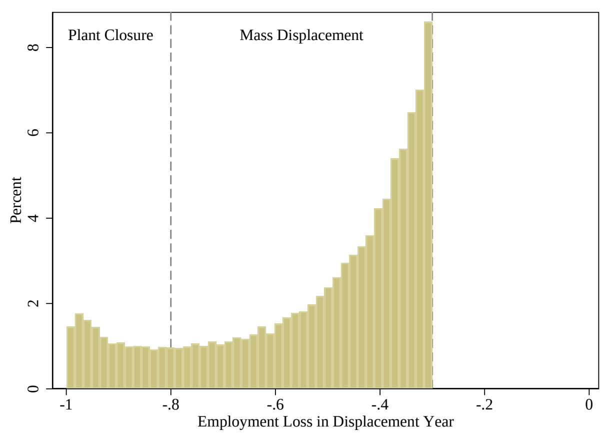
A Appendix: Figures and Tables

Figure A.1: Mass Displacement Events

(a) Number of Events by Year

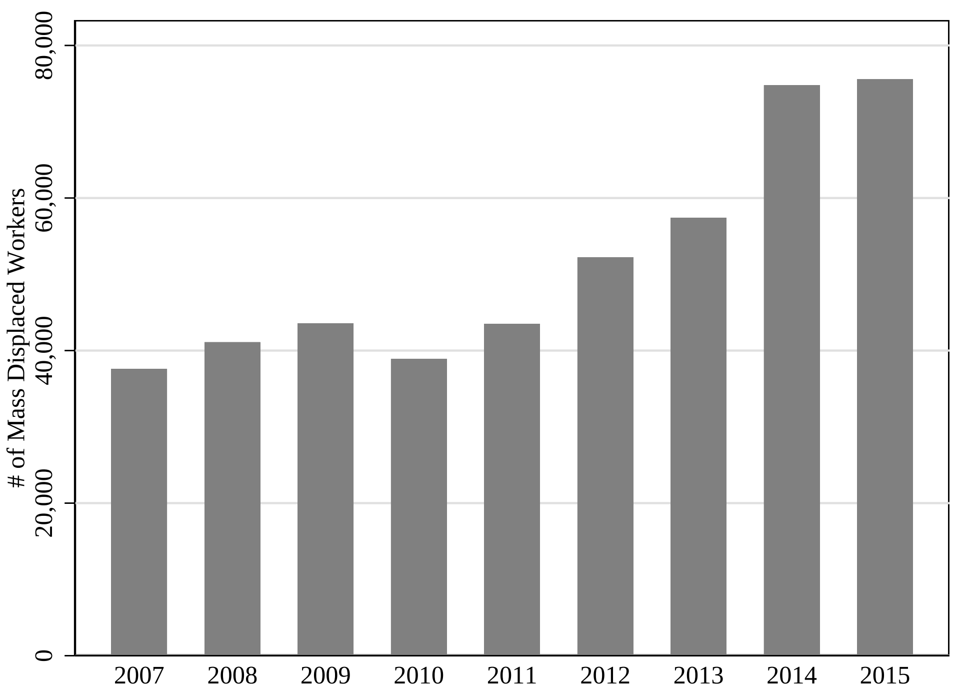


(b) Employment Loss in Displacement Year



Note: Figure A.1, Panel A, provides a yearly breakdown of mass displacement events and also reports the number of establishment closure events using a more restrictive criterion where at least 80 percent of workers are fired. Panel B shows the distribution of the employment loss during the displacement year, along with the cutoffs which were used to define mass displacement events and plant closures.

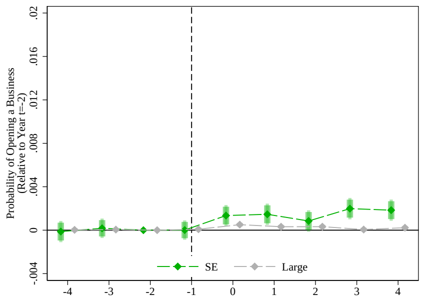
Figure A.2: Number of Mass Displaced Workers



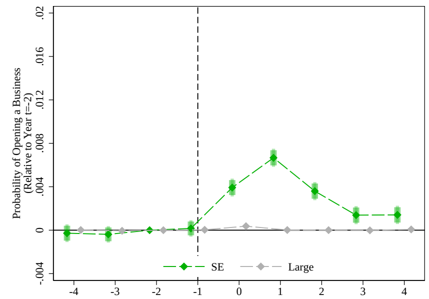
Note: Figure A.2 provides a yearly breakdown of mass displaced workers in each year. Due to the matching algorithm, the number of non-displaced workers in each cohort is identical. The 2006 cohort is excluded from the analysis, because industry information is not available in 2005 (the pre-displacement year for the 2006 cohort).

Figure A.3: Job Loss and Firm Ownership: Education

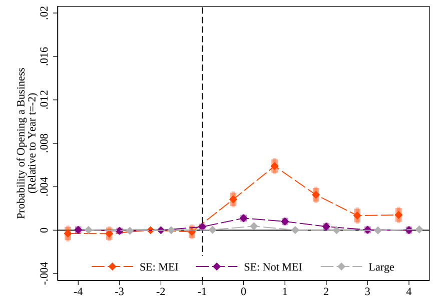
(a) Primary or Less: 2007-2008



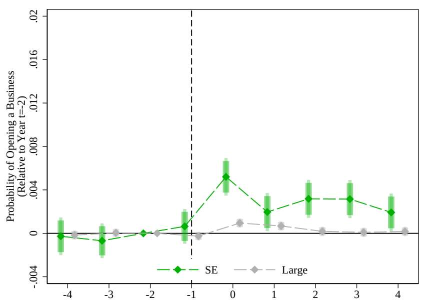
(b) Primary or Less: 2012-2013



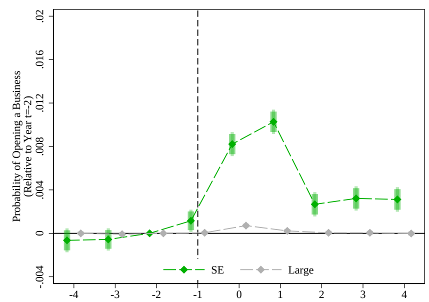
(c) Primary or Less: 2012-2013



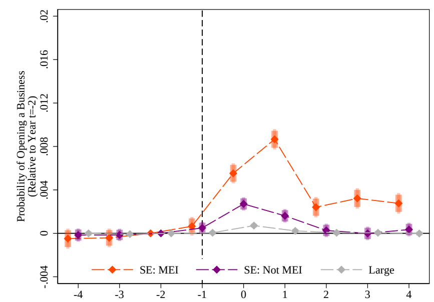
(d) High School: 2007-2008



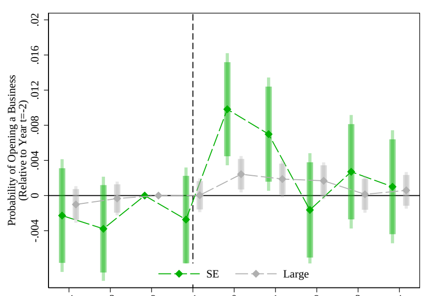
(e) High School: 2012-2013



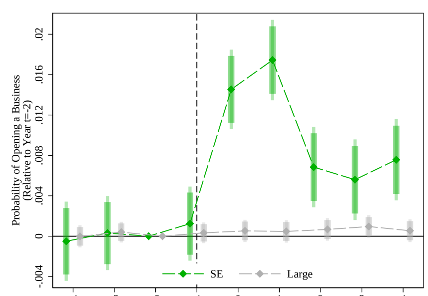
(f) High School: 2012-2013



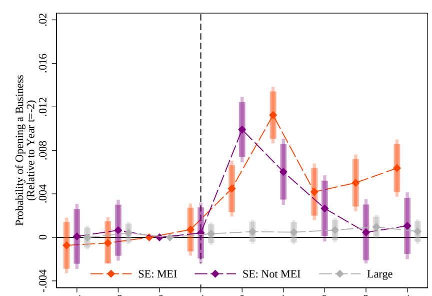
(g) College or More: 2007-2008



(h) College or More: 2012-2013



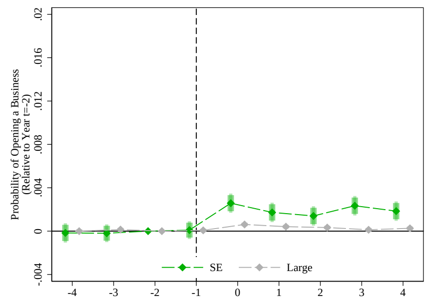
(i) College or More: 2012-2013



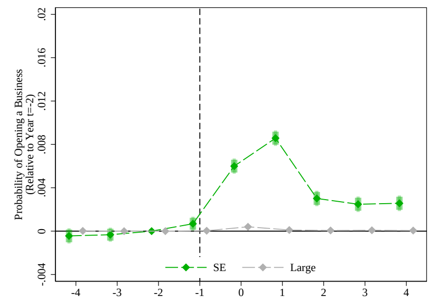
Note: Figure A.3 shows the results from estimating Equation 1. Outcome variable is a binary indicator for new firm openings. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure A.4: Job Loss and Firm Ownership: Managerial Experience

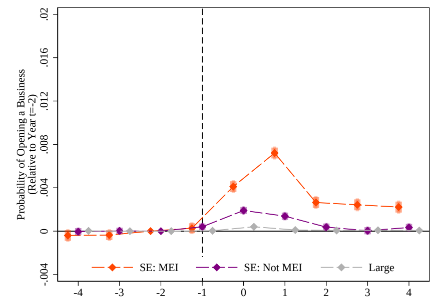
(a) Non-Managers: 2007-2008



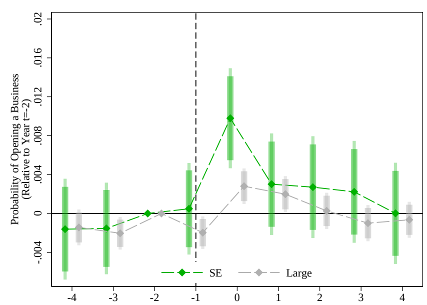
(b) Non-Manager: 2012-2013



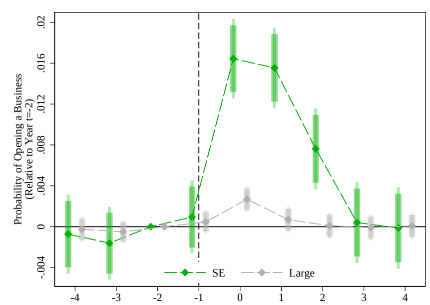
(c) Non-Manager: 2012-2013



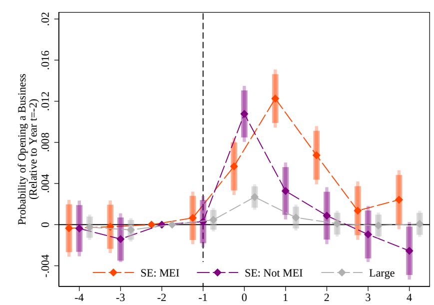
(d) Managers: 2007-2008



(e) Managers: 2012-2013



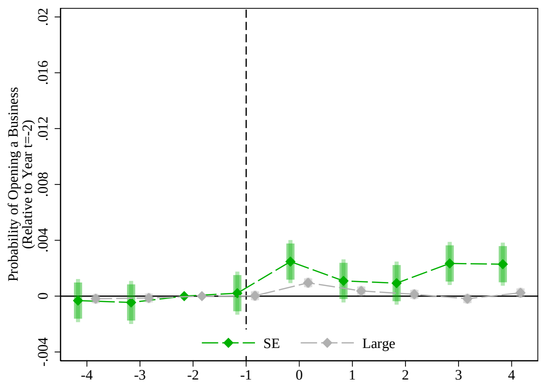
(f) Managers: 2012-2013



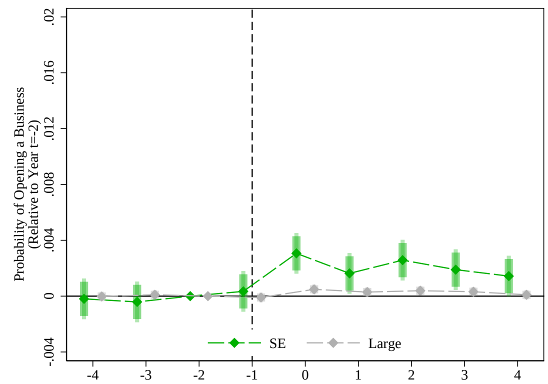
Note: Figure A.4 shows the results from estimating Equation 1. Outcome variable is a binary indicator for new firm openings. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure A.5: Job Loss and Firm Ownership: Cohort Heterogeneity

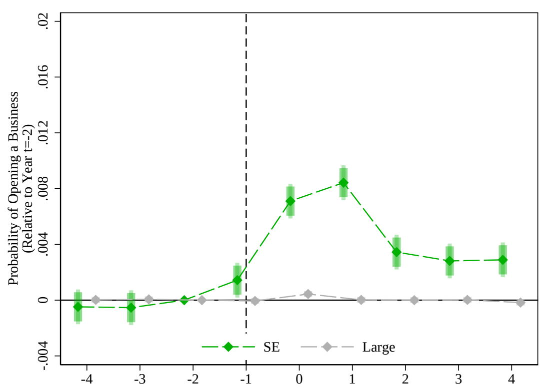
(a) 2007



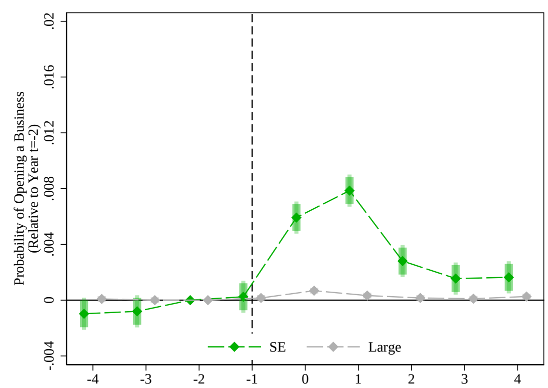
(b) 2008



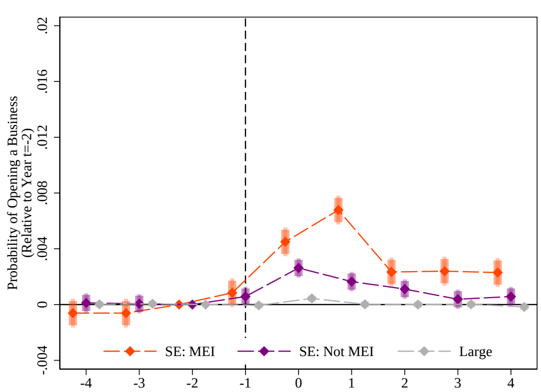
(c) 2012



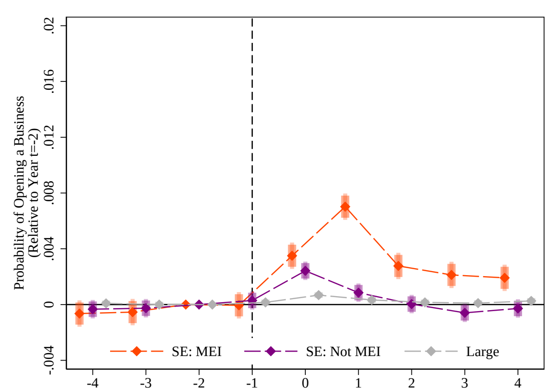
(d) 2013



(e) 2012



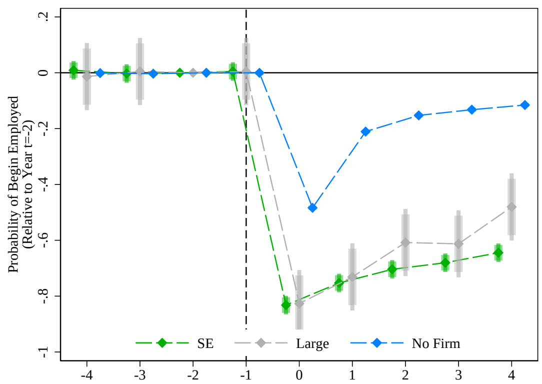
(f) 2013



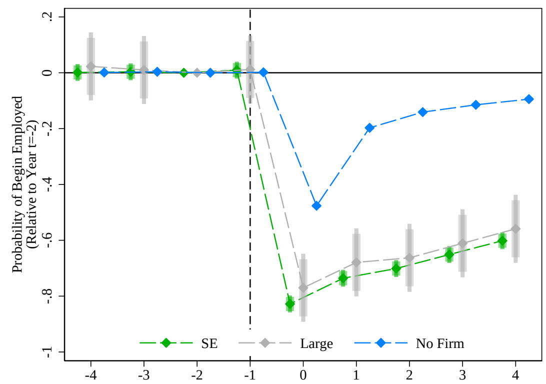
Note: Figure A.5 shows the results from estimating Equation 1. Outcome variable is a binary indicator for new firm openings. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure A.6: Job Loss and Employment: Cohort Heterogeneity

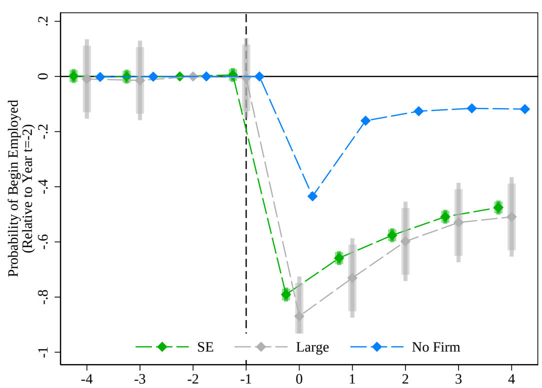
(a) 2007



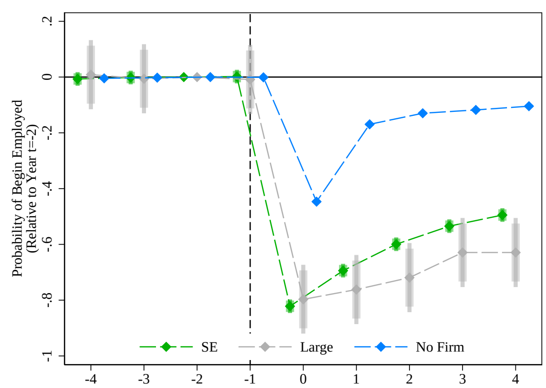
(b) 2008



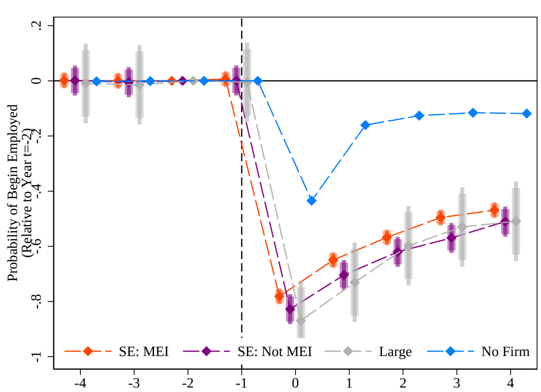
(c) 2012



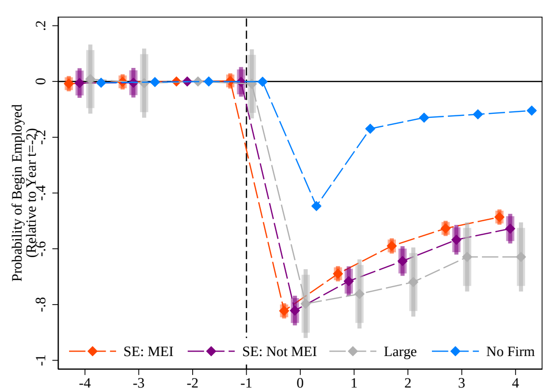
(d) 2013



(e) 2012



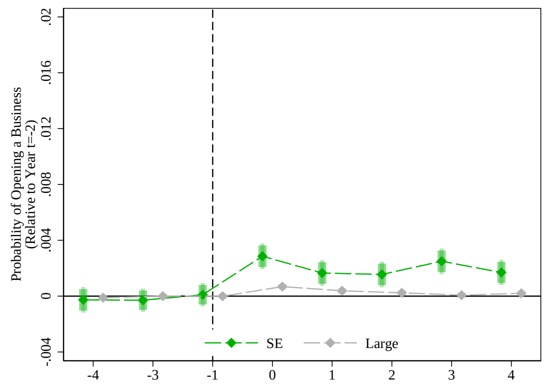
(f) 2013



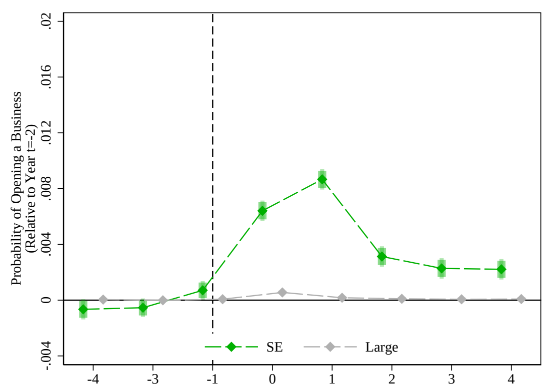
Note: Figure A.6 shows the results from estimating Equation 2. Outcome variable is a binary indicator for worker-level employment. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure A.7: Job Loss and Firm Ownership: Sun and Abraham (2021)

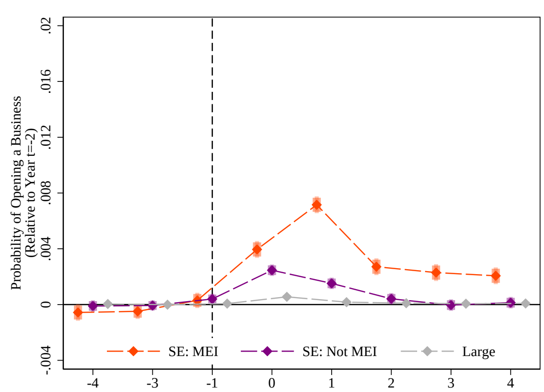
(a) 2007-2008



(b) 2012-2013



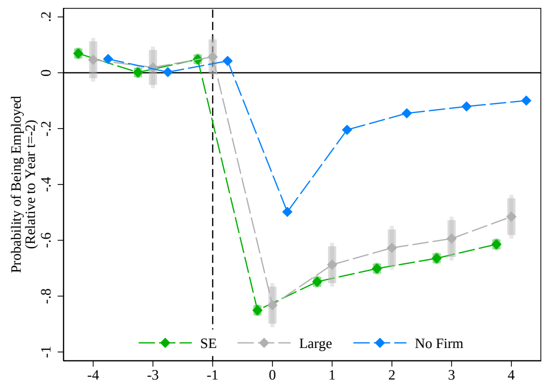
(c) 2012-2013



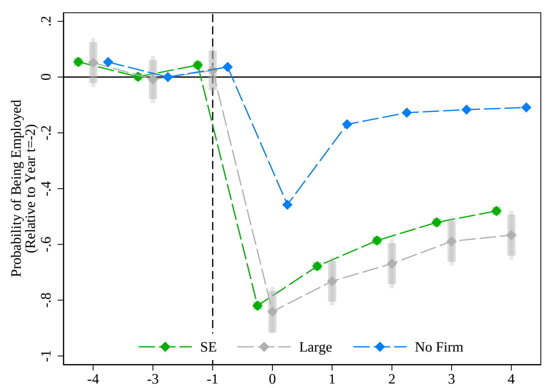
Note: Figure A.7 shows the results from estimating Equation 1 following the procedure proposed by Sun and Abraham (2021). Outcome variable is a binary indicator for worker-level employment. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure A.8: Job Loss and Employment: Sun and Abraham (2021)

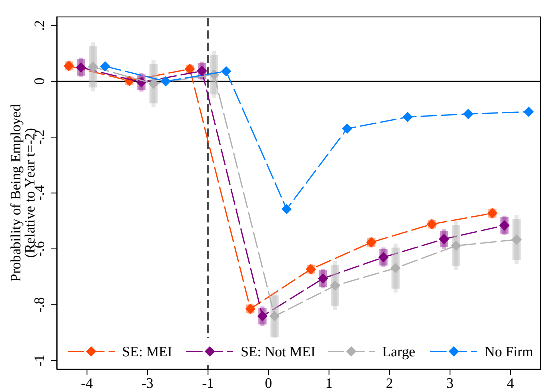
(a) 2007-2008



(b) 2012-2013



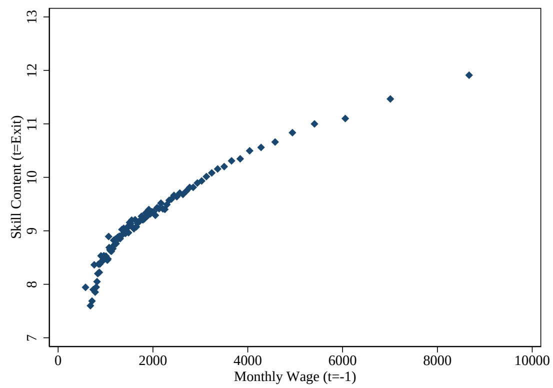
(c) 2012-2013



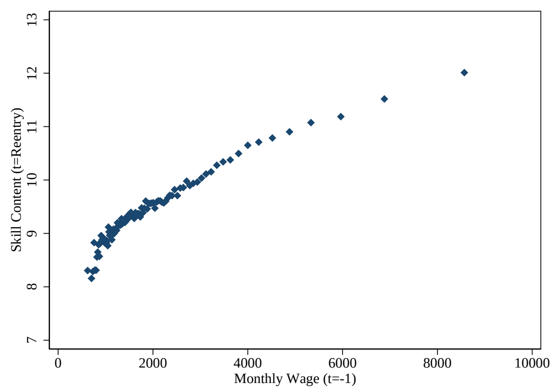
Note: Figure A.8 shows the results from estimating Equation 2 following the procedure proposed by Sun and Abraham (2021). Outcome variable is a binary indicator for new firm openings. All regressions include year fixed effects and a binary dummy indicator identifying mass displaced workers. Omitted period is $\ell = -2$.

Figure A.9: Skill Content and Wages

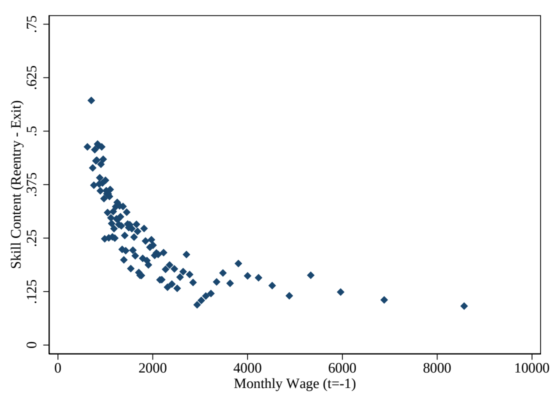
(a) Exit



(b) Reentry



(c) Reentry - Exit



Note: Figure A.9 shows how the skill content measure correlates with pre-displacement wages. Skill content is proxied by the average years of schooling of workers employed in each 3-digit occupation.

Table A.1: Summary Statistics: Matched Sample

	2007-2008		2012-2013	
	Diff.	t-Statistic	Diff.	t-Statistic
Matching Variables				
Age	0.00	0.00	0.00	0.00
Age: 29-	0.00	0.00	0.00	0.00
Age: 30-39	0.00	0.00	0.00	0.00
Age: 40+	0.00	0.00	0.00	0.00
Years of Tenure	0.00	0.00	0.00	0.00
Monthly Wage	8.39	1.12	4.65	0.66
Industry: Manufacturing	0.00	0.00	0.00	0.00
Industry: Retail and Services	0.00	0.00	0.00	0.00
Industry: Health and Education	0.00	0.00	0.00	0.00
Industry: Public Sector	0.00	0.00	0.00	0.00
Industry: Other	0.00	0.00	0.00	0.00
Region: North	0.00	0.00	0.00	0.00
Region: Northeast	0.00	0.00	0.00	0.00
Region: Southeast	0.00	0.00	0.00	0.00
Region: South	0.00	0.00	0.00	0.00
Region: Center-West	0.00	0.00	0.00	0.00
Worker Characteristics				
Race: Non-White	-0.02***	-7.25	-0.01***	-5.38
Gender: Female	0.00	0.19	0.01***	4.00
Education: Primary or Less	-0.02***	-7.73	-0.03***	-12.57
Education: High School	0.01***	6.00	0.02***	10.46
Education: College or More	0.00***	4.58	0.00***	3.99
Occupational Characteristics				
Firm Size	301.21***	39.84	135.68***	13.55
Manager	-0.01***	-7.52	-0.01***	-7.26
Firm Owner	-0.00***	-4.34	-0.00	-0.09
MEI Owner	0.00	.	-0.00***	-5.50
Observations	157408		219224	

Note: Table A.1 displays the sample characteristics of workers included in the main sample. Non-displaced and displaced workers are matched using the matching variables listed in this table. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table A.2: Δ Skill Content: 2 Digits

	All	Low	High	Non-Mgr	Mgr
	(1)	(2)	(3)	(4)	(5)
Cohort: 2007-2008, 2012-2013					
Business Owner: SE	0.103	0.144	0.107	0.059	0.389*
	(0.085)	(0.200)	(0.123)	(0.091)	(0.236)
	[0.227]	[0.471]	[0.387]	[0.513]	[0.099]
SE # Cohort: 2012-2013	-0.024	0.012	-0.060	-0.010	-0.124
	(0.094)	(0.223)	(0.140)	(0.099)	(0.272)
	[0.799]	[0.958]	[0.669]	[0.918]	[0.650]
Business Owner: Large	0.277	-0.846	0.240	0.182	0.297
	(0.247)	(0.672)	(0.390)	(0.249)	(0.753)
	[0.262]	[0.208]	[0.539]	[0.464]	[0.694]
Large # Cohort: 2012-2013	-0.041	-0.002	0.309	-0.239	1.164
	(0.399)	(1.109)	(0.631)	(0.418)	(0.965)
	[0.919]	[0.999]	[0.625]	[0.568]	[0.228]
Cohort: 2012-2013	-0.062***	-0.070***	-0.026	-0.061***	0.023
	(0.008)	(0.018)	(0.016)	(0.008)	(0.040)
	[0.000]	[0.000]	[0.113]	[0.000]	[0.570]
Mean: Not A Business Owner	0.270	0.411	0.202	0.270	0.274
Observations	149849	36040	37582	141562	8287
R-Squared	0.023	0.078	0.008	0.026	0.074
Cohorts: 2012-2013					
Business Owner: SE MEI	0.101**	0.250**	0.057	0.089**	0.235
	(0.043)	(0.103)	(0.078)	(0.044)	(0.180)
	[0.020]	[0.015]	[0.470]	[0.044]	[0.192]
Business Owner: SE Not MEI	0.071	-0.414**	0.073	-0.014	0.279
	(0.087)	(0.202)	(0.121)	(0.095)	(0.186)
	[0.417]	[0.040]	[0.548]	[0.883]	[0.133]
Business Owner: Large	0.220	-0.921	0.533	-0.072	1.410**
	(0.314)	(0.984)	(0.493)	(0.335)	(0.607)
	[0.483]	[0.350]	[0.280]	[0.829]	[0.020]
Mean: Not A Business Owner	0.235	0.328	0.199	0.229	0.323
Observations	87257	20955	21787	82111	5146
R-Squared	0.029	0.067	0.014	0.032	0.081
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Note: Table A.2 reports the results from estimating Equations 3 (Panel A) and 4 (Panel B). Outcome variable is the measure of changes in skill content. Skill content is proxied by the average years of schooling of workers employed in each 2-digit occupation. Analysis restricted to displaced workers who reentry wage employment. Standard errors in parentheses. P-values in brackets. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.