# The Labor Market Spillovers of Job Destruction*

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**Abstract**

This paper examines how job destruction impacts labor market conditions after recessionary shocks. To estimate the causal general equilibrium effect of job destruction, we combine administrative data on employment relationships with variation in the idiosyncratic layoff behavior of large firms across U.S. local labor markets. Workers who lose their job in a labor market with a one-percentage-point greater increase in the local job destruction rate experience a persistent \$700 (1.2%) greater reduction in annual earnings in the following six years, reflecting lower employment in the short term and lower-paying jobs in the medium term. These spillover effects account for one-third of the higher cost of job loss in recessions versus expansions and imply that each marginal job loser imposes an annual cost of approximately \$17,000 on other workers in the same labor market. To assess the aggregate effects of increased job destruction rates, we develop a general equilibrium search model featuring heterogeneous firm productivity, endogenous separations, and human capital scarring in unemployment. To account for the magnitude and persistence of our spillover estimates, the model requires that an increase in job loss lower the equilibrium job-finding rate, limiting workers' human capital accumulation and reallocation to more productive firms. Following negative shocks to aggregate productivity, a policymaker aiming to stabilize output should increase job retention subsidies, even though it would slow the cleansing of low-productivity jobs.

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# 1 Introduction

Recessions in the United States are often marked by an initial burst of job destruction. While workers who lose their jobs during this time experience much larger and persistent earnings losses than in recessions (Davis and von Wachter, 2011), it is unclear whether the concentration of job destruction amplifies the costs of business cycles. Theories of Schumpeterian cleansing predict that employment contraction during recessions disproportionately occurs at low-productivity firms, allowing labor to reallocate to more productive employers. The high cost of job loss during recessions may merely reflect the *selection* of which firms destroy jobs.

However, if labor market frictions limit how many high-quality jobs can be quickly created and filled, spikes in layoffs may lower the rate at which unemployed workers can find better jobs. The general equilibrium effects of job destruction would then result in *spillovers* that increase the cost of employment loss during recessions, making it potentially valuable for policymakers to save existing jobs with subsidies. Yet, despite its importance, little work has been done to quantify the magnitude of these labor market spillovers, largely because the equilibrium effects of job destruction are difficult to disentangle from the underlying productivity shocks that lead firms to lay off workers during recessions.

In this paper, we provide novel evidence on the magnitude of job destruction spillovers and use our estimates to quantitatively assess the value of countercyclical job retention subsidies. To estimate the causal effect of job loss on the equilibrium conditions of local labor markets, we develop a granular firm research design and implement it using administrative employer-employee microdata from the U.S. Census Bureau. A recession-level increase in the annual job destruction rate of 3 percentage points amplifies the earnings cost associated with job loss by 12%, leading displaced workers to lose an additional $2,100 in each of the following six years.[1] Factoring in effects on the average employed worker from lower job-finding rates, each marginal job lost imposes an additional earnings spillover cost of approximately $17,000 per year, which is about 90% of the average cost of job loss during recessions within our sample.

We calibrate a job ladder model with endogenous job destruction to match these facts and develop two additional insights. First, the spillover effects we estimate imply a meaningful reduction in output: firms do not benefit as much as workers lose from realistic job destruction shocks. Second, when policymakers only have access to a simple employment transfer, then it may be desirable to increase job subsidies to limit rising unemployment

[1] All earnings are in terms of 2015 U.S. dollars.

following an aggregate shock. Overall, our paper sheds new light on the general equilibrium forces of job loss and its policy implications, which connects the extensive work on the costs of layoffs in partial equilibrium with the study of labor market dynamics over the business cycle.

To motivate our reduced-form estimates, we first illustrate the key channels by which job loss may affect other workers in a stylized model of the labor market. An additional job loser reduces equilibrium labor market tightness – the ratio of vacancies to jobseekers – when firms face convex costs in creating new jobs. In turn, lower labor market tightness reduces both the job-finding rate of unemployed workers and shifts job surplus away from employed workers through lower equilibrium wages. As a result, we expect job destruction spillovers to impact both the intensive and extensive margin of earnings.

Estimating the magnitude of these spillovers from job loss requires one to isolate the effects of elevated job destruction from changes to the marginal productivity of labor. This is challenging: many of the economic shocks that lead a large fraction of workers to be laid off likely also impact the earnings of other workers in the same labor market, even if the layoffs had not happened. For example, due to the steep decline in housing demand in certain regions during 2007-2009 recession, the construction sector experienced an upward spike in job destruction along with a large reduction in the profitability of new jobs. As a result, across local markets, the future earnings of displaced construction workers may be negatively correlated with the local job destruction rate even absent any meaningful spillover effects.

Our empirical strategy is designed to address this fundamental identification challenge. We use cross-sectional variation in job destruction rates across local labor markets that is induced by differential exposure to the idiosyncratic shocks of large, national firms. Because shocks to job productivity are correlated within firms, employment changes by the firm's other markets predict variation in establishment-level job destruction. And because these firms exhibit large local employment shares, firm-specific contractions can induce granular variation in the local job destruction rates.

We implement our research design using administrative data from the U.S. Census Bureau in which we observe the quarterly worker earnings in the near-universe of private sector jobs in 24 states from 1994 to 2020. For each local labor market—defined as a city-by-industry pair (e.g., retail trade in Boston)—we construct a measure of the exposure to the job destruction activity of national firms. For a given market, we construct the measure by taking a weighted average of national firms' job destruction rates in other markets, where the weights are each firm's ex-ante share of total employment in the market. We then use this measure as an instrument to estimate worker outcomes up to six years following a shock to the job destruction rate. Because we condition on industry-by-time fixed effects, our instrument captures variation in changes to local job destruction independent of industry-level fluctuations over the business cycle.

Our empirical design identifies the causal spillover effects of job destruction shocks if our shift-share instrument does not systematically vary with shocks to any other determinants of worker outcomes (Borusyak et al., 2022). This condition would fail if, within sectors, certain national firms predominantly open establishments in regions where aggregate demand or labor productivity are relatively sensitive to aggregate shocks.

Two placebo tests support the validity of our identifying assumption. First, under our baseline set of controls, our market-level instrument shows no meaningful relationship with the job destruction rates of the establishments belonging to single-region firms. These are the establishments whose job destruction rates would likely be most sensitive to shocks to local conditions that would be correlated with our instrument. Second, we demonstrate that the national job destruction rate of the largest local employer does not predict the job destruction rates of the other national firms that operate in the same labor market. Therefore, any violation of our identifying assumption would have to result from shocks to local conditions that are correlated with the job destruction activity of a single firm but uncorrelated with the shocks affecting other firms in the same labor market.

After validating our research design, we then apply it to estimate the spillover effects of job destruction on workers' short- and medium-run labor earnings. Our primary sample is composed of workers who separate from their jobs during a mass layoff between 1997 and 2014. In line with existing literature, we define the cost of job loss as the difference between the earnings trajectory of displaced workers and closely matched control workers who remain employed for at least one year. In our baseline specification, we estimate that a 1 percentage point (pp) increase in the annual local job destruction rate results in a persistent 1.2 pp reduction in total earnings over the subsequent six years, relative to baseline earnings pre-displacement. Approximately 47% of the total spillover effect is driven by extended periods of nonemployment, while the remaining 53% is due to lower earnings upon reemployment.

Complementary results suggest that the spillovers we estimate primarily arise from elevated frictions in job-finding within the labor market. Among employed workers, job destruction spillovers are heterogeneous in firm-level variation of future separation risk. We find that workers at national firms in the highest quintile of future separation risk experience greater earnings spillovers, but find no significant effects at firms little-to- no job destruction in the following year. We also examine how much of our spillover estimate is driven by the effect of job loss on local demand, as workers who lose employment may reduce their consumption. In both the case where we (i) absorb common exposure to local demand from CBSA-quarter fixed effects and (ii) restrict our sample to workers in industries that produce tradable goods (Mian and Sufi, 2014), we find that the estimated spillover declines by approximately 25% relative to the baseline specification. This leads us to conclude that the majority of the effects of local job destruction shocks are driven by labor market frictions.

The congestion effects that arise from job destruction are not confined to displaced workers. Using the same empirical design, we estimate that the average employed worker in a labor market experiencing a 1 percentage point (pp) job destruction shock sees a 0.2 pp reduction in annual earnings growth over six years.[2] Combined with our results for job losers, an additional job lost has an annual $17,000 negative spillover on all other workers in the labor market, roughly one-third of which is due to the costs on recent job losers and unemployed workers.[3] Furthermore, removing the contribution of job destruction fluctuations from the earnings effect of job loss would reduce its covariance with the business cycle by one-third, in line with the fraction of unemployment volatility accounted by job loss (Shimer, 2012a).

Our reduced-form estimates show that a large fraction of the total cost of job loss on workers, especially during aggregate downturns, is the result of spillovers of individual separation decisions on labor market tightness. It is more difficult for workers to search for better jobs at a time when many other workers in the same labor market are also doing so. One might be tempted to conclude that job destruction during recessions is inefficiently high and rapid. However, such a conclusion does not follow from our reduced-form results alone. This is because our earnings estimates do not capture the potentially positive impact that job destruction may have firms' profits. Both incumbent employers (who could dissolve negative-surplus jobs) and new employers (who may find it easier to hire new workers at lower wages) could experience benefits from higher job destruction that could dominate the worker-level costs revealed by our spillover estimates.

We address this question by developing a quantitative theory of labor market dynamics, calibrated to our spillover estimates for workers. We extend past work on partial equilibrium job-ladder models (Jarosch, 2023; Krolikowski, 2017) to general equilibrium settings in which both the employment distribution across job productivity and market tightness are endogenous. To examine policies aimed at preserving jobs, we model sep-

[2] In contrast to the spillover effects on job loss, most of the impact on the average employed worker is concentrated in the first few years following the shock.

[3] This estimate comes from combining the spillover effects for the average worker with spillover effects for job losers, under the assumption that spillovers for unemployed worker are similar to those as recent job losers. Section 5 provides detail on this calculation.

aration decisions as endogenous to job productivity, which evolves stochastically over time (Mortensen and Pissarides, 1994).

In the model, job destruction shocks can impact market tightness due to limits on the creation of new jobs: a fixed mass of firms face convex costs in vacancy posting. When market conditions deteriorate, workers struggle more to find jobs, which also erodes their human capital through scarring effects. Employed workers experience lower earnings growth as well, since they face greater difficulty advancing up the job ladder by switching firms.

Calibrating these spillovers to our empirical estimates on earnings is difficult because it requires us to solve transition dynamics in a setting where the equilibrium is not block recursive in market aggregates. Moreover, because the structural parameters that determine the steady state wage distribution also impact the propagation of job destruction shocks, it is undesirable to split up estimation of the steady-state and dynamic equilibrium, as is commonly done in past work. To make progress, we instead use recent results for continuous-time heterogeneous agent models and the compute transition dynamics following a distributional impulse to the job destruction rate when calibrating the model (Bilal, 2023). We find that our quantitative model is able to replicate the empirical earnings spillovers that we estimate empirically.

We first use the model to evaluate how much of the decline in worker earnings reflect a transfer to firms through lower equilibrium wages. Our preferred calibration suggests that, following an exogenous job destruction shock, less than half of the reduction in worker earnings from the equilibrium response of tightness are compensated by benefits to firms in the form of lower wages. The remaining portion represents the productive loss from labor market spillovers, driven by lower market-level production due to extended periods of unemployment, changes in the composition of available jobs, and human capital depreciation from reduced time spent employed.

We then use the model to study the value of job-preserving subsidies. We consider a policymaker that seeks to maximize output and can an untargeted transfer to all active jobs, which is financed with a non-distionary lump-sum tax. In steady state, the optimal transfer is a *tax* on existing jobs. As the effective bargaining power of workers is high, a policymaker wants to cleanse lower productivity jobs so that workers may reallocate to more productive ones. However, given the net output loss of job destruction shocks, the policymaker would find it valuable to stabilize output with subsidies during negative aggregate shocks.

Following a brief review of the literature, the paper proceeds as follows. In Section 2, we formalize job destruction within a stylized model with search frictions. Section

3 describes our research design, which is then implemented in Section 4 to estimate the spillover costs for job losers. In Section 5, we use our estimates to approximate the cyclical impact of layoffs on earnings and the total spillover cost of a marginal job loss in the local labor market. In Section 6, we describe and calibrate our quantitative model of the labor market, which is then applied to study the welfare implications of job destruction in Section 7. Section 8 concludes.

### 1.1 Related literature

Our estimates suggest that the spillover effects of job destruction play an important role in the worker costs of business cycles. Past work has documented that workers who lose their jobs during recessions experience a large and persistent decline in earnings compared to observably similar workers who retain their jobs (Jacobson et al., 1993; Davis and von Wachter, 2011; Lachowska et al., 2020; Schmieder et al., 2023a; Bertheau et al., 2023). As noted by Davis and von Wachter (2011), standard search models (e.g., Mortensen and Pissarides, 1994) cannot easily reproduce the magnitude, persistence, and countercylicality of earnings losses found in the data. Features such as heterogeneity in job separation rates (Krolikowski, 2017; Jarosch, 2023), worker scarring effects (Huckfeldt, 2021; Jarosch, 2023) and firm- or sector-specific human capital (Burdett et al., 2020) can allow search models to better explain these earnings effects in partial equilibrium. Our paper complements this work by showing that the general equilibrium effects of elevated job destruction contribute to the countercyclical earnings losses. Relative to other proposed mechanisms (Huckfeldt, 2021), job destruction spillovers are more amenable to policy intervention that can reduce workers' short- and long-term exposure to economic downturns.

The general equilibrium forces we document provide new evidence on the importance of job destruction shocks in unemployment fluctuations over the business cycle (Elsby et al., 2009; Shimer, 2012b). Recent work, summarized in Hall and Kudlyak (2021), has emphasized how search models in which the equilibrium job-finding rate is a decreasing function of the stock of unemployed workers, transitory shocks to job destruction rates can cause a persistent decline in the equilibrium job-finding rates.[4] We contribute to this work by providing causal evidence that, consistent with these models, increases in

[4]Examples include models in which new hires being imperfect substitutes with incumbent workers (Mercan et al., 2024), vacancy costs are convex (Fujita and Ramey, 2007), there is an inelastic supply of entrant firms to replace incumbent firms that exit when jobs are destroyed, (Coles and Kelishomi, 2018), or heterogeneity in the productivity of job seekers that is unobservable to vacancy-posting firms (Restrepo, 2015; Engbom, 2021)

job destruction rates reduce the equilibrium job-finding rates of workers. Our estimates improve upon past work using structural VAR models to estimate congestion effects in aggregate time series data (Fujita and Ramey, 2007; Coles and Kelishomi, 2018; Mercan et al., 2024) as well as event-studies that study regional effects from a small sample of establishment mass-layoff events (Gathmann et al., 2020).

Finally, our paper relates to the extensive literature studying labor reallocation over the business cycle (Davis and Haltwanger, 1992; Haltiwanger et al., 2018, 2021). The increased dispersion in firm productivity distribution (Bloom et al., 2018) and higher job destruction rates among low-productivity lead to cleansing effects in recessions (Caballero and Hammour, 1994; Mortensen and Pissarides, 1994; Ilut et al., 2018; Hershbein and Kahn, 2018), which has led some to argue against countercyclical job retention programs (e.g., Barrero et al., 2020). On the other hand, reallocation during recessions can impose large and persistent costs on local labor markets most exposed to structural change (Chodorow-Reich and Wieland, 2020). Our paper quantifies an additional cost of countercyclical labor reallocation: the spillover that a job loser may have on other agents in the economy.[5] The equilibrium effects we estimate suggest that one of the primary rationales provided by the literature on why unemployment insurance (UI) benefits should rise in recessions – that workers searching harder to find a job may congest the labor market (Landais et al., 2018a,b) – also applies to job retention policies.[6]

# 2 Qualitative Model

To help contextualize our empirical results and describe our analysis, we describe job loss in a two-period version of the standard Diamond-Mortensen-Pissarides (DMP) model where we replace free entry with convex costs to job creation. In this setting, job destruction spillovers arise through general equilibrium effects on market tightness. We later quantify this key mechanism through the lens of the dynamic model described in Section 6.

[5]Other papers have attempted to measure of job-retention policies in the context of short-time work (STW) schemes in various European countries (Boeri and Bruecker, 2011; Cahuc et al., 2021; Kopp and Siegenthaler, 2021; Giupponi and Landais, 2022). Such policy variation does not exist in the U.S. due to the limited availability and take-up of STW policies (Abraham and Houseman, 2014; von Wachter, 2020a). Among these papers, only Giupponi and Landais (2022) analyzes the equilibrium effects of STW subsidies. Our paper focuses on estimating labor market spillovers with respect to worker-level outcomes instead of firm-level outcomes, which maps more closely to the labor market congestion externality that help determine whether such policies would be effective in the US.

[6]Our estimates can also be useful in understanding the labor market effects of secular shocks, such as the China trade normalization (Autor et al., 2014; Pierce et al., 2024) or the adoption of automating technologies (Acemoglu and Restrepo, 2020; Beraja and Zorzi, 2024; Lehr and Restrepo, 2022).

**Setup.** In period $t = 1$, a fraction $u$ of workers are unemployed and search for new jobs. The remaining $1 - u$ workers are employed and produce $p$ units of the consumption good, in return for a wage $w$. A representative firm creates new positions $\nu$ subject to convex costs that can be filled by unemployed workers. Matching between firms and workers is subject to search frictions: the total number of matches is determined by the function $\mathcal{M}(u, \nu)$, which is increasing in both inputs. In period $t = 2$, worker receive an endowment $W_2$ if they enter the period employed, and $U_2 < W_2$ if they are unemployed. The firm similarly receives $J_2 > 0$ for each employed worker. We assume no discounting of the future and normalize the home production of unemployed workers at $t = 1$ to 0.

We define market tightness as the ratio of available jobs per unemployed worker, $\theta := v/u$. High levels of $\theta$ reflect better employment conditions for workers, and vice versa for the firm. Labor market tightness is determined in equilibrium by the job creation of the firm, which maximizes expected profit taking the market tightness and unemployment as given:

$$\Pi_1(\theta, u) = (1 - u)J_1 + \max_{\nu \geq 0} vq(\theta)J_2 - C(\nu)$$

where $q(\theta) = \frac{M}{\nu}$ is the probability of a match that the job is filled and $J_1 = p - w + J_2$ is the value of existing jobs to the firm. Job creation costs $C(\cdot)$ are assumed to be convex: $C'(\cdot) > 0$, $MC'(\cdot) \geq 0$. Firm profits are maximized on an interior solution in which the expected value of a new job is equal to its marginal cost: $q(\theta)J_2 = C'(\nu)$. The value of employment and unemployment at the beginning of $t = 1$ is given by: $W_1 = w_1 + W_2$ and $U_1 = f(\theta)W_2 + (1 - f(\theta))U_2$, where $f(\theta) = \frac{M}{u}$ is the job-finding probability for unemployed workers.

Total expected output can be decomposed at $t = 1$ into terms of the value received by unemployed workers ($U$), employed workers ($W$), and the firm owner ($\Pi$):

$$Y(\theta) = uU_1(\theta) + (1 - u)W_1(\theta) + \Pi_1(\theta, u) \tag{1}$$

To close the model we assume that wages are determined by Nash bargaining, so that they are set for the following to hold:

$$W_1 - U_1 = \beta S_1, \tag{2}$$

where $\beta$ is the bargaining power of the worker and $S_1 := W_1 + J_1 - U_1$ is the job surplus.

**Job destruction.** We model a job destruction shock $ds_i$ as the reallocation of some employed worker $i$ employment to unemployment at $t = 1$.The following Lemma characterizes its effect:

**Lemma 1.** *Let* $1 - \omega_f = \frac{\partial \log f(\theta)}{\partial \log \theta} \geq 0$ *be the elasticity of the job-finding rate to market tightness* $\xi_v = \frac{\partial \log C'(v)}{\partial \log v}$ *be the marginal cost elasticity with respect to* $v$*. The total effect of a job destruction shock can be expressed as:*

$$\frac{dY}{ds_i} = - \underbrace{S_1}_{\text{Private surplus}} + \underbrace{\left[ u \frac{\partial U}{\partial \log \theta} + (1-u) \frac{\partial W}{\partial \log \theta} \right] \frac{\partial \log \theta}{\partial u}}_{\text{Worker spillover}} + \underbrace{\frac{\partial \Pi}{\partial \log \theta} \frac{\partial \log \theta}{\partial u}}_{\text{Firm spillover}}. \tag{3}$$

*where:*

$$\frac{\partial U_1}{\partial \log \theta} = (1-\omega_f) f(\theta) \left[ W_2 - U_2 \right], \quad \frac{\partial W_1}{\partial \log \theta} = (1-\beta) \frac{\partial U_1}{\partial \log \theta}, \quad \frac{\partial \log \theta}{\partial u} = - \frac{\xi_v}{\xi_v + \omega_f} u^{-1}, \tag{4}$$

*and* $\frac{\partial \Pi_1}{\partial \log \theta} = -(1-\beta) \frac{\partial U_1}{\partial \log \theta} - \omega_f u f(\theta) J_2$.

The two lines of (3) reflect the channels by which job destruction and impacts aggregate production. The first term captures the partial equilibrium effect of the job destruction shock, which is the lost private surplus of the separated job.[7] The remaining terms reflect the *spillover effects* that job destruction has on output through general equilibrium changes in labor market tightness. The first of these terms is the total spillover onto workers, which stems from a decline in market tightness as the number of jobseekers increases. The second term is the firm spillover effects, which reflect both higher profits from lower market tightness effects and changes to the cost of job creation as a result of the increase in unemployment. One can understand these spillovers as the changes in the value of each state holding the distribution fixed.

There are two basic ways in which workers are affected by the equilibrium of the job destruction shock. The first is through the job-finding rate, highlighted by $\frac{\partial \log U}{\partial \log \theta}$: lower market tightness makes it more difficult for workers to find new jobs. The second is through changes in the worker's outside option, which reduce their wages. In a tight labor market (high $\theta$), workers can bargain a larger share of their job's production. These two terms capture the extensive and intensive margin effects of labor market tightness on worker earnings, respectively.

Equation (4) analytically characterizes the response of market tightness to job destruction. For job destruction to have worker spillovers, the marginal cost of creating a new

[7]When separations are endogenous, bilateral efficiency of the wage mechanism (2) implies that firms would only choose to terminate jobs for which $S_1$. We allow for endogenous separations in the quantitative extension.

job must be rising in the number of jobs. The elasticity $\xi_v$ captures the ease by which firms can create new jobs and $\xi_u$ incorporates the direct effect of unemployment on hiring. In standard models with free entry from fixed costs to job creation ($\xi_v = \xi_u = 0$), an additional job seeker has no impact on equilibrium market tightness.[8] In the case where new jobs are rationed ($\xi \to \infty$), the marginal job seeker completely crowds out another worker, with market tightness response $\frac{\partial \log \theta}{\partial u} = -\frac{1}{u}$.[9]

The insights from this stylized model help inform our analysis in several ways. First, worker spillovers can be represented as changes to the value of their current employment state, which we approximate as the present-discounted value (PDV) of earnings in estimation (Section 3). Second, in the presence of convex hiring costs, we expect the most active jobseekers (like recent job losers) to be most affected by labor market congestion (Section 4). Third, understanding the full effects of job destruction in the labor market requires evaluating the firm spillover effects, which we perform in a quantitative enrichment of the model (Section 7).

# 3 Research Design

We estimate job destruction in the United States between 1997 and 2014. The 2001 recession, normalization of trade relations with China (Autor et al., 2013), and the Great Recession resulted in significant variation in the aggregate rate of job loss. To distinguish job destruction spillovers from the direct effect of productivity during this period, we implement a regional design in which we estimate the effects of job destruction on workers across local labor markets. Since we expect most equilibrium costs to fall on individuals working in similar jobs to those destroyed, our cross-sectional results are informative of aggregate worker spillovers.

## 3.1 Data

We measure earnings and job destruction using data from the Longitudinal Employer-Household Dynamics (LEHD) program of the U.S. Census, which collects employment data from quarterly unemployment insurance (UI) records across all 50 states and the District of Columbia. Our data come from 24 states that collectively account for 45%

[8] In this case, the market-tightness is pinned down by the fixed cost for a new job, so that any increase in unemployment is offset by an increase in job created by the firm.

[9] Under the Hosios condition, where $\omega_f = \frac{W_2 - U_2}{J_2 + W_2 - U_2}$, the equilibrium is efficient. As a result, the spillovers on firms and workers from the marginal job lost cancel out and there is no welfare cost from lower tightness, despite convex job creation costs. .

of private-sector employment in 2015.[10] The LEHD also includes auxiliary data on demographic information (e.g., age, sex, race, and residential census tract) and employer characteristics (industry, location, and federal tax filing identifiers). We can also observe whether the worker is employed at any job covered by UI in the United States, which enables us to track entry into and out of our sample. Our main samples are constructed from employment data between 1994 and 2020.

Employer identifiers in the LEHD are state-specific and can change following business reorganizations. We link employer identifiers across states by augmenting an internal bridge from the U.S. Census that connects tax identifiers in the LEHD with those in the Longitudinal Business Database (LBD). We define a *firm* ($f$) using the LBD parent firm identifier, which is more consistent over time and better reflects operational control than the tax-filing identifiers in the LEHD.[11]

We define a *job* as a worker-firm pair with positive earnings in the LEHD. The job with the highest earnings in quarter $t-1$ is defined as the worker's primary job at the start of quarter $t$.[12] The worker's primary employer is the firm associated with their primary job. We assign each worker to a local labor market ($m$) based on the region-by-industry combination of their primary workplace at the start of $t$. In our main analysis, the region is defined using the 2015 core-based statistical area (CBSA) definitions, and the industry is categorized at the two-digit economic sector level using the 2017 North American Industry Classification System (NAICS) codes. We refer to firm-industry-region combinations as establishments.[13]

## 3.2 Market-level measures

We construct firm- and market-level information on employment dynamics by aggregating worker-level primary job flows. We describe the two primary measures of employ-

[10]States approve U.S. Census projects on an individual basis. We list the states included in our sample in Appendix Section B.1.

[11]We define firms according to the Census `lbdfid` value. Linking the worker data to firm definitions in the LBD has the added benefit of correcting for spurious changes in job transitions that are not caught by the pre-processing performed in the construction of LEHD job identifiers.

[12]We do not observe the exact start and end dates of each job. Instead, we infer employment timing from quarterly earnings, identifying whether the worker is employed at the start of a quarter (positive earnings in $t-1$ and $t$) or the end of a quarter (positive earnings in $t$ and $t+1$), following the approach used in Abowd et al. (2006).

[13]Our use of establishment differs from the actual place of work, which is unavailable for most states. The LEHD uses demographic and geographic data to impute establishment (`SEINUNIT`) identifiers for each job. Our definition of establishments and local labor markets relies on the worker's modal industry and region, and we weight observations by this value when aggregating employment. Most workers have local labor market information with high precision in our baseline definition. Further details on our sample filters are provided in Section B.3.

ment dynamics used in our analysis.

### 3.2.1 Local Job Destruction

Our measure of job destruction is derived from the gross flows of primary jobs. For a given establishment $(f, m)$ in quarter $t$, we measure the job destruction rate $s_{f,m,t}$ as the reduction in net employment flows over four calendar quarters:

$$s_{f,m,t} = \max \left[ \frac{\sum_{h=0}^{3} \left( \text{Sep}_{f,m,t+h} - \text{Hire}_{f,m,t+h} \right)}{N_{f,m,t-1}}, 0 \right], \tag{5}$$

where $N_{f,m,t-1}$ is the establishment's employment count as of $t-1$, and $\text{Sep}_{f,m,t+h}$ and $\text{Hire}_{f,m,t+h}$ are the counts of workers separated from and hired by the establishment in quarter $t+h$, based on observed earnings changes. The market-level (i.e., local) job destruction rate is the employment-weighted average of establishment rates:

$$s_{m,t} = \left( \sum_{f} N_{f,m,t-1} \right)^{-1} \sum_{f} N_{f,m,t-1} \times s_{f,m,t}. \tag{6}$$

Aggregating job flows to track employment contractions offers several advantages over using changes in reported employment levels (e.g., $N_{f,m,t+3}/N_{f,m,t-1} - 1$), as commonly done (e.g., Davis and Haltwanger, 1992). In particular, this approach allows us to filter out earnings changes unlikely to reflect job search, such as backpay or seasonal employment fluctuations.[14] Using flows also helps us exclude abrupt employment changes due to corporate restructuring (e.g., mergers) from our measures.[15]

[14] We attempt to disregard flows corresponding to temporary (e.g., internships) or part-time positions by considering a worker employed at the firm-LLM $(f, m)$ in quarter $t$ only if (i) the worker is prime age (between 24 and 64) and (ii) it is the worker's only job with positive earnings during $t$. For $\text{Sep}_{f,m,t+h}$, we further require that the worker has been employed full-time in the job for at least two quarters. We describe the construction of job flows in detail in Section B.2.

[15] We favor the measure of job destruction (5) over gross separation flows ($\sum_{h=0}^{3} \text{Sep}_{f,m,t+h}/N_{f,m,t-1}$) because the latter are less informative about labor market congestion caused by job losses. Since 56% of vacancies are for replacement hiring, many separations do not require firms to create new jobs. As a result, gross flows are a noisier indicator of "true" job destruction (Mercan and Schoefer, 2020). A potential drawback of our measure is that changes to (5) could reflect hiring adjustments rather than actual layoffs. However, this mismeasurement is likely negligible: Davis et al. (2012) use microdata from the Job Openings and Labor Turnover Survey to show that most variation in establishment-level job destruction during our sample period is driven by layoffs rather than hiring.

### 3.2.2 National firm job destruction

We construct an instrument for the local job destruction rate (6) using variation in the job destruction of *national firms*. We define the set of national firms, $\mathcal{F}^N$, as those holding at least 10 primary jobs in at least two states with non-overlapping CBSAs.[16] Our shift-share measure of job destruction in market $m$ uses national firm activity in geographic regions, excluding the ones that encompass $m$. For a given national firm $f$, we define the corresponding national firm job destruction rate as:

$$s_{f,-m,t} = \left( \sum_{m':r(m')\neq r(m)} N_{f,m',t-1} \right)^{-1} \sum_{m':r(m')\neq r(m)} N_{f,m',t-1} \times s_{f,m',t-1}, \tag{7}$$

where we take region $r(m)$ of the labor market to be the state(s) covering the corresponding CBSA. The market-level instrument replaces the establishment-level job destruction rate in (6) with the national rate of its parent firm:

$$s^{IV}_{m,t} = (\sum_f N_{f,m,t-1})^{-1} \sum_{f\in\mathcal{F}_N} N_{f,m,t-1} \times s_{f,-m,t}, \tag{8}$$

where $\mathcal{F}_N$ is the set of national firms. Since the denominator of the instrument is the market-level employment across all establishments, including non-national firms ($f \notin \mathcal{F}_N$), the employment shares used to construct (8) do not sum to one.

## 3.3 Estimating equation

We estimate the structural equation:

$$y_{i,t+h} = \beta^{(h)} s_{-i,m,t} + \phi_m + \Gamma_1^{(h)} \mathbf{X}^W_{i,t} + \Gamma_2^{(h)} \mathbf{X}^M_{-i,m,t} + \epsilon_{i,t+h} \tag{9}$$

where $y_{i,t+h}$ is an observed outcome for worker $i$ $h$ quarters after the measure shock at $t$. To avoid capturing the employer shocks that might directly affect worker outcomes, we exclude the worker's most recent employer from all market-level measures – we denote this adjustment by a "$-i$"- subscript, e.g. $s_{-i,m,t}$. The inclusion of labor market fixed effects $\phi_m$ imply that the variation in the job destruction rate comes from deviation with respect to the within-sample market-level average. The vector $\mathbf{X}^M_{-i,m,t}$ and $\mathbf{X}^W_{i,t}$ are controls defined at the market- and worker-level, respectively, that we describe in Section 3.3.2.

We are interested in estimating the coefficient $\beta^{(h)}$, which captures the dynamic effect

[16] We enforce the restrictions on national firms at each quarter $t$, but omit time subscripts for clarity.

of local job destruction shocks on the worker outcome $y$. However, local job destruction may be endogenous to market-level conditions that affect worker outcomes through other channels. We therefore propose an instrument for the local job destruction rate $s_{-i,m,t}$ using the average job destruction rate of national firms $s_{-i,m,t}^{(IV)}$, with the first-stage equation:

$$s_{-i,m,t} = \beta^{fs} s_{-i,m,t}^{IV} + \phi_m + \Lambda_1 \mathbf{X}_{i,t}^{W} + \Lambda_2 \mathbf{X}_{-i,m,t}^{M} + \eta_{i,t+h}. \tag{10}$$

### 3.3.1 Identification

Identifying the worker-level spillover relies on the conditional orthogonality of idiosyncratic job destruction shocks to local market conditions.[17] Absent worker-specific and leave-out adjustments to market variables, Borusyak et al. (2022) show that the formal condition for the 2SLS estimate of $\beta^{(h)}$ from (9) and (10) to job destruction spillovers is:

$$\mathbb{E}\left[ \sum_{\forall f \in \mathcal{F}_N} s_{ft} \cdot \bar{\epsilon}_{ft}^{(h)} \middle| \overline{\mathbf{X}}_{ft}^{W}, \overline{\mathbf{X}}_{ft}^{M} \right] = 0 \tag{11}$$

where $\bar{\epsilon}_{ft}^{(h)}$, $\overline{\mathbf{X}}_{ft}^{W}$, and $\overline{\mathbf{X}}_{ft}^{M}$ are the weighted averages of, respectively, the structural residual, the worker-level controls, and the market-level controls, with the weights given by the firm $f$'s share of employment in the given market.[18] The exogeneity condition requires that, in a given quarter, the national firms are shedding employment are not systematically located in markets where, at this same time, the outcomes of laid-off workers are lower for reasons unrelated to the elevated rate of job loss.

### 3.3.2 Baseline controls

Absent any worker-level controls $\mathbf{X}_{it}^{W}$ or market-level controls $\mathbf{X}_{mt}^{M}$, it is reasonable to suspect that the instrument we consider does not satisfy the exogeneity condition (11). For example, the economic conditions of markets $m$ that operate in more cyclical industries (e.g., construction) will deteriorate more during national economic downturns. Since

[17]"Idiosyncratic" firm-level shocks could either reflect shocks that are truly at the level of the firm and unrelated to economic conditions in its different markets (eg. an exogenous shock to credit supply) or instead be the result of intra-firm contagion of economic shocks in certain markets to firms' establishments in other markets. Two sources of such contagion effects are binding borrowing constraints (Giroud and Mueller, 2019) or uniform national wage-setting (Hazell et al., 2021).

[18]We describe how our implementation differs from the assumptions underlying the orthogonality condition in Section C.3. In general, the differences are small in practice and are orthogonal to the key source of identifying variation conceptualized in (11). In Section A.1, we provide a formal treatment of the identification condition in an extentson of the stylized model presented in Section 2.

these markets are served by firms that likely destroy more jobs during national downturns, the estimate $\beta^{(h)}$ will be significantly non-zero even if is not actually a causal relationship between the cost of job loss and job destruction. Similar violations occur if firms happen to hire less in places with more job destruction.

To plausibility of the identification condition relies on the following set of controls we include in our baselin specification for (9). Most importantly, as suggested by the above example, we include quarter-by-industry (two-digit NAICS) fixed effects, removes variation from industry loading on the business cycle.[19]

We also include a set of time-varying market-level factors. We include the contemporaneous and lagged values of the predicted *job creation* rate of national firms, constructed in the same way the job destruction shift-share given by (8).[20] Intuitively, if a national firm experiences a negative idiosyncratic shock and destroys more jobs – but would have expanded its employment had the shock (counterfactually) not occurred – markets more exposed to this firm will experience both an increase in their aggregate job destruction rate as well as a reduction in their job creation rate. Including the job creation shift-share controls purges our job destruction instrument of these job creation effects.[21] To remove correlation in measurement error associated with using changes to employment growth as a proxy for productivity shocks, we also include a series of controls based on the weighted exposure of each national firm to local hiring and job destruction activity in other markets. We include the sum of the employment shares of national firms to control for differences in the instrument induced by the employment share of national firms.[22]

## 3.4 Validation

### 3.4.1 First stage

Figure 1 demonstrates that our job destruction instrument is a strong predictor of local job destruction. Panel 1a estimates a variant of the first stage (10) at the worker-level, where we replace the instrument by the leave-out national job destruction rate ($s_{f,-m,t}$) and the outcome by the job separation indicator $Sep_{i,t+h}$, for $h = -12, \ldots, 16$. The plot shows

[19]The inclusion of the labor market fixed effect $\phi_m$ removes static differences in labor market reallocation by firms.

[20]We provide formulas detailing the construction of all controls in Section C.1.1. All market-level controls are adjusted to exclude the worker's own firm from the measures.

[21]Essentially, purging our job destruction instrument of national firms' job creation activity ensures that its variation is driven by differences across national firms in the intensive margin of job destruction, rather than the extensive margin of whether firms are creating or destroying jobs.

[22]The conditional orthogonal conditions for shift-share instruments with incomplete market shares require the interaction of the employment share with all other controls. We find no change in our results when using this extended set, and therefore omit the interactions in our baseline specification.

that, the job destruction activity of the worker's firm in other markets is highly predictive of the worker's own separation probability.[23] The magnitude of this effect signifies that employment adjustments are meaningful correlated across establishments owned by the same parent firm.[24] Panel (b) presents a nonparametric representation of the market-level first stage (10), which shows that national firm job destruction have significant effects on local labor markets. A 1 pp increase in the exposure measure to national firm job destruction predicts a 0.75 pp increase in the average market-level job destruction rate, with an F-statistic of 93.9.

### 3.4.2 Placebo tests

The exclusion restriction requires that the national firm shocks do not sort into areas with systematically different unobserved determinants of workers or firm outcomes. Though we cannot test this condition directly, we can examine whether the employment shocks, residualized against our baseline controls, exhibit spatial correlation. We develop a series of placebo tests following the logic that idiosyncratic shocks to the firm should not be predictive of job destruction at other firms.

**Sorting by non-national firm activity** If the variation in the firm-level destruction shocks reflect a response to local labor market productivity, we may also expect that the employment of firms that operate in only one CBSA ($\mathcal{F}^L$) and therefore excluded from the set of national firms ($\mathcal{F}_N$), to be correlated with the instrument. We assess this possibility by estimating the relationship between establishment-level job destruction and the average job destruction rate of national firms:

$$s_{f,m,t} = \sum_{q=1}^{10} \beta^{(q)} 1 \left\{ Q(\bar{s}^{IV}_{-m,t}) = q \right\} + \Gamma' \mathbf{X}^M_{m,t} + \epsilon_{f,m,t}, \tag{12}$$

where $\left\{ Q(\bar{s}^{IV}_{-m,t}) = q \right\}$ is an indicator for the decile of the market-level exposure measure ($s^{IV}_{-m,t}$ from 8) divided by the local employment share of national firms. Figure 2a provides estimates of $\hat{\beta}^{(q)}$ in (12) separately for establishments owned by single-region

[23]Compared to workers at non-shocked firms, the job separation rate of workers at shocks firms remains elevated well beyond the period after the shock. In Appendix Figure 8, we show that nearly all of this effect after the first two years is due to elevated separation rates from new jobs by comparing the cumulated separation rates in Figure 1a to changes in the firm identifiers.

[24]Appendix Table 4 presents direct evidence to this point. The table shows that, among establishments owned by national firms in our sample, 32% of the variation in establishment-level job destruction rates is explained by the identity of the parent firm ($f$). In contrast, the identity of the local labor market ($m$) explains only 11% of the variation.

firms and those belonging to national firms.[25] Compared to the strong response of establishment owned by national firms, job destruction at single-regions appears to have little relationship with the market-level instrument.

**Sorting among national firms** Even in the absence of a common shock at the level of local labor markets, it is possible small and large firms load differently on common productivity shocks (Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020). Market segmentation by employer size or differences in access to capital markets may lead to a non-response of local firms while generating correlated shocks to national firms that would lead to potential violations of our exclusion restriction. We examine whether firm-level shocks capture this variation by ranking firms by their local employment share in a CBSA-NAICS2-quarter cell ($R$ ) and then estimating the correlation of the largest employer's job destruction ($R = 1$) on other firms in the labor market:

$$s^{(R)}_{f,-m,t} = \beta^{(R)} s^{(1)}_{f,-m,t} + \Gamma' X_{m,t} + \epsilon_{f,m,t}, \quad R = 2, 3, \ldots \tag{13}$$

If the market-level instrument uses job destruction from national firms responding to a common productivity shock, then we would expect that $\beta^{(R)} > 0$.[26]

Figure 2b presents estimates of $\beta^{(R)}$ separately for the second-to-tenth largest employers as well as the average from the remaining national firms ($R > 10$). As we would expect, the unconditional correlation between national firm shocks is positive, with magnitudes ranging between 0.04 to 0.15. When we condition on industry-by-quarter and labor market fixed effects, however, we find a precise lack of positive correlation between the national job destruction rate of the largest firm does of the other large firms that operate in the same labor market. This continues to hold when we include linear market-level controls that used in our baseline specification. Given that the the top 10 set of national firms make up around 20% of the total employment in the average labor market in our sample, the lack of correlation in job destruction rates among national firms suggests that these measures can be considered conditionally idiosyncratic from the perspective of labor markets.

[25] We perform covariate-adjustment and calculate standard errors following the procedure outlined in Cattaneo et al. (2024). A very small fraction of multi-region firms that do not pass the restrictions we place in constructing (8) are excluded, though their response is consistent with single-region firms

[26] Greenstone et al. (2020) perform a similar exercise to examine the spatial correlation in bank lending.

# 4 Spillovers on the Cost of Job Loss

Having validated the research design, we estimate the causal equilibrium effects of job destruction. Section 4.1 describes the sample of job losers we use for our baseline specification. Section 4.2 presents our baseline spillover estimates. These estimates are based off comparing the short- and medium-run earnings consequences of losing one's job in a mass layoff event across local labor markets with different (instrumented) aggregate job destruction rates. In Section 4.3, we show that our baseline estimates are robust to a battery of alternative specifications. In Section 4.4, we examine changes to characteristics of employers as a result of local job destruction.

## 4.1 Baseline sample and outcome variables of job losing-workers

We describe the individual-level sample used to obtain our baseline estimates. We follow past work that estimates the earnings cost of job loss by matching workers who separate from their job during a mass layoff to similar workers in the same labor market that remain employed for at least one year.

### 4.1.1 Worker sample

To build a sample of laid-off workers, we start by taking the set of all prime-age workers in the LEHD that, during a quarter $t$, separate from their job.[27] The LEHD data do not contain direct information on whether a separation event is the result of the worker being laid off or choosing to quit.[28] Inspired by the the literature on job loss effects (discussed in Section 1.1), we therefore only consider separation events to be layoffs if they are part of a broader, firm-wide mass layoff event. Following Davis and von Wachter (2011), we define a mass layoff event as occurring when an establishment of over 50 workers contracts its employment by 30% or more over the following year.[29] This yields a sample of job-losing workers that consists of 6.525 million job loss events (worker-quarter observations)

[27]On top of the prime-age and separation requirements, we apply additional data filters to ensure that we can accurately measure the worker's future jobs employment-related outcomes. Appendix Section B.3 lists the complete set of requirements.

[28]In search models with bilaterally-efficient bargaining, a meaningful distinction between layoffs versus quits does not exist (Shimer, 2012b). In reality, the difference in the type of separation matters. For example, Flaaen et al. (2019) find that workers who claim to have been involuntarily laid off from their job experience substantially greater earnings decreases than workers who claim to have voluntarily quit.

[29]Restriction on firm size limits the degree to which mass layoff events are driven by idiosyncratic decisions of a small number of workers.Appendix Section B.4 contains the full details on our definition of mass layoff events.

corresponding to 6.077 million unique workers in approximately 3,900 market-quarters.[30]

**Matched control sample** Studies that estimate the impact of job loss on workers often focus on outcomes adjusted by a proxy for the counterfactual in the absence of layoffs. This proxy is typically constructed from matching each laid-off worker with a control worker—an individual who was not laid off but shares similar observable characteristics and at a comparable job (von Wachter, 2020b).

For the purpose of estimating spillover effects, it is unclear whether it is sensible to take differences in job-loser outcomes with respect to a matched, job-staying control worker for two reasons. First, any selection in which workers get laid off would only threaten the orthogonality condition of Section 3.3 if the local job destruction rate endogenously induces a change in the composition of layoffs (e.g. towards less productive workers). But empirically, there does not appear to be a significant relationship between our job destruction instrument and observable characteristics of mass laid-off workers (Appendix Table 7). Second, non-job losing workers likely have *non-zero* exposure themselves. For example, workers stable jobs may experience reduced earnings due to a decline in their outside option from lower market tightness. Subtracting off the difference from matched non-job losing worker would capture how local job destruction rates affect the *marginal cost of losing one's job*, rather than the earnings of job losers, which is likely to be lower.

Given this uncertainty, we present our baseline estimates for both job losers and the matched control separately in addition to the standard difference. We find a unique matched control for each job loser $i$, $c(i)$, within a fine demographic-market-quarter cell that has a similar predicted separation propensity but does not separate from their job for at least four quarters.[31] We provide details on the matching procedure in Section B.5.

### 4.1.2 Worker outcome variables

We use data from the LEHD to build variables that describe either the intensive (wages) and extensive (employed or not) margins of their labor market outcomes. These variables do not condition on the worker staying in the same labor market as the original job destruction shock

[30] Following disclosure guidelines from the U.S. Census Bureau, we round all sample counts and estimates derived from administrative microdata.

[31] To mitigate the possibility that we are disproportionately selecting high-productivity workers with this last requirement, we only consider non-separators whose firms exhibit stable annual growth rates ($-5\%$ to $5\%$) over the four quarters starting with $t$.

We first construct $\text{Earn}_{it}$, the dollars earnings across all jobs covered by our sample of states in quarter $t$ for worker $i$. We define the worker's *base earnings* $\overline{\text{Earn}}_{it}$ as their average earnings in the three years prior to $t$, restricted only to quarters for which the worker is employed at both the beginning and end of the quarter.[32] For the quarters $t+h$ after the layoff event, we take the ratio $\text{Earn}_{i,t+h}/\overline{\text{Earn}}_{it}$ as our primary measure of the worker's change in earnings from before the layoff to $h$ quarters after it. We also estimate the dollar-value of the earnings effect by taking the difference between $t+h$ earnings and base earnings, $\text{Earn}_{it+h} - \overline{\text{Earn}}_{it}$.

To capture effects of job destruction spillovers on the extensive margin of quarterly employment, we create an indicator for employment, $\text{Emp}_{i,t+h}$, that equals one if, in quarter $t+h$, the worker has positive earnings across any US state, including those for which do not observe their precise earnings. We also consider the impact on labor force exit by defining a long-term nonemployment indicator $\text{LT-Nonemp}_{i,t+h}$, which equals one if the worker is not observed to be employed in eight quarters leading up to quarter $t+h$.

## 4.2 Results: Job loss spillovers

### 4.2.1 Path of spillover effects

Figure 3 presents our baselines estimates of the spillover of job destruction onto laid-off workers. Each point represents the difference 2SLS estimates of $\beta^{(h)}$ from (9) between our job loser sample and the matched controls.[33] In panel 3a, we present estimates where the dependent variable is the earnings ratio, $\frac{\text{Earn}_{i,t+h}}{\overline{\text{Earn}}_{i}}$, in the 12 quarters prior and the 24 quarters following the job destruction shock, normalized to reflect the effect of a one percentage point change in the job destruction rate.[34] In the quarter following the layoff event, workers who lose their job in a labor market where the job destruction rate is 1 pp higher experience a 1.2 pp greater decline in average quarterly earnings over the following 24 quarters. The earnings spillover we estimate is persistent with little sign of recovery: after six years, job losers in markets with one pp more job destruction have 1.1 (SE: 0.22) pp lower earnings.[35]

[32] We restrict to full-quarter employment when constructing base earnings to avoid constructing artificially low base earnings from periods where the worker made job transitions (hiring or separations).

[33] In particular, we estimate (9) separately for job losers ($\hat{\beta}^{(h)}_{JL}$) and job stayers ($\hat{\beta}^{(h)}_{JS}$), and present the coefficients as $\hat{\beta}^{(h)} = \hat{\beta}^{(h)}_{JL} - \hat{\beta}^{(h)}_{JS}$. Standard errors are two-way clustered by CBSA and date of job loss. See Section C.1 for details.

[34] To satisfy the limitations on disclosed output, we present estimates from every other quarter when plotting local projection estimates. When use all coefficients when constructing net present value outcomes.

[35] Appendix Figure 9 presents the spillovers separately for job losers and the matched control group.

In Figure 3b, we estimate the spillover effects on employment for job losers, relative to the matched control sample. Non-employment accounts for most of the earnings spillover effects we find: job losers in more shocked labor markets have a 0.96 (SE: 0.33) pp higher chance of being unemployed after $h = 2$ quarters. While the employment spillovers decline following the shock, the effect is still persistent: by $h = 24$ quarters, workers in more shocked labor markets have a 0.39 (SE: 0.13) pp greater likelihood of nonemployment.

#### 4.2.2 Cumulated earnings spillover effects

Table 1 presents our baseline estimates of the spillover effects when cumulated over the 24 quarters of the post-layoff event window. Column (1) provides the results from the local projection of the net present value (NPV) earning ratio from $h = 0$ to $h = 24$, using annual interest rate of 5%.[36] The coefficient in the first row ("Job Loser") of column (1) implies that a 1 pp higher job destruction rate decreases the NPV of a laid-off worker's earnings by an amount equal to 0.3231 (SE: 0.078) of the worker's average pre-layoff quarterly earnings.

In the third row ("Difference") of column (1), we present estimates of the spillover on the difference between job loser and job stayer earnings, which reflect a discounted sum of the effects in Figure 3a. Our estimate implies that a 1 pp higher job destruction rate decreases the NPV of losing one's job by an amount equal to 0.2618 (SE: 0.050) quarters of pre-layoff earnings. Compared to the effect of spillovers on job stayers (row 2), our spillover estimates are driven declines in job loser outcomes rather improvement for job stayers. When scaled by the mean earnings cost of job loss (6.55 quarters), a one percentage point job destruction shock causes the NPV of job loss effects to increase by 4.0%.

In column (2), we estimate the earnings spillovers in dollar terms. A 1 pp higher job destruction rate leads the costs of job loss to increase by \$4,190 (SE: 987), or roughly \$700 per year. When summing quarterly indicators for employment (column 3), we find that job loses in more shocked labor markets spend an additional 0.128 (SE: 0.029) quarters in non-employment compared to their matched job-stayer. Overall, our estimates imply that laid-off workers experience significantly greater losses in earnings when searching for a new job in a labor market with a high job destruction rate.

[36] We follow Davis and von Wachter (2011) in computing the discounted sum. The estimate of the NPV spillover effect equals $\sum_{h=0}^{24} \hat{\beta}^{(h)} \times \frac{1}{(1+r)^h}$, where $r$ is the quarterly rate that corresponds to 5% annual interest.

#### 4.2.3 The role of nonemployment

Mechanically, two channels account for worker earnings spillovers: a greater time spent non-employed (extensive margin) and lower earnings conditional on employment (intensive margin). To gauge the relative contribution of each, in Section C.2 we calculate the earnings spillover from Table 1, column (1) attributable to the extensive margin effect. We find that the extensive margin accounts for 47% of the estimated 0.2618 quarters of earnings spillovers from a 1 pp shock to the local job destruction rate.[37]

The fact that greater nonemployment account for nearly of half of the earning spillovers suggests a central role of the job-finding rate in the equilibrium effects we estimate. Workers who have a more difficult time finding a new job immediately after being laid off tend to become less attached to the labor force, which can result from being discouraged to look for new work, duration dependence in unemployment (Kroft et al., 2013), or a loss in job security (Jarosch, 2023).[38] In Table 1 column (4), we show that at least some of the spillover effect is accounted for by greater long-term nonemployment: a 1 pp higher job destruction rate increases the probability of experiencing nonemployment for 8 consecutive quarters by 0.47 pp (SE: 0.13).

### 4.3 Robustness of baseline estimates

Table 2 provides evidence that our spillover estimates are robust to adjustments of our baseline empirical design. We group alternative specifications based on whether they make adjustments to the shock measurement (A), controls (B), or sample (C and D).

Panel A considers alternative shock measurements. Row 2 provides the spillover estimate when we do not exclude the worker's own firm from market-level measurements. We find that the decline in the spillover effect on job loss costs ($-0.2093$ from $-0.2618$) is driven entirely by estimating a larger spillover effect on job stayers ($-0.1185$ from $-0.0613$).[39] Row 3 shows that our estimate changes little if we granular IV construction

[37]We provide two caveats to this decomposition. First, because we can only measure employment at the quarterly frequency, some of the earnings effect that we label as "intensive-margin" reflect nonemployment during the quarter that the worker is hired. Second, we assume that the income lost from nonemployment spillover at $t + h$ is equal to the average earnings among the set of workers employed at that quarter for each sample. However, it is possible that the counterfactual earnings of the margin non-employed worker would be lower than the average employed worker, as would be the case if workers faced idiosyncratic shocks to their productivity and chose job search effort endogenously.

[38]It also may be the case that the earnings spillovers reflect are a result of differential selection out of the sample of states for which we observe earnings. We check this possibility by estimating the employment using indicators for earnings within our sample's set of states and indicators for the full set of states provided by Census. We find little differences in employment spillovers between the two measures.

[39]The lack of adjustments highlights the importance of estimating spillovers at the job level: without

of Gabaix and Koijen (2019) and remove the unweighted average of national job destruction rates from the instrument. In row 4, we show that adjust the window over which we cumulate the shocks: constructing annual flows starting from $h = -2$ instead of $h = 0$ leaves the estimate unchanged.

In Panel B, we consider the inclusion of additional controls to the baseline specification. The estimated 6-year spillover effects remain unchanged if we include fixed effects for tenure-age-sex combinations (5), lags in the endogenous measure of local job destruction and job creation (6), or fixed effects for the worker's firm (7).[40] We find that the estimate declines by 15% when we include the propensity score for separations that we use to match workers, which may be partially due to the fact that matched workers with higher separation risk would be expected to face greater spillovers from local job destruction.

Our estimates are also stable if we consider alternative sample definitions highlighted in Panel C. In contrast to common practice in the literature estimating job loss costs, we do not condition on observing the worker following job loss. Reassuringly, our estimates are not driven by sample exit: conditioning on workers with at least one quarter of earnings following job loss (9) or employment by the end of the sample period (10) does little to change our estimates. We also see that the earnings spillovers are not driven by industries that were highly exposed to the global financial crisis: in row 11, excluding finance, insurance, and real estate (FIRE, NAICS 52/53) and construction (23) leads to a similar estimate of spillovers as in the baseline specification.

#### 4.3.1 Aggregate Demand channel

In standard theories of business cycles under incomplete markets, job loss results in lowered local spending as a result of liquidity constraints. Lower consumer demand makes the creation of new jobs less profitable for firms, particularly in the presence of wage rigidities. Empirically, regional evidence on the presence of Keynesian multipliers has relied on the comparison of employment in non-tradeable industries with significant home-bias, such as consumer retail or food services (Nakamura and Steinsson, 2014; Mian and Sufi, 2014; Chodorow-Reich et al., 2021).

We use a similar logic to evaluate the contribution of demand effects to the estimated earnings spillovers. We estimate the baseline specification (9) in the subsample of trade-

excluding the worker's own employment history, estimates of the form (33) incorporate direct productivity shocks that workers may experience through their firm.

[40]When including firm fixed effects, we include an indicator for the set of workers that have unique employers to avoid dropping observations.

able industries that include Oil and Gas Extraction (NAICS 21) and Manufacturing (31-33).[41] Table 2, row 12 reports the spillover estimates on six-year relative earnings. Compared to the coefficient of -.2618 from our baseline specification, we find that a 1 pp job destruction shock leads to -.200 (SE: 0.065) quarterly earnings effect in tradeable industries.

Alternatively, we can purge our estimates from common loadings on local demand with the inclusion of CBSA-quarter fixed effects. We therefore rely on national firm shocks across industries within a region. The remaining variation in job destruction would be Row 13 of Table 2 reports that our estimates of the earnings spillovers similarly declines to -.180 (SE: 0.066).[42] The similarity between the estimates from these two alternative specifications suggests that most of the spillover effects we capture do not reflect local demand effects.

#### 4.3.2 Heterogeneity by separation risk

We estimate significant job destruction spillovers for job losers, relative to job stayers, because the former are more exposed to greater labor market frictions as a result of elevated job loss. In Section C.4, we consider an alternative design where, instead of conditioning on job loss, we heterogeneity in spillovers among workers with different levels of future separation risk, as proxied by their (leave-out) national firm job destruction rate in the following year. We find that employed workers in the highest quintile of separation risk have greater earnings losses from elevated market-level job destruction in the following six years (Appendix Figure 15. In comparison, there are no spillovers for workers firms with the lowest level of future separation risk.

### 4.4 Reallocation across firms

While we document a negative equilibrium of market-level job destruction on worker earnings, it may be possible some of the worker costs are offset by benefits to firm owners as a result of greater availability of job seekers or lower wages. Unfortunately, we lack data on firm profits at the same granularity and frequency that would let us quantify the

[41] We follow two-digit industry definitions to follow our preferred definition of local labor markets. Industry-based classifications also include Agriculture (11) among the set of tradeable industries (Mian and Sufi, 2014). However, we exclude worker cohorts from this industry as a substantial fraction of agriculture workers are not covered by unemployment insurance laws underpinning LEHD data collection.

[42] We omit CBSA-quarter fixed effects in our baseline design due to the possiblity that they might represent "bad controls" – i.e., capture some of the true spillover effects – if a job destruction shock in a given CBSA-sector has negative spillovers to the labor market conditions in other sectors within the same CBSA.

fraction of worker earnings reduction that are implicit transfers to firms.[43] Instead, we extend our worker-level analysis to assess whether job destruction induces changes in the composition of firms at which job losers are employed.[44]

We consider two firm-related outcomes. First, we construct a measure of a firm's wage premium by estimating the firm fixed effects from a decomposition of worker annual earnings Abowd et al. (1999). We follow the existing literature in constructing estimates of the firm wage premia, $\Psi^t_f$ using rolling five-year windows prior to job loss date $t$.[45] We then estimate (9) under our baseline specification by replacing the worker outcome with the difference in the wage premia of their primary employer relative to the pre-shock period, $\Psi^t_{f(i),t+h} - \overline{\Psi}^t_i$. Importantly, we hold the estiamtes of the firm wage premia fixed and restrict to the subset of workers employed at $t+h$ when estimating the local projection.

Appendix Figure 10a plots difference between the estimated coefficients for employed job stayers and job losers, using the national-firm instrument to instrument for local job destruction. We find that local job destruction shocks drives job losers to join firms with lower wage premia. Following a 1 percentage point shock to local job destruction, job losers are employed by firms that pay 1.3% lower earnings compared to job stayers three years after the shock. Because firm wage premia are fixed as of period $t$, the subsequent recovery is evidence of workers climbing back up the job ladder over the medium-term. The decline in firm wage premia is consistent with recent work that finds a significant correlation between job loss costs and changes to firm wage premia over the business cycle (Schmieder et al., 2023b). It also suggests that changes to the composition of available jobs could be an important source of the equilibrium effects on worker earnings.

The decline in firm wage premium among job losers can either reflect firms that extract greater rents from workers or a decline in job productivity. To separate these channels, we use data from the Census LBD Revenue (LBD-REV) files, which contains annual firm-level measures of revenue, employment, and payroll for approximately 50% of the jobs in our sample.[46] For our measure of labor productivity, we use the rank of the firm's revenue per worker within their the primary four-digit NAICS industry. As a result, our

[43] Representative establishment-level data from the Economic Census is collected once every five years. Annual data, such as from Longitudinal Business Database Revenue files (LBD-REV) are provided at the firm level for a subset of organizations.

[44] We provide an evaluation of the total benefits of job destruction within through the lens of our structural model in Section 7.1.

[45] Details are provided in Section C.5.

[46] We have access to revenue files until 2019, so we exclude the 2014 of cohorts from our estimation. In estimating models with LBD-REV data, we include a dummy variable for whether the worker is missing LBD-REV data in a given quarter to keep the sample consistent across the entire window.

measure is better suited to capture productivity effects from within-industry reallocation than cross-industry reallocation. Similar to the firm wage, we use the change in revenue productivity rank relative to the average between $h = -12$ to $h = -1$ as our the outcome. In Appendix Figure 10b, we find that the negative equilibrium effects of job destruction on firm wage premia appear to result from the reallocation of job losers to firms with lower rank productivity. The similar pattern between the measures of revenue productivity and firm wage premia spillovers suggests that elevated rates of job destruction may worsen the reallocation of workers to more productive positions.

When instead consider the changes in firm composition for the *average* employed worker in the labor market, we get a somewhat different picture. Appendix Figure 11 plots the same outcomes of changes to firm wage premia (11a) and rank labor productivity (11b) for a random sample of workers employed as of $t-1$ that satisfy our baseline restrictions. We find that cohorts in local labor markets with a 1 pp job destruction shock face a decline in firm wage premia over the following six years, though we are underpowered to detect significant effects. On the other hand, the rank labor productivity *increases* for these workers, which is consistent with cleansing effects of destroying low-productivity jobs (as proxied by the firm).

# 5 Total spillover effect of job loss

In this section, we evaluate the importance of the worker spillovers for aggregate labor market activity. We first show that job destruction spillovers significantly contribute to the elevated costs of job loss during recessions (Section 5.1). We then estimate the effect of spillovers on the average worker in the labor market (Section 5.2) which help us provide an approximation of overall cost of a marginal job lost on the labor market (Section 5.3).

## 5.1 The countercyclical costs of job loss

Our estimates in Section 4.2 isolate the effect of job destruction on the costs of job loss. To evaluate the magnitude of our estimates, we provide a basic decomposition of the contribution of job destruction over the business cycle. Our calculation assesses how much lower the costs of job loss would be under a counterfactual set of economic shocks that led to similar decline in productivity no fluctuations in the local job destruction rate.

Let $\text{Loss}_{it}^{(Est)}$ be the estimates six-year relative earnings losses of a worker $i$ in our mass layoff sample in quarter $t$, relative to the matched control worker. We construct the counterfactual earnings loss $\text{Loss}_{it}^{(Smooth)}$, by removing the contribution of local job destruction rate fluctuations from the earnigs loss estimates:

$$\text{Loss}_{i,t}^{(Smooth)} := \text{Loss}_{i,t}^{(Est)} - \hat{\beta} \times (s_{-i,m,t} - \bar{s}_m) \tag{14}$$

where $s_{-i,m,t}$ is the worker's local job destruction rate at time of separation, and $\bar{s}_m$ is the counterfactually smooth job destruction rate (i.e., the average rate in the LLM over our full sample period). The contribution of job destruction, $\hat{\beta}$ in (14), comes from our baseline spillover estimate from Column (1), Row (3) of Table 1. Assuming that our estimates identify the earnings spillovers, $\hat{\beta} \times (s_{-f,m,t} - \bar{s}_m)$ provides a lower bound on the contribution of job destruction to the countercyclical costs of job loss.[47]

Figure 4 plots the time-aggregated series of estimated and counterfactual earnings losses, along with the local job destruction series, for each quarter in our sample. By comparing the actual mean job loss effect (green) with the counterfactual effect (yellow), we can see the extent to which, according to our estimates, the increase in the cost of job during recessions is accounted for by increased job destruction. In both the 2001 and 2007-09 recessions – which featured large spikes in destruction rates – our exercise suggests that the cost of job loss would have reached a peak value that was around $10 - 15\%$ lower had job destruction activity remained flat.[48] The standard deviation of $\text{Loss}_t^{(Smooth)}$ is around 25% less than that of $\text{Loss}_t^{(Est)}$, implying that volatility in job destruction rates meaningfully contributes to time-series variation in the cost of job loss.

Formally, we quantify the contribution of job destruction to the countercyclical costs

[47] A more precise decomposition requires aggregating our local estimates of job destruction to the national level. However, we consider the aggregate effects of a job destruction shock to be larger at the national level for three reasons. First, our local job destruction rates are measured for CBSA-by-industry local labor market (LLM) definitions, and therefore ignore the contribution of spillovers from job destruction by workers in adjacent labor markets. In Appendix Figure 12 provides evidence indicating that large job destruction shocks lead job losers to reallocate to different industries and migrate out of their current CBSA. Second, much of the variation we use strips does not account for cross-LLM demand spillovers, which we expect to be positive (in Section 4.3.1 we discuss the within-LLM effects). Third, in principle, a nationwide job destruction shock could lead to an endogenous loosening of monetary policy that softens the labor market impacts of the shock, but are not captured when using regional variation. However, the recessionary episodes our sample period (2001 and 2007-09) featured policy interest rates that were close the effective lower-bound, especially once labor market conditions had reached their respective troughs. While a nationwide job destruction shock could lead to an endogenous loosening of monetary policy that softens the labor market impacts of the shock that is not captured by our regional variation, the zero-interest rate environment limits this effect in a manner similar to the aggregation of regional fiscal multipliers (Chodorow-Reich, 2019).

[48] Note that in Figure 4, the counterfactual job destruction series exhibits small fluctuations over time. This is because in our counterfactual exercise, we impose job destruction rates that are flat at the level of a *local market*. Since different local markets have different values of $\bar{s}_m$, and the distribution of mass layoffs across different local markets can change between quarters, the average of $\bar{s}_m$ among workers in our mass layoff sample is not constant over time.

of job loss by estimating the following relationship:

$$Loss_{it}^{(x)} = \alpha^{(x)} + \gamma^{(x)} cycle_t^{(x)} + \epsilon_t \tag{15}$$

where $x \in \{Est, Smooth\}$ and $cycle_t$ is some measure of the business cycle. The ratio of estimates $\gamma^{(Smooth)}/\gamma^{(Actual)}$ shows the proportional reduction in the countercyclicality of job loss effects under the smooth job destruction series. Appendix Table 6 shows this estimate under three different cyclical indicators.[49] Columns (1)-(2), which set $cycle_t$ to be the national job destruction rate, show that more than 40% of the time-series relationship between job loss effects and the job destruction rate can be accounted for by the causal effect of job destruction itself. Columns (3)-(4) and (5)-(6) show that around 25% and 36% of the relationship between the cost of job loss and, respectively, four-quarter real GDP growth and the four-quarter change in the unemployment rate are due to the spillover effects of job destruction.

Our spillover estimates suggest that a significant portion of the countercyclical costs of job loss are driven by spikes in job destruction. However, it is important to note that the majority of the the cyclicality appears to be driven by shocks to other factors (such as the productivity of new jobs). Moreover, the difficulties in job creation (such as from a restriction to credit supply) can help exacerbate job destruction spillovers, as more jobs are lost at a time when aggregate recruiting is low.[50]

## 5.2 Spillovers on the average worker

In this section, we study whether the equilibrium effects of elevated job destruction extend beyond job losers. We estimate the market-level spillover effects outcome a random sample of 23.5 million worker-job events that satisfy our baseline restrictions. In contrast to the samples described in 4.1, we only condition on the worker being employed in the period before the job destruction.

Figure 5 plots estimates $\hat{\beta}^{(h)}$ of the local projection of cumulative earnings on local job

[49]Our decomposition does not account for potential feedback effects between the job destruction rate and the business cycle indicators. The regressions with $Loss_{it}^{(Smooth)}$ as the dependent variable should thus not be interpreted as what the relationship between the cyclical indicator and the cost of job loss would have been under the smooth job destruction counterfactual.

[50]An alternative, dampening effect on the magnitude of spillovers during recessions comes from the fact that more jobs are lost at a time when unemployment is higher, so that the contribution from each job lost is lower (captured by (4)). Appendix Figure 13 shows that the total earnings spillovers are larger when the stock of recently nonemployed is high, which suggests that the amplifying force prevails.

destruction:

$$\text{NPV}\left(\sum_{s=0}^{h}\frac{\text{Earn}_{i,t+s}}{\overline{\text{Earn}}_i}\right) = \beta^{(h)}s_{-i,m,t} + \phi_m + \Gamma_1^{(H)}\mathbf{X}_{i,t}^W + \Gamma_2^{(h)}\mathbf{X}_{-i,m,t}^M + \epsilon_{i,t+h}, \tag{16}$$

where $\text{NPV}\left(\sum_{s=0}^{h}\text{Earn}_{i,t+s}/\overline{\text{Earn}_i}\right)$ is the net-present-value of cumulated earnings relative to the base earnings, and $h$ is the horizon of the at which we measure total earnings. Figure 5 plots estimates of cumulative spillover effect $\hat{\beta}^{(h)}$ (blue) for $h = 0$ to $h = 24$. Compared to the effects on job loss (green), the average worker experiences lower and limited earnings reduction. By four years, the earnings loss appears to stabilize. At six years, we find that the average worker experience 0.0502 (SE: 0.035) quarters of pre-period earnings loss following a 1 pp increase in the job destruction rate.[51]

## 5.3 Total cost of the marginal job lost

We use our estimates of job destruction spillovers on individual earnings to approximate the total worker spillover effect of a single job lost.[52] Using equation (3) from Section 2, we can express the total spillover cost on workers as the spillover effect on job destruction, scaled by how an additional job lost changes the job destruction rate, $\frac{ds}{d\,\text{job loser}}$

$$\text{Spillover Cost of Job Lost} = \frac{ds}{d\,\text{job loser}} \times N_m \left[\underbrace{\frac{dW}{ds}}_{\text{1. Effect on employed}} + \underbrace{u \times \left(\frac{dU}{ds} - \frac{dW}{ds}\right)}_{\text{2. Rel. effect on the unemployed}}\right], \tag{17}$$

where $N_m$ is the number of workers in the labor market and $u$ is the unemployment rate. We rearrange the worker spillover effect terms in brackets in two parts: the average spillover on employed workers (1) and the relative intensity of spillovers on the unemployed (2).

Connecting (17) to our spillover estimates requires several assumptions. First, we restrict workers to value employment states $W_i$ according to their expected income stream. This assumption allows to approximate the first-term, $\frac{dW}{ds}$, by the NPV of six-year earnings loss for the average worker from Section 5.2 (-0.0502). Next, we impute the second

[51] The six-year effect is no longer significant at the 5% level, which reflect the variance in earnings outcomes that are cumulated over time. The negative spillover effect for the average worker is significant in the first five years of the event, with a p-value less than 0.01 in the first two years of the shock.

[52] This calculation excludes the effect on the welfare whose job is being destroyed, consistent with the construction of job destruction measure for each worker. Under job destruction decisions that are bilaterally efficient, the worker would be indifferent between staying at the firm and their outside option.

term as the difference in the spillover effects between job loser and job stayer – Table 1, Column 1 (-0.2618) – in Section 4.2, scaled by the average unemployment rate in our sample (0.061).[53] Implicitly, we expect the projected earnings effect on the unemployed to be comparable to that of a recent job loser. As our baseline estimates are in quarters of earnings, we rescale each effect by the base earnings of the average worker ($15,490) and job loser ( $13,390 ) separately.

As the marginal marginal effect of an additional job loser on the job destruction is $\frac{ds}{d \text{ job loser}} = \frac{1}{N_m \cdot (1-u)}$ by definition, the total cost is independent of market size. Combining these effects, we have that the estimated total cost of the marginal job lost in our sample is:

$$\frac{1}{1-0.061} \times [0.050 + 0.061 \times 0.2618] \times 100 = \$105,000. \tag{18}$$

Annually, our estimates suggest that the marginal job lost in our sample imposes a cost of approximately $16,800 per year (1.09 quarters of earnings per year). These estimates thus imply that the decision of a firm to destroy a job imposes a fairly sizable spillover on workers that participate in the same local labor market.

While this back-of-the-envelope calculation provides a benchmark to which we may compare the costs of job-saving programs, several caveats apply to this quantification. First, we implicitly assume that the spillover effects on the unemployed, relative to the unemployed, are approximated by the spillover effects on job loss. Second, our estimates do not capture the full net-present value of the spillover effects as we restrict the estimates to the first six-year following the job destruction shock. Third, our estimates do not account for spillover of job destruction on adjacent labor markets. In general, these simplifications would likely increase the calculated spillover costs to be a lower bound on the overall effects of job destruction.

Our data and research design is not well-suited to measure the spillover effects of job destruction on firm profits, the third term in (3). Quantifying the firm effects that would be consistent with the estimated observed worker costs is a key motivation for developing the quantitative model in Section 6. In Section 7.1, we use our calibrated quantitative model to estimate the firm-side effects, relative to worker earnings costs, to provide an assessment of the total welfare effects.

[53] Alternatively, we can use proxy by the number of people unemployed in a given labor market by the estimated stock of workers whose jobs were destroyed over the previous two years and who had not yet found a job by time $t$, Section C.6 details this procedure and calculates this stock of nonemployed to be 0.050 in our sample.

# 6 Quantitative Model

Our empirical evidence suggests that job destruction significant negative spillovers for workers. But what does the presence of spillovers imply for overall aggregate welfare and policy design? In this section, we take the first step in answering these questions by developing a quantitative model of the labor market and calibrate it to our evidence on job destruction spillovers. We then use this model to determine the overall welfare effects and the implication for employment subsidies in the presence of aggregate shocks in Section 7.

The model we develop in Section 6.1 enriches key elements of the stylized environment we presented in Section 2. Our model extends past work on partial equilibrium job-ladder models (Jarosch, 2023; Krolikowski, 2017) to general equilibrium settings in which both the distribution of job productivity and market tightness are endogenous. In order to calibrate the model to the earnings moments in our data, we allow for on-the-job search and set wages according to the sequential-auction with bargaining protocol of Cahuc et al. (2006). To study policies that aim to save jobs, we allow separations decisions to be endogenous and job productivity to stochastically evolve over time and for unproductive matches to be privately dissolved (Mortensen and Pissarides, 1994).

## 6.1 Setup

We model a labor market that is populated by a unit measure of workers and a positive mass of firms. Firms are owned by a representative capitalist to which all profits are remitted. Time is continuous and all agents discount the future at rate $\rho$. Jobs, which we define as firm-worker pairings, are heterogenous in productivity, which evolves stochastically. The distribution of jobs is endogenous in the model: it is determined by the recruiting decisions of firms, the evolution of the productivity of existing jobs, and the job acceptance decisions of workers. Worker heterogeneity is summarized by $y \in \mathcal{Y}$, which includes their employment status, current job productivity $x \in \mathcal{X}$, human capital $h \in [\underline{h}, \overline{h}]$, and the index of their outside option $r \in \mathcal{X}$. We denote the distribution of employment states by $g_t(y)$.

### 6.1.1 Preferences

Workers can either be unemployed, employed, or out of the labor force. When employed, they supply one unit of labor inelastically in exchange for a wage $w_t(y)$. When unemployed, they engage in home production to consume $b > 0$ . When workers exit the labor force, they do so permanently and receive a flow income that we normalize to zero. Both wages and benefits are denominated in the single consumption good produced by all workers in the economy. Workers have linear preferences over this consumption good, and do not have access to a savings device. Lifetime expected utility is expressed as the present discounted value of flow income, conditional on the workers current state:

$$W_t(y) = E_t\left[\int_0^\infty e^{-\rho(s-t)} w_t(y_{s+t}) ds | y_t = y\right] \tag{19}$$

where for convenience we allow the wage function $w_t(\cdot)$ to reflect benefits when $y$ denotes a state of non-employment.

### 6.1.2 Production

Firm operate a production technology that exhibits constant returns to scale in labor, which allows to express production in terms of the distribution of workers across jobs.[54]

A single job produces $p(h, x, z)$ of the consumption good, which increasing in the worker's human capital ($h$), idiosyncratic job productivity ($x$) and common productivity $z \in \mathcal{Z}$. Job productivity is bounded over $[\underline{x}, \overline{x}]$ and evolves stochastically according to the diffusion:

$$dx = \mu(x)dt + \sigma(x)d\mathcal{W}_x \tag{20}$$

where $\mathcal{W}_x$ is a Wiener process and $\mu(x) \in \mathbb{R}$, $\sigma(\cdot) > 0$ are the drift and volatility of the productivity process. Human capital reflects recent job experience: it drifts up at rate $\psi_e(h)$, and down by $\psi_u(h)$. The set of production states can be expressed as $\mathcal{X} = \{\{b\} \cup [\underline{x}, \overline{x}]\}$, where we use $b$ to denote production during unemployment.

### 6.1.3 Recruitment

In addition to production, firms decide whether to hire workers for new jobs and whether to maintain existing jobs. Recruiting by firms is done through posting vacancy for jobs with known productivity.[55] The distribution of new jobs for which firms can recruit is

[54] The CRS assumption on firms' production technology implies that our model does not admit a notion of firm size and that all dispersion in productivity is generated by search and matching frictions. Despite the fact firm size plays an important an important role in labor market dynamics, we abstract from this dimension for two reasons. First, wage determination with a nondegenerate firm distribution is intractable without strong assumptions on the contracting environment. Second, ignoring the firm size distribution simplifies the mapping between role of job-retention policies and their pass-through to separation decisions. In practice, it is straightforward to introduce an idiosyncratic state that is distinct from match productivity for the single firm-worker case.

[55] When job productivity is unknown, productivity shocks may also capture a "sullying" effect on jobs, whereas less productive matches are created during recessions Barlevy (2002). In our model, this channel is

exogenous and denoted by $dF(x)$, and the mass of potential new jobs is normalized to one. Firms advertise jobs of type $x$ with an intensity $v_t(x)$ that depends on the firm's valuation of the worker-filled-jobs $J_t(\cdot)$, the current employment distribution, and convex recruiting costs $\mathcal{C}(v_t)$, where $C'(\cdot) > 0$, $C''(\cdot) \geq 0$. The aggregate recruiting intensity, which we refer to as vacancies, is given by $\nu_t = \int_x v_t(x)dF(x)$.

### 6.1.4 Random search and matching

The allocation of workers to new positions is subject to matching frictions. Unemployed workers search for work with an exogenous intensity that we normalize to one. Employed workers also search at an intensity rate $\phi$ relative to the employed. The aggregate search intensity of workers is given by $e_t = u_t + (1 - u_t)\phi$, where $u_t$ is the unemployment rate. Search is undirected in the labor market, where workers and firms successfully meet each other at a rate proportional to their search intensity. The overall frequency of meetings between workers and firms is given by $M_t = \mathcal{M}(\nu_t, e_t)$, where the matching function $\mathcal{M}(\cdot,\cdot)$ is weakly increasing in both arguments and exhibits constant returns-to-scale. Workers only accept jobs that increase their expected lifetime earnings.

### 6.1.5 Wages

Wages are determined according to a slight modification of the sequential-auction-with-bargaining mechanism of (Cahuc et al., 2006). In addition to human capital and match productivity, worker wages also depend on their bargaining threat point, which we define to be $r \in \mathcal{X}$ and determined by the sequential auction procedure described below. For a worker $y = (h, x, r)$, we define the expected PDV value of production for a job of productivity $x$ as $V_t(h, x)$, the PDV of production in unemployment as $U_t(h)$, and the total job surplus as $S_t(h, x) = V_t(h, x) - U_t(h)$. Wages $w_t(y)$ for worker are set to satisfy

$$W_t(y) - U_t(h) = S_t(h, r) + \beta\left(S_t(h, x) - S_t(h, r)\right) \tag{21}$$

where the firm surplus is the remaining value $J_t(y) = S_t(h, x) - W_t(y) - U_t(h)$. Under this wage mechanism, the private surplus of a job is not a function of the worker's reservation job, which only helps determine the division of rents. The worker's decision to move once contacted is determined entirely by the relative productivity of the new job.

reflected in job creation low productivity matches which are only available following declines in the value of unemployment. Engbom (2021) studies this type of mechanism in a setting where elevated separation rates deteriorate match quality through the additional applications that unemployed workers may send.

In equilibrium, unemployed workers (i.e. $S_t = 0$) accept all job offers and have wages determined via standard Nash bargaining.[56]

#### 6.1.6 Job transitions

When a worker meets a new job with productivity $x'$, one of three situations may arise. If $x' \leq r(y)$, then the worker rejects the job match. If $r(y) < x' \leq x(y)$, the worker will use the incoming offer to bargain up her wage at the existing firm. Finally, if $x' > x$, the worker will switch to the more productive job and use the previous previous firm's productivity as the threat point for the new match.[57]

#### 6.1.7 Separations

Existing jobs can be terminated in one of four ways. First, workers permanently exit the labor market at an exogenous rate $\kappa$, at which point they are replaced by a labor market entrant with the same human capital in unemployment. Second, jobs are exogenously destroyed at rate $\delta$, which leaves workers in unemployment and firm owners with a scrap value that we normalize to 0.[58] Third, workers may quit for a new job (or to unemployment) if it increases their lifetime utility.

Fourth, firms may choose to destroy a job when it is no longer expected to be profitable, i.e. when $J_t(y) \leq 0$. Our wage mechanism results in bilaterally efficient separations: the jobs that the firm would destroy are exactly those that the worker would not prefer over unemployment. The job destruction decision is characterized by a productivity threshold $x_t^*(h)$ where any job with productivity $x \leq x_t^*(h)$ is destroyed for workers of type $h$ and $x_t^*(\cdot)$ is defined by the indifference between the worker's (and firms) outside options and maintaining the job:

$$V_t(h, x_t^*(h)) = U_t(h) \tag{22}$$

This form of endogenous job destruction reallocates workers to productive matches

[56] As idiosyncratic job productivity evolves, wages can be negotiated by mutual consent following Postel-Vinay and Turon (2010). This occurs when the firm's surplus value would be negative under the worker's current bargaining threat point.

[57] The wage bargaining mechanism implies that the worker state is updated after a job meeting to $\tilde{y} = (h, \tilde{x}, \tilde{r})$, where $\tilde{x} = \max\{x, x'\}, \tilde{r} = \max\{\min\{x, x'\}, r\}$. Implicit in our characterization is that the worker's valuation of jobs is monotonic in job productivity $x$, which is guaranteed by the flow production and our wage assumption.

[58] We imply that jobs feature no embodied capital that the firm owners may value. In practice, if jobs require capital to be maintained, then counteryclical movements in the opportunity cost of a filled job may induce firms to engage in greater restructuring (Koenders and Rogerson, 2005).

when search effort on the job is lower than when unemployed.

## 6.2 Equilibrium

The equilibrium can be succinctly characterized by a coupled system of partial differential equations. First, the Hamilton-Jacobi-Bellman (HJB) equation characterizing the joint value of production during employment, $V_t(h, x)$ and the value of unemployment $U_t(h)$. This equation embeds the flow production for each possible type of employment along with the continuation value embedding movements in productivity and job transitions. Second, the Kolmogorov Forward (KF) equation describes the evolution of $g_t(y)$ following the idiosyncratic shocks experienced by workers.

The following proposition characterizes the equilibrium of the model in the absence of aggregate shocks.

**Proposition 6.1.** *The deterministic equilibrium of the labor market is defined by the sequence of value function $V_t : \left[\underline{h}, \overline{h}\right] \times \mathcal{X} \to \mathbb{R}$ and worker distribution $g_t : \mathcal{Y} \to \mathbb{R}$ for $t \geq 0$ that satisfy the following equations*

$$\begin{aligned}
\rho V_t(h,x) =& p(h,x,z) + \mathcal{A}_x(x)[V] + \psi^e \partial_h V_t(h,x) + \partial_t V_t(h,x) \\
& - \delta\left(V_t(h,x) - U_t(h)\right) - \kappa V_t(h,x) \\
& + \phi f(\theta)\beta \int_x^{\overline{x}} \left(V_t(h,x') - V_t(h,x)\right) dH_t(x), \quad x \geq x_t^*(h) \\
V_t(h,x) =& U_t(h), \quad x \leq x_t^*(h) \\
U_t(h) =& b - \psi^u \partial_h U_t(h) + \partial_t U_t(h) - \kappa_u U_t(h) + f(\theta)\beta \int_x^{\overline{x}} \left(V_t(h,x') - U_t(h)\right) dF_v(x)
\end{aligned} \tag{23}$$

*The distribution of productive states, follows, for $x > x_t^*(h)$:*

$$\begin{aligned}
\partial_t g_t(h,x) =& -(\delta+\kappa) g_t(h,x,w) - \psi^e(h)\partial_h g_t(h,x) - \partial_x(\mu(x) g_t(h,x)) + \frac{1}{2}\partial_{xx}(\sigma_x^2(x) g_t(h,x)) \\
& + f(\theta_t)\frac{v(x)}{\nu}\left(u_t(h) + \phi s^x(h)\left(G_t^{(h)}(x) - G_t^{(h)}(x^*(h))\right)\right) - \phi g_t(x)(H_t(\overline{x}) - H_t(x)),
\end{aligned} \tag{24}$$

*with $g_t(h,x) = 0 for x \leq x_t^*(h)$ for employed workers and*

$$\partial u_t(h) = (\delta+\kappa)(G_t(h,\overline{x}) - G_t(h,x^*(h))) - u_t(h) f(\theta_t) - \psi^u(h)\partial_h(u_t(h)) + dg(h,x^*(h)) \tag{25}$$

*with a boundary condition where: $dH(x) = \int_{\underline{x}}^{x} \frac{v(x)}{\nu} dF(x)$ is the cdf of unfilled jobs; $s^x(h)$ is the* *share of human capital $h$; $u_t(h)$ is the unemployment mass of workers with human capital $h$; and $G^{(h)}(x)$ is the marginal CDF of job productivity, conditional on human capital $h$.*

The HJB (23) and KF (24) equations, provide a complete characterization of the dynamics of the labor market – all other features of the economy depend only on the contemporaneous values $V_t(\cdot), g_t(\cdot)$, which we describe in Section A.3 in greater detail. In addition, the time derivative of the value function as the inner product $\partial_t V_t(\cdot) = \langle \partial_g V(\cdot, g), \partial_t g_t(\cdot) \rangle$, where $\partial_g V(\cdot, g)$ encodes the Frechet derivative of the value function from infetesimal changes to the distribution, which we call the deterministic impulse value. By substituting in for $\partial_t V_t(\cdot)$, (23) no depends explicitly on $t$. Computing the deterministic impulse value at the steady state of the model provides a convenient means of approximating transition dynamics following shocks to the *distribution of workers* as a result of job destruction.

## 6.3 Model Estimation

We estimate the model in three steps. First, we parametrize several of the structural functions in the model. We then externally calibrate a set of parameters to standard values in the literature. Finally, we estimate the remaining parameters using method of simulated moments (MSM), using a combination of analytic expressions (for labor market flows and wage statistics) and simulated worker earnings paths (for the dynamic job loss estimates). Estimating the model to fit our estimates of worker spillovers requires solving the model's steady state equilibrium as well as the transition dynamics following a job destruction shock for every evaluation of the parameter space.

### 6.3.1 Parametrization

We estimate the model in the absence of aggregate risk.[59] We make the following parametric assumptions to estimate the steady state of the model. Worker production when employed is set to be $p(h, x, \bar{z}) = \overline{z_0} + hx$. We set the diffusion process of idiosyncratic job productivity to follow Geometric Brownian motion by setting $\mu(x) = \mu_x x$ and $\sigma(x) = \sigma_x x$. We assume that human capital accumulation and unemployment scarring are both constant drift rates in $\log(h)$: $\psi^e(h) = \psi_e$ and $\psi^u(h) = \psi_u$. We parameterize the matching function as a Cobb-Douglas production function $\mathcal{M}(e_t, \nu_t,) = C_m e_t^{1-\omega} \nu_t^{\omega}$ where $\omega$ is the elasticity of the job-finding rate with respect to market tightness $\theta_t = \frac{\nu_t}{e_t}$ and $C_m \geq 0$ is the matching efficiency. On the firm side, we set the cost function to take

[59] This assumption is relaxed when we consider the stabilizing effects of employment subsidies in Section 7.2.

the form: $\mathcal{C}(v) = \frac{C_v}{1+\xi} v^{1+\xi}$m where $\xi \geq 0$ is the marginal cost elasticity to vacancy intensity. Because the scalar factor in the cost function cannot be separately identified from matching efficiency, we normalize $C_v = 1$. We parametrize the distribution of new jobs $dF(x)$ to follow a Beta$(a_\beta, b_\beta)$ over $[\underline{x}, \overline{x}]$, where $a_\beta$ and $b_\beta$ are positive.

#### 6.3.2 External calibration

We estimate the model at the monthly frequency. The discount rate $\rho$ is set to target an annual interest rate of 5%. The labor force exit rate $\kappa$ is set to match a career length of 35 years. We also allow for the unemployed to exit at an added rate $\kappa_u$ that is set to be half of the employed worker's exit rate. The matching elasticity to market tightness $\omega$ is set to 0.5 following Moscarini and Postel-Vinay (2021).

#### 6.3.3 Internal estimation

The remaining parameters $\Omega = \{b, C_m, \beta, a_\beta, b_\beta, \mu_x, \sigma_x, \psi_e, \psi_u, \phi, \xi, \delta, z_0\}$ are internally calibrated to three sets of moments.[60] The first set reflect labor market flows commonly targeted in the calibration of macroeconomic models of labor search (Shimer, 2005). We use the 2014 Current Population Survey to construct monthly unemployment-employment (UE), employment-employment (EE), and employment-unemployment (EU) transition rates, following Engbom (2021).[61] Because around half of job transitions lead to earnings losses, which is excluded from our model, we calibrate the model to 0.5 of the EE rate. We also include a moment correspond to the ratio between the flow benefit during unemployment ($b$) and the average labor productivity of unemployed workers, which we set to 0.47 following Chodorow-Reich and Karabarbounis (2016).

The second set of moment captures the earnings distribution and average job loss effects, commonly used in partial equilibrium models of worker earnings dynamics (e.g., Jarosch, 2023). We target the cumulative, six-year job loss effects on earnings and employment using estimates in our primary sample of job losers. We additionally target the average difference in the earnings of job losers when employed and the average cumulated earnings for the average employed worker. We also target the cross-section distribution of wages by including the ratio between 90th percentile and the median (P90/P50) along with the median and the 10th percentile (P50/P10) of quarterly earnings from the sample used to estimate the average worker spillovers in Section 5.2.

[60]We describe the estimation aproach in detail in Section D.2.

[61]We rely on the CPS to construct these flows instead of the LEHD for several reasons. First, the quarterly frequency of the LEHD data yields imprecise measures of labor market flows. Second, we are unable to distinguish between unemployment and labor force exit in our earnings data.

The third set of parameters targets the spillover effects of job destruction that we estimate in Section 4. We target the effect of a 1 pp increase in job destruction on the six-year cumulative (i) job loss effects on earnings and employment; and (ii) average earnings of employed workers. The earnings estimates helps discipline the model to generate negative spillovers on workers, and targeting employment ensures that the job destruction shock is producing an empirically consistent decline in market tightness.

The first two set of moments only require solving the steady state distribution of the model, which we do so using finite differences on the discretized state space (Achdou et al., 2022), modified to account for the endogenous job destruction decision.[62] In order to estimate the spillover effects, we compare the steady-state job loss effects to the effect of a 1 pp unexpected increase in the job destruction rate at the time of the job loss event. In order to do so, we solve for the transitions dynamics using a first-order approximation to the Master equation representation of our economy (Bilal, 2023). Further details are provided in Section D.2.

## 6.4 Calibration

Table 3 presents the results of the calibration. For each parameter in the internal estimation, we provide a corresponding moment that serves to identify its value, though all parameters in the model are estimated jointly. Our calibration appears to fit the wage moments of the model quite well. In particular, we are able to match the relative earnings spillover the job destruction shock, though slightly less of this effect is attributed to nonemployment relative to the model. Similarly, we are able to close match the job loss effects, though earnings loss in the model is slightly higher than in the data. Relative to the monthly employment flows, our model tends to overstate UE transitions and understate the separation rate and EE flows.

The negative job productivity drift and large volatility result imply that around half of the monthly EU rate in the model is attributable to endogenous separations.[63] This is made apparent in Appendix Figure 14, which shows many of the new jobs created are at the low end of the productivity distribution and require time to be more productive ($\mu_x > 0$).

Two forces are important in generating the spillover effects of job destruction. First,

[62]From the firm's perspective, the decision to destroy a job is an optimal stopping problem in which the exit value ($U_t(\cdot)$ is endogenous to market conditions. To account for this nonlinearity, we use an iterative operative splitting scheme to determine the value function.

[63]The presence of endogenous separations help generate "slippery rungs" at the bottom of job ladder without the need to explicitly model separation heterogeneity across jobs, as in Jarosch (2023).

we estimate a high convexity of vacancy posting. As a result, job creation is less responsive to lower market tightness. Second, we find a large gap between job learning and unemployment scarring. As a result, the longer time spent in unemployment translates into lower wages and further pushes down job creation.

**Path of job loss and spillover effects** While we target the the cumulative job loss effects for both earnings and employment, it is useful to assess whether the dynamic of these effects are consistent with the persistence we observe in the data. Figure 6 presents these results over the six-year period. In the first row, we plot the quarterly spillover effects of earnings (green) and employment (purple) against the model-implied series. We find that our model generates the same level of persistence in worker spillover effects for both outcomes, with a magnitude slightly smaller than the empirical estimates. In the second row, we plot the difference in means of both outcomes between job losers and job stayers. We find that we are able to produces the same degree of persistence in job lost costs, though the short-term earnings loss is larger in the model.

# 7 Welfare assessment

We use our model to evaluate the general equilibrium effects of job destruction on the labor market. In Section 7.1, we complement the back-of-the-envelope calculations in Section 5.3 by estimating the equilibrium welfare effects of an exogenous shock to the rate of job loss. We then consider the policy implications of these spillovers in Section 7.2 by studying the optimal generosity of a simple employment subsidies to existing jobs.In both settings, we denote welfare as the present-discounted value of production net of creation costs in the economy or, equivalently, the sum of value functions across all agents (present and future). In the steady state equilibrium without aggregate shocks, the corresponding social welfare function (SWF) equivalently in terms of agent values or net output:

$$\begin{aligned} \text{SWF} &= \int_y W(y)g(y)dy + \int_y J(y)g(y)dy + \int_h U(y)\overline{g}_h(h)dh + \int_x \Pi(x)dF(x) \\ &= \frac{1}{\rho}\left[\int_{y\in Y} p(y)g(y)dy - \int_x C(v(x))dF(x)\right], \end{aligned} \tag{26}$$

where $\overline{g}_h = (\kappa + u(h)\kappa_u)g_t(h)$ is distribution of labor market entrants, $u(h)$ is the mass of unemployed workers with human capital $h$, $g_t(h)$ is the marginal distribution of human capital, $p(y)$ is worker production, and $v(x)$ is the profit-maximizing recruiting intensity chosen by firms.

## 7.1 Employer valuation of job loss

Earnings spillovers from elevated job loss may reflect two different sources. First, they can reflect per-capita loss in productive capacity from workers (i) remaining unemployed longer, (ii) losing job-related human capital, and (iii) being matched to worse jobs. Second, the losses may a shift in job surplus from workers to firms as a result of lower outside options. We use our calibrate model to distinguish between these two forces and recover the model-implied effect on aggregate production efficiency.

We assess the aggregate efficiency through the dynamic extension of (26), where we decompose PDV of the first-order effect of the job destruction shock $dS$:

$$\begin{aligned}\frac{d\text{SWF}}{dS} &= \int W_0(y)\partial_S g(y)\,dy + \int J_0(y)\partial_S g(y)\,dy \\ &+ \int \partial_S W_0(y)\,dG(y) + \int_0^\infty e^{-\rho t}\left[\int_h \partial_S U_t(y)\overline{g}_h(h)dh\right] \\ &+ \int \partial_S J(y)\,dG(y) + \int_0^\infty e^{-\rho t}\left[\int_x \partial_S \Pi(x)dF(x)\right]\end{aligned} \tag{27}$$

As before, we decompose the welfare effects of the shocks in two parts. The first line is the partial equilibrium of changes in the worker distribution from job destruction, holding prices (e.g., vacancies, wages, and market tightness) constant. The cost of workers who lose their job is the difference between the expected cumulative earnings relative to unemployment, and for firms it is the future profits lost from the job. The second and third line represent the spillover effects of the job destruction shock, which alter the valuation of each state. The second term reflects the total worker spillovers of job destruction, captured by how the valuation of different employment states change for both existing workers and future labor market entrants. The final term is the spillover effects on firms, which is determined by changes in the valuation of existing jobs as well as expected profits from new jobs created in the future.

We evaluate the welfare effects in terms of expected production following a job destruction shock. Our estimates provide a conservative upper bound on the firm benefits by ignoring the cost of vacancy creation, which cannot be separately identified from the efficiency in the matching technology, $C_m$. As a result, our welfare decomposition is with respect to the quasi-rents of jobs, which is done by replacing $\Pi(x)_t$ with $q(\theta)\overline{J}(x)_t = q(\theta)\int_{y:x(y)<x} J(y)g(y)dy$ in the third line of (27).

Figure 7a provides estimates of the total change in aggregate efficiency for each of these components following a one percentage point shock to the job destruction rate.

Following a one percentage point increase in the job destruction rate among the low-productivity jobs. On the margin, spillovers account for 62% of the overall lost wages of workers. Comparing the spillover on firms (profits) with the earnings spillover, we see that employers retain around 48% of every dollar lost by workers due to spillovers, leading to a net decline in expected production over the duration of the shock. In Figure 7b, we show the evolution of firm and worker rents over the duration of the shock. The hump-shaped behavior of profits reflects the fact that the benefit that firms receive from lower market tightness in the short-run is done by the decline of human capital for workers as a result of extended non-employment.

## 7.2 Value of Job Retention Subsidies

The wave of job destruction observed during recessions can help amplify the costs of recessions, as more workers are displaced at a time when hiring is low. Does this mean that policymakers should extend employment subsidies to curb the rate of job loss? While mitigating labor market spillovers is valuable, employment subsidies are only marginal for jobs that are relatively low productive. Retaining these workers therefore comes at the cost of limiting labor reallocation to growing areas of the economy and generate the dispersion in the marginal product of labor across the cross-section of firms (Hopenhayn and Rogerson, 1993). Assessing the value of these job transfers relies on understanding the tradeoff between mitigating spillovers and facilitating reallocation.

Because our model is calibrated to replicate both the dispersion in earnings and the spillover from job loss, it is well-suited to quantify the value of employment subsidies. We consider a social planner that seeks to maximize the expected value of production in the economy, given deterministic transition dynamics $\{\Omega_t\}_{t\geq 0}$ and common discount rate $\rho$.

In order to isolate the competing effects of congestion and reallocation, we restrict a social planner to a single lump-sum employment subsidy of $\{\tau_t\}_{t\geq 0}$ given to all active jobs, and financed by a lump-sum tax on all workers. The transfer changes the flow value to be $p^{\tau}(h_y, x_y, z) := p(h_y, x_y, z) + \tau$ for all jobs without affecting the direct benefits of unemployment. As a result, these transfers allow the planner adjust the productivity threshold $x^*(\cdot)$ at which endogenous separations occur.

### 7.2.1 Steady state

We consider the optimal level of the employment transfers without aggregate shocks, $\tau_{ss}$. We set the policy such that:

$$\tau_{ss} = \arg\max_{\tau} \text{SWF}(\tau) - (1-u)\tau$$

where SWF($\tau$) is the modified social welfare function (26) with the employment subsidy.[64] Because agents are forward-looking, job creation is also impacted by $\tau$ in addition to the endogenous separation margin.

Under our preferred calibration, we find that the optimal subsidy is negative ($\tau_{ss} = -10.35$), which leads to a 1.08% increase in expected production relative to the no-policy (NP) case. Reminiscent of earlier work by (Hopenhayn and Rogerson, 1993) in heterogeneous firms models, we find that the planner would like to raise the productivity threshold for separations by implementing a tax on jobs, which makes firms more willing to layoff workers at unproductive jobs. In Appendix Figure 16, we show the change in the distribution of job productivity as a result of the policy. Implementing the employment tax leads more workers to be reallocated to higher productivity jobs in the steady state, by "cleansing" marginally productive jobs.[65] At the same time, the steady state unemployment rate increases by 3% as a result and the worker share of total production declines significantly.

# 8 Conclusion

This paper estimates the spillover effects of job destruction on workers in the United States. We find that job destruction has persistent effects on worker earnings and employment, and contributes meaningfully to the costs of recession for households. Whereas policymakers may be cautious about limiting productive reallocation during normal times, the strength of spillovers could suggest a motive to slow job loss during recessions through employment subsidies. The estimates of worker costs we provide can help inform the design of effective fiscal policy measures that can help mitigate household exposure to

[64]Because we only allowing the planner to use a restricted set of policy instruments, the optimal linear subsidy does not coincide with the first-best distribution of employment, vacancies, and market tightness that maximizes production. While standard benchmarks for efficiency – such as the Hosios condition – no longer hold in a setting with a job ladder and heterogeneous workers, the optimal allocation involves implementing firm-specific subsidies for job creation.

[65]The loss of low-productivity jobs also leads to a decline in the bargaining threat points as shown in right panel of Appendix Figure 16.

aggregate shocks.

Two natural research directions stem from our paper. First, future work should focus on understanding how the general equilibrium effects from labor market congestion changes the optimal mix of fiscal policy between unemployment insurance expansions and job support programs during recessions. Second, it is important to better document the firm response equilibrium job destruction. For example, the welfare implications of job destruction shocks may differ if the sluggish response of job creation is due to firms' investment in new technology that does not complement the skills of displaced workers (Hershbein and Kahn, 2018).

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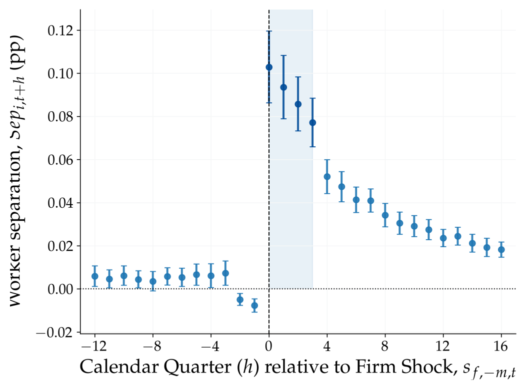
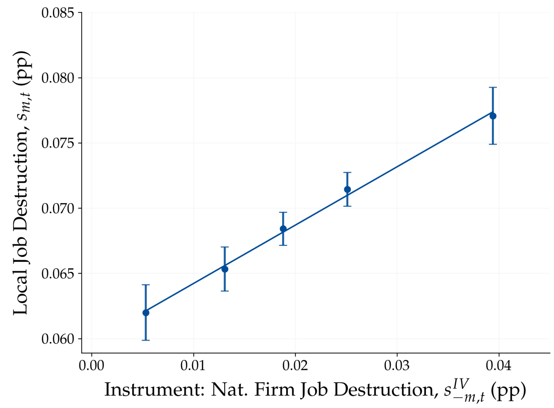
# Figures

Figure 1: First stage effects of national firm job destruction.

(a) Worker separation at shocked firms




(b) Market-level job destruction

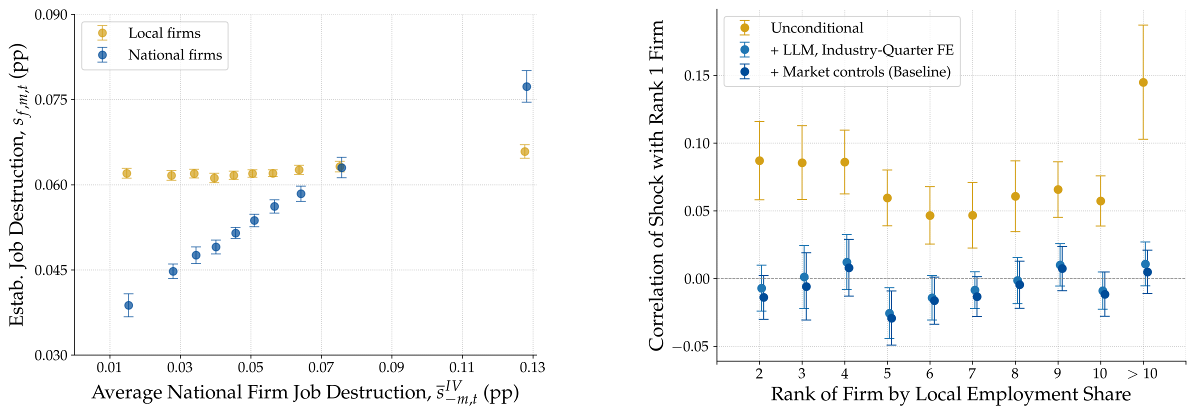



*Notes:* This figure displays the relationship between national firm and local job destruction. Panel 1a plots coefficients from estimating $S_{i,t+h} = \beta s_{f(i),-m(i),t} + \phi_m + \Gamma_1^{(h)} \mathbf{X}^W_{i,t} + \Gamma_2^{(h)} \mathbf{X}^M_{m,t} + \epsilon_{i,t+h}$ for $h = -12, \ldots, 16$ among the sample of workers employed at national firms ($\mathcal{F}^N$). The outcome $\text{Sep}_{i,t+h}$ is an indicator for whether the worker $i$ is observed to separate from their primary employer at quarter $t+h$, accounting for firm restructuring and name changes, and $s_{f(i),-m(i),t}$ is the national job destruction rate of the worker's primary employer. We use the controls from our baseline specification in Section 3.3. The shaded area represents the period over which cumulate gross flows to construct $s_{f(i),-m(i),t}$. Panel 1b plots estimates from the regression $s_{m,t} = \sum_{k=1}^{5} \beta^k Q_k(s^{IV}_{mt}) + \phi_m + \mathbf{X}^M_{-i,m,t} + \epsilon_{i,t}$, where $Q_k(s^{IV}_{mt})$ is an indicator whether the market-level instrument job destruction belongs in the $k$-th quintile. The plotted line corresponds to the first stage coefficient $\hat{\beta}^{fs}$ of (10) without worker-level adjustments (slope: 0.75, SE: 0.08). Local job destruction rates are measured at the level of NAICS2-CBSA market $m$. Standard errors are two way clustered by CBSA and quarter.

Figure 2: Conditional sorting of job destruction shocks across local labor markets.

(a) Between local and national firms

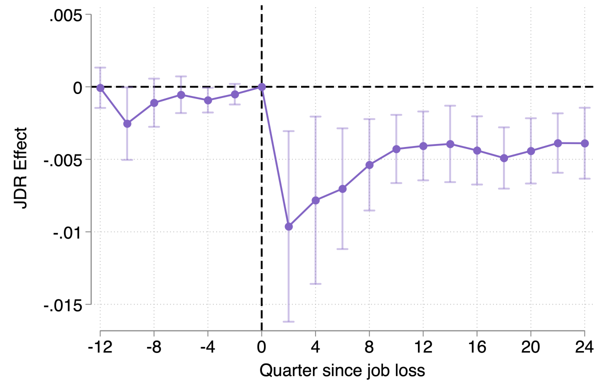
(b) Between national firms




*Notes:* This figure displays estimates from spatial sorting in firm-level job destruction shocks across local labor markets. Panel 2a plots coefficients $\hat{\beta}^{(q)}$ from (12), estimated separately for establishments owned by single-region ("local") firms and establishments owned by national firms. The predicted effects are plotted against the average job destruction of national firms in the local labor market. Panel 2b plots estimated coefficients $\hat{\beta}^{(R)}$ (13) for national firms ranked R=2 to R=10 in terms of the local employment share in each labor-market-quarter. We also include a separate group for the average job destruction rate of national firms outside of the top ten (>10). Both the outcome and regressor variables are normalized to have standard deviations equal to one. The "Unconditional" series refers to the raw correlations between the leave-out national firm job destruction rate. The series "LLM, Industry-quarter FE" plots regression-adjusted correlations from including fixed effects for the local labor market (industry-region pair) and for industry-quarter pairs, where the industry is taken to be two-digit 2017 NAICS code. The series "baseline" additionally includes the market time-varying controls described in Section 3.3.2. In both figures, standard errors are two-way clustered by CBSA and quarter.

Figure 3: Effects of market job destruction shock on earnings and employment outcomes of job losers


(a) Earnings



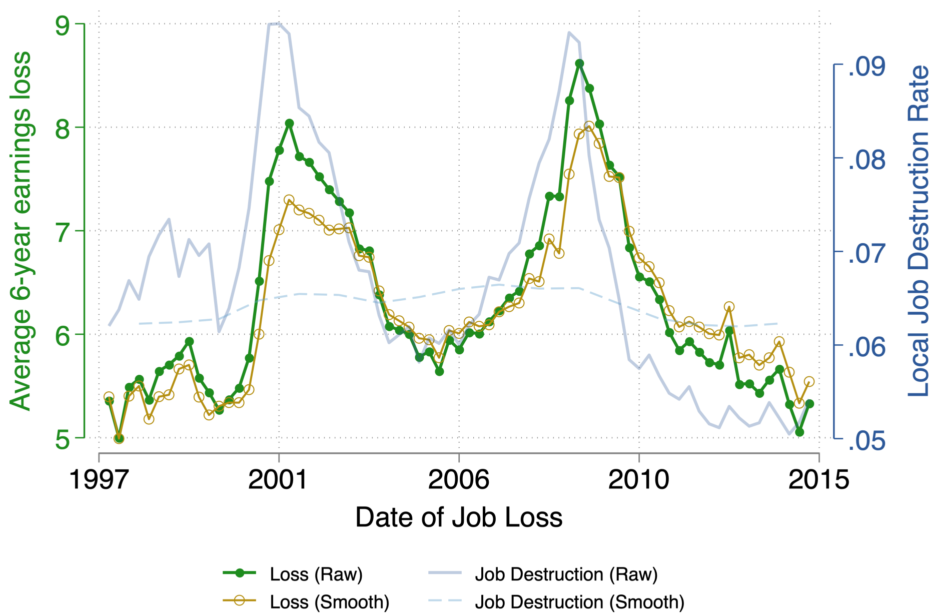

(b) Employment

*Notes*: This figure shows our local projection estimates of the effect of job destruction shocks on the outcomes of job losers relative to a match control group of job stayers. Each point represents the 2SLS estimate of the difference between the spillover effects on job losers ($\hat{\beta}^{(h)}_{JL}$) and job stayer ($\hat{\beta}^{(h)}_{JS}$) from (9) under our baseline specification, reproduced below:

$$y_{i,t+h} = \beta^{(h)}_k s_{-i,m,t} + \phi_m + \Gamma^{(h)}_1 \mathbf{X}^W_{i,t} + \Gamma^{(h)}_2 \mathbf{X}^M_{-i,m,t} + \epsilon_{i,t+h}$$

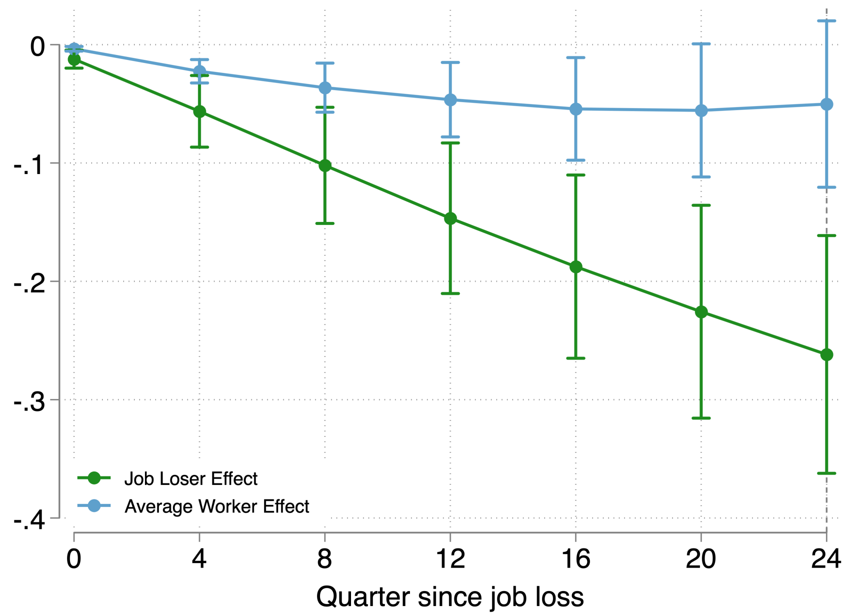
for $k = JL, KS$, $h$ is the quarter relative to the job loss event ($t$). Coefficients estimates are scaled to reflect a 1 pp increase in the local job destruction rate, $s_{-i,m,t}$. Panel (a) shows estimates when $y_{i,t+h}$ is the worker's average earnings in the adjacent quarters $t+h-1$ and $t+h$, relative to base earnings, $\text{Earn}_{i,t+h}/\overline{\text{Earn}}_i$. Panel (b) shows estimates when $y_{i,t+h}$ is the an indicator variable whether is employed with strictly positive earnings at the beginning of the quarter, $Emp_{i,t+h}$. Job losers are matched to job stayers with the closest predicted separation propensity in the same NAICS2-CBSA-Age-Sex-Tenure cells, where age bins are over the intervals $[25, 30, 35, 40, 45, 50, 55]$ and tenure bins are over the years $[0, 1, 3, 6, > 10]$. Details on the matching procedure are provided in Section B.5. The vector $X^M_{mt}$ consists of the following market-level controls: two-digit NAICS-by-quarter fixed effects, the share of $m$'s quarter $t$ employment that is in establishments of national firms, eight lags of the shift-share job destruction instrument $s^{IV}_{-f,mt}$, the shift-share job creation instrument (from quarters $t-8$ to $t$) given by (80), and the predicted employment growth of the CBSA based from $t$ to $t+h$ (based off aggregate two-digit NAICS growth rates over this horizon and the CBSA's quarter $t$ employment shares by sector). The regressions also include time-invariant fixed effects for the market $\phi_m$. The regressions attach equal weight to each job loser. Standard errors are double clustered by quarter of job loss $t$ and by CBSA.

Figure 4: Average cost of job loss, actual versus counterfactual under smooth job destruction rates



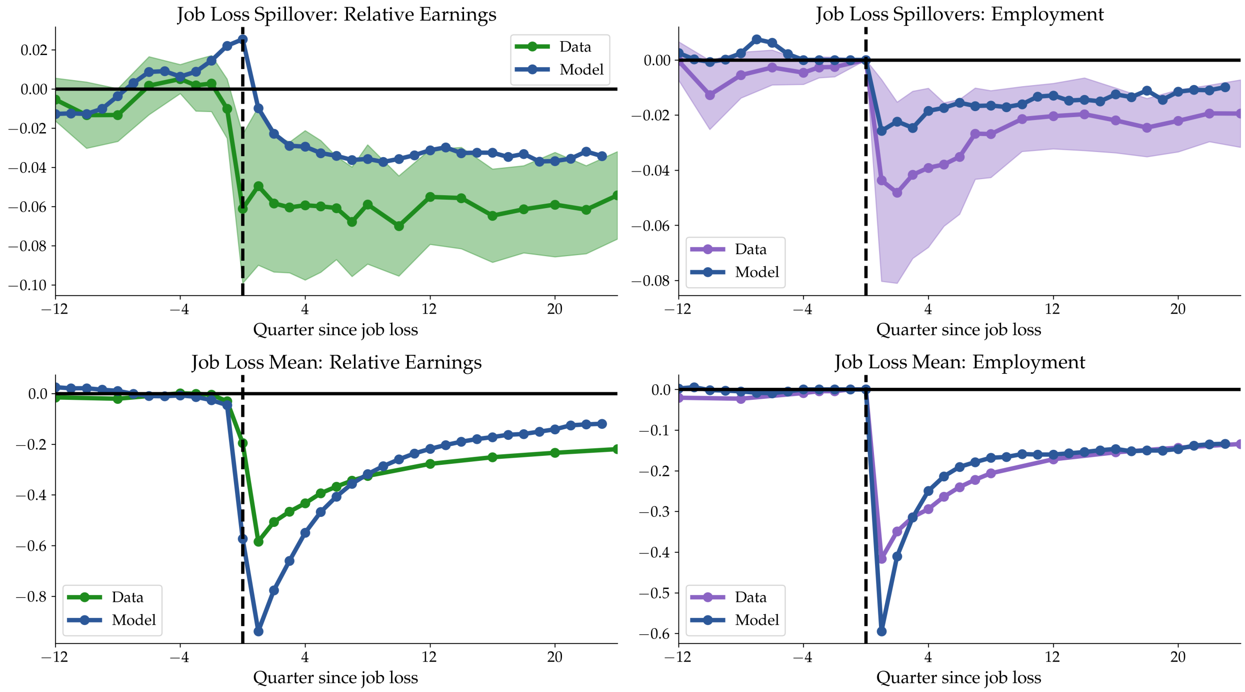

*Notes:* This figure shows the aggregate means of the cost of job loss and job destruction rates for each quarter in our sample. The green-closed circle line,$\text{Loss}_{i,t}^{(Est)}$, is the NPV of the difference between the average six-year earnings of job losers and matched control sample. The yellow-open circle line is this variable under the counterfactual of a constant local job destruction rate, $\text{Loss}_{i,t}^{(Smooth)}$, defined in (14). See Section 5.1 for further details. The solid blue line shows the actual job destruction rate for each quarter, averaged over the markets of the workers in the job loser sample. The dashed blue line shows the average of the smooth job destruction series; it equals the average of the market-level mean job destruction rate over our sample period.

Figure 5: Cumulative effects of market job destruction shock on relative earnings, job loss vs. average worker



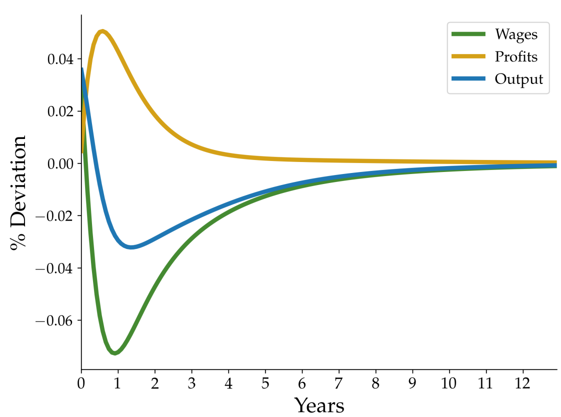

*Notes*: This figures plots estimates of the cumulated earnings spillovers for the average worker and job loser. The average worker effect (blue) consists of coefficients $\beta^{(h)}$ from the two-stage least-square estimation of (9), using national firm job destruction as the excluded instrument and the NPV of earnings relative to the pre-shock, $\sum_{s=0}^{h} \text{Earn}_{i,t+s}/\overline{\text{Earn}_i}$ as the outcome variable. The estimates are constructed from a random subsample of worker-date observations described in Section 5.2 and include the set of contorols from our baseline specification. The job loser plot (green) correspond to the difference in spillovers between the spillovers of the job loser sample relative to the matched control group using the same specification as that of the average worker effect. Standard errors correspond to the 95% confidence interval and are two-way clustered by CBSA and shock date $t$.

Figure 6: Model vs. Data: Job loss and spillover paths

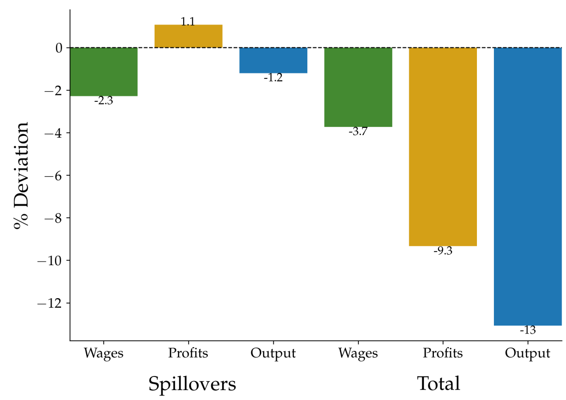



*Notes*: Coefficients are scaled by 0.05 JD shock. Data moments for job loss effects comes from the sample of workers in the first quintile of the market-level job destruction instrument.

Figure 7: Welfare effects of a shock to job destruction.




(a) Welfare decomposition of Job destruction shock




(b) Net production

*Notes*: This plots shows the simulated effects of a 1 percentange point job destruction shock on output and its division between firms and workers. Panel (a) displays the impulse report of output and its division between The job destruction shock is parameterized to affect low-productivity jobs. The y-axis gives the percent deviation relative to one month of output in the steady state equilibrium.

# Tables

Table 1: Displaced Worker Spillover Effects after 24 quarters

| | (1) | (2) | (3) | (6) |
|---|---|---|---|---|
| | Earnings (Qtrs) | Earnings (USD) | Total employment | Long-Term Nonemployment |
| Job Loser | -.3231 | –6147 | -.1102 | .003987 |
| | (.07784) | (1645) | (.03133) | (.001313) |
| Job Stayer | -.06132 | –1959 | .01824 | -.0006738 |
| | (.0424) | (1010) | (.01077) | (.0004734) |
| **Difference** | -.2618 | –4188 | -.1284 | .004661 |
| | (.05048) | (987.1) | (.02879) | (.001307) |
| Mean (Job Loser) | 16.94 | –71410 | 18 | .2837 |
| Mean (Job Stayer) | 23.49 | 13640 | 22.8 | .09559 |
| **Mean (Difference)** | –6.55 | –85050 | –4.8 | .18811 |

*Notes*: This table displays our baseline estimates of how job destruction shocks affect the labor market outcomes of job losers. For a worker $i$ who at the start of quarter $t$ holds a job in local labor market (MSA-two digit NAICS pair) $m$, we estimate the cumulated effects, $\beta^{(sum)}$ from the following adaptation of (9):

$$y_{i,t}^{sum} = \beta^{(sum)}\widehat{s}_{-f,mt} + \phi_m + \Gamma_1^{(sum)}\mathbf{X}_{i,t}^{W} + \Gamma_2^{(sum)}\mathbf{X}_{-i,m,t}^{M} + \epsilon_{i,t}$$

where $\widehat{s}_{-f,mt}$ is the predicted value from the first-stage regression (10), using national job destruction exposure, $s_{-i,m,t}^{IV}$, as the excluded instrument. Rows 1 and 2 provide estimates of the equilibrium job destruction effects on the sample of job loser ($\widehat{\beta}_{JL}^{(sum)}$) and matched job stayers ($\widehat{\beta}_{JS}^{(sum)}$), described in Section 4.1. Row 3 provides the difference between the job loser and job stayer effects, ($\widehat{\beta}(sum)_{JL} - \widehat{\beta}_{JS}^{(sum)}$), with standard errors constructed for the test $\widehat{\beta}(sum)_{JS} = \widehat{\beta}_{JL}^{(sum)}$. The controls are the same as those used in the baseline specification and described for Figure 3. The outcome variable $y_{i,t}^{(sum)}$ is a measure of the worker's cumulative earnings and employment outcomes over the six-year horizon $t$ to $t+24$; from columns (1) to (4), it is set to: (1) the NPV of average quarterly earnings relative to base earnings, $\text{Earn}_{t+h}/\overline{\text{Earn}}$ from $h = 0$ to $h = 24$; (2) the NPV of the difference between the dollar amount of earnings from $t$ to $t+24$ and base earnings, $\text{Earn}_{t+h} - \overline{\text{Earn}}$; (3) the number of quarters in which the worker is employed over $t$ to $t+24$; and (4) an indicator variable for whether, over $t$ to $t+24$, the worker has a stretch of at least eight consecutive quarters of not being employed. The bottom panel of the table shows the mean values of each of the respective dependent variables. The regressions and means attach equal weight to each job loser and control pair. Standard errors are double clustered by quarter of job loss $t$ and by CBSA.

Table 2: Estimates of job destruction on laid-off worker NPV: alternative specifications

| Row | Model Description | Estimate | SE |
|---|---|---|---|
| 1 | Baseline | -0.2618 | 0.05048 |
| | Panel A: Alternative Shock Measurements | | |
| 2 | Include own firm | -0.2093 | 0.07507 |
| | Job Stayer | -0.1185 | 0.04371 |
| | Job Loser | -0.3279 | 0.07507 |
| 3 | GIV specification | -0.2651 | 0.05608 |
| 4 | Measure JDR over $t-2$ to $t+1$ | -0.2522 | 0.0575 |
| | Panel B: Alternative Controls | | |
| 5 | Fine demographic controls | -0.2811 | 0.05061 |
| 6 | Control for lags of local JDR/JCR | -0.2488 | 0.05195 |
| 7 | Include FE for worker's firm | -0.2395 | 0.05402 |
| 8 | Control for matching propensity score | -0.2243 | 0.0584 |
| | Panel C: Sample filters | | |
| 9 | At least one quarter of earnings | -0.2601 | 0.04935 |
| 10 | Employed by year 6 | -0.2685 | 0.05638 |
| 11 | Exclude workers in construction and FIRE sectors | -0.2712 | 0.05063 |
| | Panel D: Local Demand Contribution | | |
| 12 | Tradable industries | -0.2007 | 0.06436 |
| 13 | CBSA-Quarter FE | -0.18 | 0.06575 |
| | Panel E: Alternative Labor Market Definitions | | |
| 14 | CBSA | -0.552 | 0.1763 |
| 15 | CBSA $\times$ NAICS3 | -0.195 | 0.04432 |

*Notes*: This table reports the results of estimating the spillover effects of job destruction on laid-off workers under alternative specifications. Apart from adjustments described in the "Model Description", we use the same baseline specification and report outcomes for the NPV of relative earnings, $\sum_{h=0}^{h=24} \text{Earn}_{i,t+h}/\overline{\text{Earn}}_i$. Row 1 replicates the result from Table 1, column 1. The description of the remaining rows are provided in Section 4.3. Standard errors (SE) are two-way clustered by CBSA and date of job loss ($t$).

Table 3: Parameter Estimates

| Parameter | Notation | Estimate | Moment | Data | Model | Source |
|---|---|---|---|---|---|---|
| | | | Panel A: External Calibration | | | |
| $\rho$ | Discount Rate | 0.00407 | Annual Interest Rate | - | 0.05 | - |
| $\omega$ | Matching Elasticity | 0.5 | | | - | Moscarini and Postel-Vinay (2021) |
| $\kappa_u$ | Labor force exit | 0.00245 | | - | - | |
| $\kappa_u$ | Unemployed Labor force exit | 0.00123 | | - | - | |
| | | | Panel B: Internal Estimation | | | |
| $b$ | Unemployment flow value | 2.07 | Benefit-ALP ratio | 0.47 | 0.237 | Literature |
| $\bar{z}$ | Aggreate productivity | 1.64 | Unemployment rate | 0.0613 | 0.101 | BLS |
| $\delta$ | Exogenous Job Destruction | 0.0147 | EU rate | 0.025 | 0.0148 | CPS |
| $\phi$ | Employed search intenisty | 0.0217 | EE rate | 0.0125 | 0.000489 | CPS |
| $C_m$ | Matching efficiency | 0.122 | UE rate | 0.16 | 0.195 | CPS |
| $\beta$ | Wage Bargaining | 0.533 | Job loss effect: Earnings when employed | 0.142 | 0.162 | LEHD |
| $\mu_x$ | Log Productivity Drift (-) | 0.039 | Job loss effect: Earnings | 6.55 | 7.77 | LEHD |
| $\sigma$ | Log Productivity Volatility | 0.166 | Job loss effect: Employment | 4.8 | 4.58 | LEHD |
| $(a^\beta, b^\beta)$ | Beta Distribution | (32.6,26.8) | Wage Dispersion (P50/P10, P90/P50) | (0.5,0.52) | (0.42,0.354) | LEHD |
| $\psi_e$ | HC: job experience | 0.205 | Annual wage growth | 1.02 | 1 | LEHD |
| $\psi_u$ | HC: scarring (-) | 0.221 | Spillover effect: Earnings | 0.707 | 0.713 | LEHD |
| $\xi$ | Vacancy posting elasticity | 18.6 | Spillover Effect: Employment | 0.347 | 0.356 | LEHD |

*Notes:* Estimated parameters of the quantitative and moments used for estimation. Panel A lists the parameters that were externally calibrated. Panel B lists the estimates of the internally calibrated parameters, along with the moment that best identifies it among those jointly used in estimation. All transition rates (EE, UE, EU) are calculated from the BLS Current Population Survey (CPS).

## Census Disclaimer

Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2590. (CBDRB-FY24-P2590-R10998). This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation.

# Appendices

## A Theory

### A.1 Model extension to generate identification conditions

In this section, we derive the conditions under which our research design identifies the spillover effects from job destruction, $\beta^{(h)}$ in (9). For simplicity, we suppress time-subscripts and define the data-generating process at the establishment level, aggregated from worker-level outcomes. We also assume that each region contains one single industry, which gives a set of weaker conditions for identification to be satsified. Without loss of generality, we use $i$ to significant these establishments, which are specific market ($m$) and firm ($f$) specific combination. We use $m(i)$ and $f(i)$ throughout to refer to the market and firm of the establishment, respectively. $i = m(i) \times f(i)$.

**Data-generating process.** The underlying data-generating process for the separation propensity of establishments $i$, which we refer to as the job destruction rate, is given by:

$$s_i = \Gamma_s' \mathbf{x}_i + \alpha^{(i)} p_i + \alpha^{(f)} q_{f(i)} + \alpha^{(m)} r_{m(i)} + \eta_i \tag{28}$$

where $\mathbf{x} = \left\{ \mathbf{x}_i^M, \overline{\mathbf{x}_i}^W, \phi_m \right\}$ is the baseline set of observables and the establishment-specific error term $\eta_i$ is mean-zero and indepedent. The separation propensity is a function of unobserved productivity shocks that can occur at the establishment-, firm-, and market-level, where $\alpha_i, \alpha_f, \alpha_m \in \mathbb{R}$ describe the sensitivity of the separation propensity to these shocks, respectively. Like $\eta_i$, we assume that $p_i$ is independent across establishments. The firm-level shocks take the form:

$$q_f = u_f + a_f' z \tag{29}$$

where $u_f$ is idiosyncratic component of the firm shock that is independent across firms, $z$ is a $Z \times 1$ vector of common factors, and $a_f$ is a $Z \times 1$ vector of firm-specific loadings on these factors.[66] The market-level shocks are similarly given by:

$$r_m = v_m + b_m' z \tag{30}$$

[66] One can interpret these common factor as aggregate shocks $z_t$ that firms and markets may differential load onto.

where $v_m$ is the idiosyncratic component of the market shock that is independent across markets, $b_m$ is a $Z \times 1$ is the loading of market $m$ on the common factors. Unconditionally, we allow for firms and markets to have correlated shocks through loading on the same factors. The data-generating process for worker outcomes is given by:

$$y_i = \beta s^{(M)}_{m(i)} + \Gamma'_y \mathbf{x}_i + \gamma^{(p)} p_i + \gamma^{(f)} q_{f(i)} + \gamma^{(m)} r_{m(i)} + \epsilon_i, \tag{31}$$

where $s^{(M)}_{m(i)}$ is the market-level job destruction rate ($s_{mt}$ in the main text), and $\beta$ captures the spillover effects of job destruction. Unobserved productivity shocks $\left\{p_i, q_{f(i)}, r_{m(i)}\right\}$ can impact worker outcomes in addition to their separation propensity for each establishment.

**Connection to Section 2.** The data-generating process described above can be seen as an extension to the qualitative model presented in Section 2 in the following way. Fist, we assume that there $M$ segmented labor markets, which may differ in terms of their structural parameters (e.g., $\xi_v$). Second, we assume that there are multiple firms, each of which has an exogenous quantity of existing jobs across labor markets and can post jobs of heterogenous productivity. Weighting each 'job' from Section 2 by $N_{fm}$ lets us recover the establishment-level data-generating process described above. Finally, we assume that at the beginning of the period, all jobs are hit with a productivity shock, with variation that loads on common factors $z$ and has firm- and market-specific idiosyncratic components.

**Matrix form** It is convenient to work with the vector representation of the data generating process. Let $s$ denote the $I \times 1$ vector of establishment separation propensities and similarly define $s^{(M)}$ as the $M \times 1$ vector of market-level separation propensities, which we refer to as local job destruction. We let $O$ be the $I \times F$ matrix tracking establishment ownership, where $O_{if} = 1$ if establishment $i$ is owned by firm $f$ and 0 otherwise. Similarly define $L$ to be the $I \times M$ matrix of establishment locations. We re-express the data-generating process as:

$$s = \Gamma'_s \mathbf{X} + \alpha^{(i)} p + \alpha^{(f)} Oq + \alpha^{(m)} Lr + \eta \tag{32}$$

$$y = \beta s^{(M)} + \Gamma'_y \mathbf{X} + \gamma^{(p)} p + \gamma^{(f)} Oq + \gamma^{(m)} Lr + \epsilon \tag{33}$$

$$q = u + A'z \tag{34}$$

$$r = v + B'z \tag{35}$$

In what follows, we use $\Omega$ to denote covariance matrix of the random variables, e.g. $\Omega_z = E[zz']$.

**National firm shocks.** Our instrument is constructed from observed job destruction rates $s$. Let $n$ be the $I \times 1$ vector of establishment employment counts. We let $N_f^{(F)}$ be the total employment of firm $f$ across establishments, so that $N^{(F)} = O'n$. We similarly define market size $N^{(M)} = L'n$.[67] We define the market shares of each establishment as $\Lambda^M$, where $\Lambda^M_{im} = \frac{n_i}{N^M_{m(i)}}$. We similarly define $\Lambda^F$ to be the matrix containing the share of firm employment at each establishment, i.e. $\Lambda^F_{if} = \frac{n_i}{N^F_{f(i)}}$.

Recall that the national firm job destruction rate, leaving out market $m$, is $s_{f,-m} = \sum_{i:f(i)=f,i\neq i'} \frac{n_i}{N^M_{m(i)} - N_{i'}} s_i$ where $i'$ is the establishment in market $m$ owned by firm $f$. Denote the leave-out aggregation of establishment outcomes to the firm level as $\widetilde{\Lambda}^F$:

$$\widetilde{\Lambda}^F = D^F_{-e}\left(O\Lambda^{F\prime} - D^F_e\right) \tag{36}$$

where $\mathbf{I_d}$ is the $I \times I$ identity matrix, $D^F_e$ is the diagonal of employment shares within firms, $D_{e,ii} = \frac{n_i}{N^F_{f(i)}}$, and $D^F_{-e}$ is the diagonal matrix of denominator corrections for the firm-level aggregation, accounting for single-market firms:

$$D^F_{-e,ii} = \begin{cases} 1 & \text{if } n_i = N^F_{f(i)} \\ \frac{N^F_{f(i)}}{N^F_{f(i)} - N_i} & \text{otherwise} \end{cases}$$

Note that under this form, firms with only a single establishment would have a leave-out firm shock of 0. The vector of firm-level shocks, $\delta$ as:

$$\delta := \widetilde{\Lambda}^F s \tag{37}$$

Due to the leave-out correction, $\delta$ is of length $I$.

**Leave-out correction for market spillovers** In order to isolate the spillover effects of job destruction from direct effects that firm shocks may have on worker outcomes, we also perform a leave-out correction for all market-level shocks. We define the leave-out aggregation of establishment outcomes to the market level as $\widetilde{\Lambda}^M$:

$$\widetilde{\Lambda}^M = D^M_{-e}\left(L\Lambda^{M\prime} - D^M_e\right) \tag{38}$$

[67]These employment counts are measured in the period before job destruction is realized.

where $D_e^F$ is the diagonal of market shares, $D_{m,ii} = \frac{N_i}{N_{m(i)}^M}$, and $D_{-e}^M$ is defined similarly as $D_{-e}^F$. We denote the leave out correct market-variable by a $-i$ subscript, i.e. $s_{-i}^{(M)} = \widetilde{\Lambda}^M s$.

**Control-residualized variables.** Given the set of baseline controls $\mathbf{X} = \left\{\mathbf{X}^M, \overline{\mathbf{X}}^W, \phi_m\right\}$, we define the variables residualized against controls as, e.g., $y^\perp = y - \Gamma_y' \mathbf{X}$.

**Identification assumption** Under the specified data-generating process, the following assumption is sufficient for the identification of the spillover effects of job destruction:

**Assumption A1.** *Conditional on controls* $\mathbf{X}$*, then the firm- and market-loadings on aggregate shocks are mutually uncorrelated:* $E[(OA + LB)E[z^\perp z^{\perp\prime}](OA + LB)'] = D$*, where* $D$ *is a diagonal matrix.*

**Identification**

**Proposition A.1.** *(Identification.) Let* $\{\lambda_{kt}\}$ *be the set of fixed effects for industry-by-quarter pairs,* $\{\phi_m\}$ *market-level fixed effects, and* $\mathbf{X}_{mt}$ *be the set of time-varying baseline controls. Under Assumption A1, then:*

*(i) the firm-level job destruction shocks are conditionally quasi-random with respect to the set of fixed effects and controls:* $E\left[s_{f,-m,t} | \{\phi_m\}, \{\lambda_{kt}\} \mathbf{X}_{mt}\right] = \mu c_{f,t}$ *where* $c_{f,t}$ *are indicators for the industry-by-quarter cluster of firm shock (ii) with regularity conditions (B1 and B2 of Borusyak et al. 2022), the estimator:*

$$\hat{\beta} = \frac{Cov(y^\perp, \widetilde{\Lambda}^M \delta^\perp)}{Cov(\widetilde{\Lambda}^M s^\perp, \widetilde{\Lambda}^M \delta^\perp)} \tag{39}$$

*consistently identifies* $\beta$, $\hat{\beta} \xrightarrow{p} \beta$.

To prove Proposition A.1, we make use of Lemma 2.

**Lemma 2.** *For* $I-$ *length vector* $x$*, define the double-leave-out correction as* $T(x) = \widetilde{\Lambda}^M \widetilde{\Lambda}^F x$*, where*

$$T(x)_i = \sum_{\substack{j:\, m(i)=m(j), \\ f(i)\neq f(j)}} \widetilde{\omega}_k^M \sum_{\substack{k:\, m(j)\neq m(k), \\ f(j)=f(k)}} \widetilde{\omega}_k^F x_k, \tag{40}$$

*where* $\widetilde{\omega}$*: correspond to the appropriate leave-out corrected employment share. Then the following hold:*

1. $Cov[p, T(p)] = 0$

2. $Cov[Ou, T(Ou)] = 0$

3. $Cov[Lv, T(Lv)] = 0$

*Proof.* We use the mean-0 construction of the $p, u, v$ to write:

$$Cov[x, T(x)] = E[x'T(x)] = E\left[x_i \sum_{\substack{j:\, m(i)=m(j), \\ f(i)\neq f(j)}} \widetilde{\omega}_k^M \sum_{\substack{k:\, m(j)\neq m(k), \\ f(j)=f(k)}} \widetilde{\omega}_k^F x_k\right] \tag{41}$$

$$= \sum_{\substack{j:\, m(i)=m(j), \\ f(i)\neq f(j)}} \widetilde{\omega}_k^M \sum_{\substack{k:\, m(j)\neq m(k), \\ f(j)=f(k)}} \widetilde{\omega}_k^F E\left[x_i x_k\right] \tag{42}$$

1. $E[p_i p_k] \neq 0$ if and only if $i = k$. However, inspecting the summation terms (42), we see the at for all $i$, $m(i) = m(j) \neq m(k)$. As $i$ and $k$ are equal if they are the identical firm-market pairing, then $E[p_i p_k] = 0$ for all $k$ in the summation (42). As a result, $Cov[p, T(p)] = 0$.

2. Similarly, $E[(Ou)_i, (Ou)_k] \neq 0$ if and only if $f(i) = f(k)$. But $f(i) \neq f(j) = f(k)$ for all $i$, which implies that $E[(Ou)_i, (Ou)_k] = 0$ for all $k$ in the summation (42). As a result, $Cov[Ou, T(Ou)] = 0$.

3. $E[(Lv)_i, (Lv)_k] \neq 0$ if and only if $m(i) = m(k)$. But $m(i) = m(j) \neq m(k)$ for all $i$, which implies that $E[(Lv)_i, (Lv)_k] = 0$ for all $k$ in (42). As a result, $Cov[Lv, T(Lv)] = 0$.

□

*Proof.* Let $\widehat{\widetilde{\Lambda}^M s^\perp} = \widehat{\psi}\widetilde{\Lambda}^M \delta^\perp$ be the predicted values from the first stage (68). Consider the structural equation (33), residualized against observable $\mathbf{X}$:

$$y^\perp = \beta\widetilde{\Lambda}^M s^\perp + \gamma^{(p)} p^\perp + \gamma^{(f)} Oq^\perp + \gamma^{(m)} Lr^\perp + \epsilon^\perp \tag{43}$$

Expanding the covariance of the worker outcome with the instrument:

$$Cov(y^\perp, \widetilde{\Lambda}^M \delta^\perp) = \beta Cov(\widetilde{\Lambda}^M s^\perp, \widetilde{\Lambda}^M \delta^\perp) + \gamma^{(p)} Cov(p^\perp, \widetilde{\Lambda}^M \delta^\perp) + \gamma^{(f)} Cov(Oq^\perp, \widetilde{\Lambda}^M \delta^\perp) \tag{44}$$

$$+ \gamma^{(m)} Cov(Lr^\perp, \widetilde{\Lambda}^M \delta^\perp) + Cov(\epsilon^\perp, \widetilde{\Lambda}^M \delta^\perp) \tag{45}$$

$$\tag{46}$$

We consider each term:

**A:** $Cov(\widetilde{\Lambda}^M s^\perp, \widetilde{\Lambda}^M \delta^\perp)$ is recovered from the first stage equation (68).

**B:** $Cov(\epsilon^\perp, \widetilde{\Lambda}^M \delta^\perp) = 0$ by the fact that $\epsilon_i$ are independent.

**C:** Consider $Cov(\widetilde{\Lambda}^M p^\perp, \widetilde{\Lambda}^M \delta^\perp)$. Substituting for $\delta$:

$$\begin{aligned} Cov(p^\perp, \widetilde{\Lambda}^M \delta^\perp) &= Cov\left[p^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^f s^\perp\right] && (47)\\ &= Cov\left[p^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F \left(\alpha^{(i)} p^\perp + \alpha^{(f)} Oq^\perp + \alpha^{(m)} Lr^\perp + \eta^\perp\right)\right] && (48)\\ &= \alpha^{(i)} Cov\left[p^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F p^\perp\right] && (49)\\ &= 0 && (50) \end{aligned}$$

where in the first line we use the definition of the firm shocks (37), we use the specified data-generating process for s in (32), and the independence of $p_i$ in the third line. The final line uses the Lemma 2 for the leave-out correction.

**D:** Next, consider unobserved firm productivity:

$$\begin{aligned} Cov(Oq^\perp, \widetilde{\Lambda}^M \delta^\perp) &= Cov\left(Oq^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F s^\perp\right) && (51)\\ &= Cov\left(Oq^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F \left(\alpha^{(i)} p^\perp + \alpha^{(f)} Oq^\perp + \alpha^{(m)} Lr^\perp + \eta^\perp\right)\right) && (52)\\ &= \alpha^{(f)} Cov\left(Oq^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F Oq^\perp\right) + \alpha^{(m)} Cov\left(Oq^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F Lr^\perp\right) && (53)\\ &= Cov\left[OAz^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F \left(\left(\alpha^{(f)} OA + \alpha^{(m)} LB\right) z^\perp\right)\right] && (54) \end{aligned}$$

The first four lines proceed as before, using the independence of $q$ across firms. We then use Lemma 2 to show that $Cov\left(Oq^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F Oq^\perp\right) = 0$.

**E:** Consider $Cov(Lr^\perp, \widetilde{\Lambda}^M \delta^\perp)$. The expansion proceeds similarly to that of $Cov(Oq^\perp, \widetilde{\Lambda}^M \delta^\perp)$:

$$\begin{aligned} Cov(Lr^\perp, \widetilde{\Lambda}^M \delta^\perp) &= Cov\left[Lr^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F \left(\alpha^{(i)} p^\perp + \alpha^{(f)} Oq^\perp + \alpha^{(m)} Lr^\perp + \eta^\perp\right)\right] && (55)\\ &= Cov\left[LBz^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F \left(\left(\alpha^{(f)} OA + \alpha^{(m)} LB\right) z^\perp\right)\right] && (56) \end{aligned}$$

where the last line uses Lemma (2).

Combining these terms,

$$Cov(\widetilde{\Lambda}^M y^\perp, \widetilde{\Lambda}^M \delta^\perp) = \beta Cov(\widetilde{\Lambda}^M s^\perp, \widetilde{\Lambda}^M \delta^\perp) \tag{57}$$

$$+ Cov\left[\left(\gamma^{(f)} OA + \gamma^{(m)} LB\right) z^\perp, \widetilde{\Lambda}^M \widetilde{\Lambda}^F \left(\left(\alpha^{(f)} OA + \alpha^{(m)} LB\right) z^\perp\right)\right] \tag{58}$$

Under Assumption A1, the second term is zero, and so

$$\hat{\beta} = \frac{Cov(y^\perp, \widetilde{\Lambda}^M \delta^\perp)}{Cov(\widetilde{\Lambda}^M s^\perp, \widetilde{\Lambda}^M \delta^\perp)} = \beta \tag{59}$$

□

### A.1.1 Connection to validation exercise

We can use this framework to understand the implications for our validation exercises for the assumptions under which we identify $\beta$.

**Sorting among national firm shocks** . Recall that we estimate the following relationship between national job destruction rates:

$$\delta_m^{(R)} = \gamma \delta_m^{(1)} + \Gamma_R' \mathbf{X} + \epsilon^{(R)}, \tag{60}$$

where $\delta_m^{(R)}$ is the national firm shock of the $R$-th largest employer in market $m$, projected onto the firm shock of the largest national employer and the set of baseline controls. Define $P_R$ to be the $E \times L$ matrix with values equal to one if the establishment (row) contains the $R$-th largest employer in the market (column) and zero otherwise. Then our rank-test can be expressed as:

$$P_R' \delta = \gamma^{(R)} P_1' \delta + \epsilon^{(R)} \tag{61}$$

Using the definition of $\delta$, $\gamma = \frac{Cov(P_R' \delta^\perp, P_1' \delta^\perp)}{Cov(P_1' \delta^\perp, P_R' \delta^\perp)}$, where is numerator can be decomposed as:

$$Cov(P_R'\delta^{\perp}, P_1'\delta^{\perp}) = Cov\left[P_R'\widetilde{\Lambda}^F s^{\perp}, P_1'\widetilde{\Lambda}^{F\prime} s^{\perp\prime}\right] \tag{62}$$

$$= Cov\left[P_R'\widetilde{\Lambda}^F\left(\alpha^{(f)}Oq^{\perp} + \alpha^{(m)}Lr^{\perp}\right), P_1'\widetilde{\Lambda}^{F\prime}\left(\alpha^{(f)}Oq^{\perp} + \alpha^{(m)}Lr^{\perp}\right)\right] \tag{63}$$

$$= Cov\left[P_R'\widetilde{\Lambda}^F\left(\alpha^{(f)}Oq^{\perp} + \alpha^{(m)}Lr^{\perp}\right), P_1'\widetilde{\Lambda}^{F\prime}\left(\alpha^{(f)}Oq^{\perp} + \alpha^{(m)}Lr^{\perp}\right)\right] \tag{64}$$

$$= Cov\left[P_R'\widetilde{\Lambda}^F\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^{\perp}, P_1'\widetilde{\Lambda}^F\left(\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^{\perp}\right)\right] \tag{65}$$

$$+ Cov\left[P_R'\widetilde{\Lambda}^F\alpha^{(m)}Lv, P_1'\widetilde{\Lambda}^F\alpha^{(m)}Lv\right] \tag{66}$$

where, as above, we use the fact that $\delta^{(R)}$ and $\delta^{(1)}$ have no row-wise overlap. Note that in addition to the covariance in common loading factors in the first line, we have an additional line that captures "market overlap" between the firms that are effectively captured as measurement error in the idiosyncratic firm shock (since we cannot observe firm-level productivity). We can rewrite this first term as $\sum_m \tilde{\omega}^F_{f_R,m}\tilde{\omega}^F_{f_1,m}\sigma^2_{v,m}$.

If we aggregate across all national firms ($\mathcal{F}^N$), then we can drop the permutation matrices and express the covariance as:

$$Cov\left[\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^{\perp}, \widetilde{\Lambda}^F\left(\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^{\perp}\right)_{\mathcal{F}^N}\right] + Cov\left[\alpha^{(m)}\left(Lv\right)_{\mathcal{F}^N}, \widetilde{\Lambda}^F\alpha^{(m)}Lv\right] \tag{67}$$

where the subscript $\mathcal{F}^N$ denotes the set of firms with at least two establishments. Interpreting the validation exercise, we found that $\hat{\gamma}^R \approx 0$ for (effectively) all $R > 2$.

**National vs. local firms** . Next, we consider the relationship between the national firm shocks and the local firm shocks. We consider the following variant of the first stage relationship:

$$s_L = \psi \cdot \widetilde{\Lambda}^M\delta + \Gamma_{fs}'\widetilde{\Lambda}^M\mathbf{X} + \nu \tag{68}$$

for the set of $I_L$ that have single establishments. Recall that, under (36), $\delta_f = 0$ for these sets of firms and so $\widetilde{\Lambda}^M\delta = \Lambda^M\delta$ in (68). Note that, after residualizing against controls, $\psi = Cov(s_L^{\perp}, \delta^{\perp})/Cov(s_L^{\perp}, s_L^{\perp})$. Decomposing the numerator and using the fact that the set of firms in $s$ and $\delta$ are dijoint:

$$
\begin{aligned}
Cov(s_L^{\perp}, \delta^{\perp}) &= Cov\left(s_L^{\perp}, \widetilde{\Lambda}^F s^{\perp}\right) && (69)\\
&= Cov\left(\left(\alpha^{(i)} p^{\perp} + \alpha^{(f)} O q^{\perp} + \alpha^{(m)} L r^{\perp} + \eta^{\perp}\right), \widetilde{\Lambda}^F \left(\alpha^{(i)} p^{\perp} + \alpha^{(f)} O q^{\perp} + \alpha^{(m)} L r^{\perp} + \eta^{\perp}\right)\right) && (70)\\
&= Cov\left(\left(\alpha^{(f)} O A z^{\perp} + \alpha^{(m)} L B z\right)_L, \widetilde{\Lambda}^F \left(\alpha^{(f)} O A z^{\perp} + \alpha^{(m)} L B z\right)\right) && (71)\\
& && (72)
\end{aligned}
$$

Because the market-level instrument and the left-hand-side feature a disjoint set of firms, only the common loadings between the two are relevant. The validation results suggest $\hat{\psi} \approx 0$ for these firms, which suggest that the exogeneity condition is plausible.

## A.2 Quantitative model expressions

**Firm valuation of jobs**

$$J_t(y) = E_t\left[\int_0^{T(y_t)} e^{-\rho(s-t)}\pi(y_s)ds + \bar{J}(y_{T(y_t)})|y_t = y\right], \tag{73}$$

where the profits $\pi(y_s) := p(x(y_s), z_s) - w(y_s)$ is the flow production net of worker wages and $\bar{J}(y_T)$ is a potential transfer to the firm at the end of the job's duration, $y_{T(y_t)}$.

## A.3 Additional equilibrium conditions of Proposition 6.1

The equilibrium of the labor market is the set of (i) value functions $\{U_t(\cdot), J_t(\cdot), W_t(\cdot)\}$, (ii) worker distribution $g_t(\cdot)$, (iii) recruiting intensity $v_t(\cdot)$, (iv) job destruction thresholds $x_t(\cdot)$, and (iv) market tightness $\theta_t$ such that:

Wage-bargaining with sequential auction (21),

$$J_t(y) = V_t(h(y), x(y)) - W_t(y) - U_t(h(y)) \tag{74}$$

$x_t(\cdot)$ is determined by (22) for all $h$, $v_t(x)$ solves:

$$\mathcal{C}_t'(v_t(x)) = q(\theta)\int_y 1\{x(y) \leq x\} J_t(y)g_t(y)dy \tag{75}$$

and market tightness $\theta_t = \frac{\nu_t}{e_t}$, where $e_t = u_t + \phi(1 - u_t)$ and $\nu_t = \int_x v_t(x)dF(x)$; $dH_t(x) = \frac{v_t(x)}{\nu_t}dF(x)$, $f(\theta) = M_t/e_t$, $q(\theta) = M_t/\nu_t$; and $\mathcal{A}_x(x)[\cdot]$ is the generator corresponding to the diffusion process (20).

# B Data and Measurement

## B.1 List of LEHD states

The states included in our sample are Alabama, Arizona, California, Connecticut, Delaware, Massachusetts, Maine, Maryland, Missouri, North Dakota, New Jersey, New Mexico, Nevada, New York, Ohio, Oklahoma, Pennsylvania, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, and Wisconsin.

## B.2 Measuring job flows

### B.2.1 Firm and job definitions

**Jobs** We define a job as a unique relationship between a worker identifer ('pik') and firm identifiers in the LEHD ('SEIN') derived from tax filing. In particular, we use the longitudinal 'fid' identifier available in the most recent snapshot of the LEHD, which corrects for spurious job transitions using observed worker flows between establishments. We restrict our sample to worker-year observations for which job identifiers are available.[68]

**Earnings** We deflate earnings to 2015 USD using the BLS Consumer Price Index (CPI-U) and top-code quarterly earnings to $ 150,000 in earnings. We define the primary job of the firm as of period $t$ as the one with the greatest earnings in period $t$.[69] We define the base quarterly earnings for date $t$ as the ratio of total quarterly earnings between $t-1$ to $t-12$ divided by the number of quarter for the count of quarters for which earnings is positive over the same period.[70]

Following Autor Dorn Hanson Song (2014), We identify workers as being "attached to the labor force' if their earnings in the past year is greater than workers 1600 hours (= 40 weeks at 40 hours per week) at the 2007 federal minimum wage ($5.85)

**Worker and Job characteristics.** We assign workers to industries and CBSAs based on the respective modal values from the imputed establishments in the LEHD Jobs file that are linked to the employer characteristics file. We use demographic characteristics (Sex, birth year, and race) using person-level files that are derived from the Decennial Census and SSA Numident files.

**Linking parent firm identifiers** We develop a crosswalk between firm identifiers in the LEHD ('SEIN') and those in the LBD to construct employment for national firms, which makes adjustments to the existing linkages based on the firm 'alpha' available in the LEHD. We use this crosswalk to link individuals to parent firm identifiers from the LBD ('lbdfid'). This is the notion of firm used in the main text.

[68]The 'fid' identifiers are found in the Job History Files (JHF). In some cases, data from the JHF may start later than the full earnings history available at the worker level, which typically reflects data quality issues in the employer characteristic files for the first few years in which a state is included in the LEHD.

[69]If the worker is not employed in period $t-1$, we define the primary job using quarter $t$ earnings.

[70]We have experimented with different extending the horizon over which we measure base earnings or restricting the measure to quarters in which the worker is observed to employed at both the beginning and end of the quarters. The results are unaffected by these modifications,

To construct firm-level job flows, we require that the linked LBDFID firm must (i) have at least one establishment in the same or neighboring state at the matched SEIN. We exclude parent firms for which establishments are identified to be patrolling processing services (NAICS code: 541212) or temp agencies (561311).

### B.2.2 Job destruction measurement

We describe our construction of the local job destruction measure in greater detail. For a given worker $i$, define the indicator for (permanent) separations $S_{it} = 1$ if the worker is last observed to have earnings at their primary employer at quarter $t$. We measure $S_{it}$ in two steps. First, we use a longitudinal notion of the job that corrects for spurious transition in the employment identifiers at the SEIN-level by using the Census-provided `fid` variable to track jobs. This identifier links employment spells across `SEIN` in cases where the transition between firms is deemed to be spurious according to the LEHD Successor-Predecessor (SPF) file. Workers at a given job may have multiple job spells, which are defined in the LEHD as periods of employment at the firm separated by at least one-quarter of nonemployment. In the second step, we collapse multiple job spells into a single job history and define $S_{it} = 1$ to be the last quarter of the `SEIN`-based job history *and* their primary employer `lbdfid` identifiers differs between $t$ and $t+1$ if employed. This final adjustment serves as a precaution for job transitions that may be spurious but are missed by standard adjustments using only identifiers in the LEHD. We similarly define and indicator for (new) hiring $H_{it} = 1$ if the worker is first observed to have positive earnings at their quarter-$t$ employed at either $t$ or $t-1$, and their primary employed lbdfid differs between $t$ and $t-1$.

We construct quarterly job flows using the following procedure. First, for each quarter $q$ , we define the set of workers between the ages of 24 to 64 that satisfy one of the following set of conditions (i) [$E_{sq}$] hold a single at the beginning of the quarter, has at least two quarters of positive earnings at the current job and at least \$3,000 of earnings in the past year; or (ii) holds a single job by the end of the quarter and is not in the first year for which the worker's state enters the LEHD sample [$E_{hq}$]. These serve as denominator from which we measure job flows.[71] We then flag job separations for workers in quarter $q$ and the next 3 quarters as well hires at $q$ and the previous 3 quarters. For a given

[71] In practice, constructing flows from only from (i) does not make much difference for the firm-level series This procedure ensures, however, that quarterly separation and hiring rates are bounded between 0 and 1.

establishment $j$ , we define the cumulated job separation rate $s^c_{jq}$ and hiring rate $h^c_{jq}$ as

$$\text{Sep}_{f,m,t} = \frac{\sum_{i:m(i)=i\&f(i)=f} \sum_{h=0}^{3} \text{Sep}_{i,t+h}}{N_{f,m,t}} \text{Hire}_{f,m,t} = \frac{\sum_{i:m(i)=i\&f(i)=f} \sum_{h=0}^{3} \text{Hire}_{i,t+h}}{N_{f,m,t}} \tag{76}$$

In other words, we define our baseline measure of separations as the fraction of workers at time $q$ employed at $j$ that leave the job at some point over the next four quarters. Similarly, we define the hiring rate as the workers set of workers who find a job at the firm, relative to the number of workers as of quarter $q$.

- Since we only track separations of workers who were employed at the firm at time $t$, our measure of separations, $\text{Sep}_{f,m,t}$ is bounded between 0 and 1 by construction. However, this is not the case $\text{Hire}_{f,m,t}$ as more workers can be hired than were initially employed.

Our baseline measure of job destruction rate is the separation rate net of hiring when the firm is contracting:

$$jdr^c_{sq} = \max\{s^c_{jq} - h^c_{jq}, 0\} \tag{77}$$

where we define the job creation rate symetrically as $jcr^c_{sq} = \max\{h^c_{jq} - s^c_{jq}, 0\}$.

- Note that the sample restricts flows to worker who hold one job as of quarter $t$. Thiis is meant to avoid the counting of part-time job transitions, where the assumption that workers are attached to a single firm may be less likely to hold.

- Our notion of job destruction and job creation rates do not exactly match those using the Davis and Haltwanger (1992) approximation. We use the average employment in the previous quarter as the denominator when constructing employment flows as that corresponds more closely to the shares used in the construction of national job destruction rate (we wouldn't want to use employment from periods after the shock, as is done in DFH). In particular, we only count as a job as being destroyed if there are more worker outflows than replacement hiring for the same 'type' of worker (i.e. single job, working age). Our measurement is useful due to the fact that the firm-level identifers (lbdfid) are not fully longitudinal. [We can illustrate this case with an example where one firm buys another establishment, and leads to a jump in the hiring rate but little change in separation because we know who was working at the firm as of three quarters ago].

- Our age restriction helps avoid labor market flows that reflect short-term positions during schooling (e.g., internships) and early retirement for which job destruction is unlikely to exert congestion effects among full-time workers. Similarly, multiple job holders likely reflect part-time work for which our single-worker, single-job framework is less likely to apply and reflect only 5% of the labor force (Bailey and Speltzer 2020) . We include a minimum earnings threshold to avoid the inclusion of temporary positions or backpay that does not reflect a stable job that a worker can attain.

## B.3 Baseline sample: initial restrictions

We describe the baseline restrictions for the samples used to estimate worker spillovers. For a given quarter $t$, we first restrict workers to those that meet the following criteria: (i) age is between 25-54 years as of $t$ (prime-age workers); (ii) hold single job at the beginning of $t$; (iii) Both the CBSA for the worker's residence and place of worker have sufficient coverage by our subset of LEHD states;[72] (iv) is not employed in the following industries at $t$: Agriculture (11) Other Serivces (81) , Public Administration and Government (92), Accounting, Tax Preparation, Bookkeeping and Payroll Services (5412. and Employment Services (5613); (v) Attached to the labor force in the past year; (vi) state associated with current job entered the LEHD sample at least before $t - 12$ ; (vii) At least four quarters of positive earnings at primary employer; (viii) successfully linked to `lbdfid` identifier; and (ix) Firm has at least 50 employees in the worker's CBSA in the past year; (x) the worker does not have positive earnings in other states not covered by our sample of LEHD states between $t - 12$ and $t$.

## B.4 Baseline sample: mass layoff definition

We define an employer as undergoing a mass displacement event at quarter $q$ if it satisfies one of the following definitions.

**Displacement DvW** : Growth rates are based on the employment reported for the `SEIN` associated with the firm from the LEHD Employer Characteristics File. The firm is reported to have at least 50 workers as of $q - 4$; The ratio of $q + 4$ employment to $q - 4$ employment is between 0.01 and 0.7; $q - 4$ employment is less than 130% of $q - 8$ employment; $q + 8$ employment is less than 90% of $q - 4$ employment

**Displacement FSS** : Growth rates are based on the employment reported for the `SEIN` associated with the firm from the LEHD Employer Characteristics File. The firm is

[72] In particular, we restrict the set of CBSAs to those where at least 80% of 2005 employment is within our sample of states.

reported to have at least 50 workers as of $q-3$; the ratio of $q+1$ employment to $q-3$ employment is between 0.01 and 0.7.

**Displacement LBD** : Growth rates are based on annual changes in employment from establishments in the LBD, aggregated to `lbdfid`-by-CBSA pairs in each year. The firm is reported to have at least 50 workers as of last March (the date at which employment is measured for the LBD) and the change in employment of the firm between between last March and next March is greater than 30%.

The first displacement definition is used by Davis and von Wachter (2011) and the second definition is used by Flaaen et al. (2019) in studying the earnings effects of job loss. Our implementation of both these definitions in the LEHD uses `SEIN` identifiers to establish consistency with their approach, where information on local employment changes are not used. These two definitions exclude the possibility of spurious firm exists by requiring that the firm must have positive employment following the mass layoff event. The third definition uses information on local employment from the LBD. Because we measure employment growth using longitudinal establishment identifiers that are then aggregated to the local parent-firm, this definition accounts for business ownership changes and therefore allows firm exit in the region. Pooling mass layoff across different even definitions ensures that our results are robust to the adjusts in how displacements events and helps to increase our sample size for detecting local spillover effects.

We defined the set of of worker-quarter events that constitute our displacement sample as those where (a) the worker satisfies the baseline restrictions above, (b) the worker is observed to separate from the firm at $t$ and (c) the firm's primary employer at the beginning of quarter $t$ satisfies at least one of the displacement event definitions.[73]

## B.5 Baseline sample: matched control group

We construct a comparison group for the sample of displaced worker events using the following procedure. First, we restrict worker-dates to those that (a) satisfy our baseline

[73]Note that some theoretical ambiguity in the expected direction of the selection bias. If separations by incumbent firm-worker matches were bilaterally efficient, then the lower outside option induced by spikes in job destruction would lead only the least-valuable matches to separate. To the extent that the value of a worker's current job is correlated with the cost of job loss (e.g.m if it reflects a worker-specific component of productivity), this would bias our estimates towards finding more negative earnings effects of job destruction spillovers. On the other hand, suppose that the separation decision of a firm-worker match is partially based on the probability that, after a separation occurred, the firm would be able to recall their most productive workers from unemployment (Fujita and Moscarini, 2017). Then, the decrease in the market-level job-finding rate induced by a spike in job destruction would lead firms to disproportionately increase the separation rate of relatively productive workers, biasing our baseline estimates towards finding less negative earnings effects of job destruction spillovers.

restrictions (b) have primary employers with at least 50 workers in the CBSA in the past year and have local firm growth rates between -5% to 5% in the current year (c) the primary job of the worker does not change between $q$ to $q+3$. The requirement that the firm not experience large changes in the growth rate help ensure that we comparing workers who differ in the underlying employment distress experienced by their primary employer (Flaaen et al., 2019). We allow workers in the comparison group to leave their primary employer or be included as part of future displacement events.

We construct our comparison by matching each displaced worker-event to a job stayer in two steps. First, we match exactly on NAICS3, CBSA, 5-year age bins, sex, 4 tenure bins, and whether their primary employer is a national firm. Then, for each displaced worker-event, we find the job stayer with the most similar earnings covariates prior to the displacement quarter. Following past literature, we use the following coviarates the log of each of the past 3 years of annual earnings, the number of quarters employed in the past 3 years, the log of firm size, and the number of quarters with positive earnings at the current employer. We use the Mahalabanois distance metric to greedily create matches without replacement. We follow Abadie and Imbens (2006) in including the regression-adjusted differences in covariates as a control in our estimates of worker spillovers using the procedure outlined in Imbens (2015).

# C Empirics

## C.1 Details on baseline specification

### C.1.1 Formulas for market-level controls

In this section, we provide the explicit formulas for the market-level controls described in the main text.

We define the establishment-level job creation rate similarly to the job destruction rate:

$$c_{f,m,t} = \max\left[\frac{\sum_{h=0}^{3}\left(\text{Hire}_{f,m,t+h} - \text{Sep}_{f,m,t+h}\right)}{N_{f,m,t-1}}, 0\right]. \tag{78}$$

The net job creation rate is the difference between the job creation and the job destruction rate.

$$nc_{f,m,t} = c_{f,m,t} - s_{f,m,t}. \tag{79}$$

Due to the filters we impose in tagging job separations and hires, the net job creation rate does not always correspond exactly to the year-on-year growth rate from establishment-level employment, $\frac{N_{f,m,t-1}}{N_{f,m,t+3}} - 1$.

Predicted job creation rate of national firms:

$$h_{f,-m,t} = \sum_{m':r(m')\neq r(m)} \left( \frac{N_{f,m',t-1}}{\sum_{m''\neq m} N_{f,m'',t-1}} \right) \times h_{f,m',t} \tag{80}$$

where $h_{f,m',t}$ is the establishment-level job creation rate, which is defined similarly to the job destruction rate as the growth rate of firms that are expanding.

## C.2 Decomposition of extensive margin spillover

Under the assumption of no intensive margin spillovers – i.e., that conditional on $Emp_{i,t+h} = 1$, the earnings ratios of laid-off workers are the same in LLMs with different job destruction rates – the extensive margin effect is the spillover effect on employment at $t+h$ scaled by the average earnings ratio of workers in our mass layoff sample with positive earnings at $t+h$.

We then take the sum of these extensive margin effects to arrive at the estimates in column (3).[74] Since this sum would equal the overall earnings effects in column (1) if there were no intensive margin effects, we can interpret the estimates of column (3) as capturing the contribution of the extensive margin to the overall spillover effects of job destruction.[75]

[74]Precisely, if $\beta_h$ is the coefficient estimate from (9) under the dependent variable $Emp_{i,t+h}$, and $\overline{ratio}_{t+h}$ is the average earnings ratio of workers in our mass layoff sample, i.e.

$$\overline{ratio}_{t+h} = \sum_{\forall i:Emp_{i,t+h}=1} \frac{Earn_{i,t+h}}{\overline{Earn}_{it}} \times \frac{1}{\sum_{\forall i} Emp_{i,t+h}}$$

then the extensive margin contribution equals

$$\sum_{h=0}^{32} \beta_h \times \overline{ratio}_{t+h} \times \frac{1}{(1+.05)^h}$$

For the matched control specification, we subtract from $\overline{ratio}_{t+h}$ the similarly-defined average ratio among control group workers (conditional on the control worker's given treated worker being employed at $t+h$).

[75]There are two caveats to this statement. First, our measure of the extensive margin of employment, $Emp_{i,t+h}$, equals one if the worker is employed at any time during the quarter $t+h$, even if she is non-employed for a substantial overall fraction of the quarter (e.g., two months). The LEHD does not allow us to observe such high-frequency (intra-quarter) non-employment spells. This will lead us to understate the importance of non-employment effects in our decomposition of the earnings spillover estimates. Second, the decomposition that we conduct implicitly assumes that, absent any intensive margin spillover effects, the average complier in our mass layoff sample – i.e, worker who, as a result of a high value of our job destruction instrument, goes from $Emp_{i,t+h} = 0$ to $Emp_{i,t+h} = 1$ – would have earned the same labor

## C.3 Spillover identification

**Definition of market-weighted residuals**

$$\bar{\epsilon}_{ft}^{(h)} = \sum_{\forall m} \left( \frac{N_{f,m,t-1}}{N_{m,t-1}} \right) \cdot \bar{\epsilon}_{mt}^{(h)}$$

for $\bar{\epsilon}_{mt}$ the average of the worker-level residuals $\epsilon_{imt}$ for workers in the regression who were laid off from a job in market $m$.

**Difference between implementation and assumptions for (11)** For ease of presentation, the condition presented here only applies under two assumptions: (i) each market $m$ has an equal (effective) regression weight; and (ii) we do not construct the instrument leaving out the job destruction activity in the market $m$ itself. Neither of these conditions holds in our setting: (i) as the regressions are run at the worker-quarter level, more weight is put on markets with more laid-off workers in the given quarter; and (ii) we leave out job destruction activity in the market (as well as in other sectors in the market's CBSA) when constructing the instrument.

## C.4 Distressed search and the concentration of JD shocks

Our preferred theory as to why the spillovers effects on job losers (and the unemployed more generally) are large is that they must engage in a form of intensive search at a time when the job destruction rate is high. However, it is likely that employed workers may also experience large spillover effects if they anticipate that their job may be destroyed in the near future as they would also engage in distressed job.

We consider an alternative design in which, in lieu of conditioning on job loss, we estimate the heterogeneity in spillovers among workers with different levels of ex-ante propensities to seek new jobs. We proxy the search intensity of workers using the (leave-out) national job destruction rate at their own firm, $s_{f(i),-m,t}$ among a random subsample of employed workers at national firms.[76]. The national firm job destruction rate provides a measure of worker's separation risk that, when leaving out the worker's own LLM, is

income during $t+h$ as the average (quarter $t$) laid-off worker for whom $Emp_{j,t+h} = 1$. But it is plausible that such compliers would have experienced a greater earnings loss than the average employed worker in our mass layoff sample, had they been employed; this would be the case, for example, in a setting with random search, heterogeneous post-layoff shocks to worker productivity, and endogenous search effort. All else equal, this would lead us our decomposition to overstate the importance of the extensive margin.

[76]The job-events we measure pass the same baseline restrictions on working-age, tenure, and LLM coverage as described in Section 4.1

not endogenous to the characteristics of either the worker or market conditions.

We estimate the following extension of (9):

$$y_{i,t} = \sum_{j=1}^{5} \Big( \alpha_j + \beta_j \times s_{-f,mt} + \Gamma_j^W X_{it}^W + \Gamma_j^M \mathbf{X}_{mt}^M + \lambda_{kt} \Big) \cdot Q_{f(i,t)}^{(j)} + \psi_f + \phi_m + \epsilon_{it} \tag{81}$$

where $Q_{f(i,t)}^{(j)}$ denotes the quintile of the national separation rate of the worker's firm. By including quintile-specific time-by-sector fixed effects ($\lambda_{kt}$), the coefficients $\beta_j$ are estimated by comparing two workers who, at the same point in time, have jobs at firms with the same job destruction behavior and in the same sectors, but in local markets that are more versus less exposed to separation shocks from other firms. We control for worker- and local market-level characteristics, allowing them to vary by $Q_{f(i,t)}^{(j)}$ to account for the potential selection of different types of workers into being employed in risky jobs. In addition to the set of controls for the baseline specification, we also include a fixed effect for the worker's firm, $\psi_f$, to account for potential sorting of workers across with varying employment dynamism.

Figure 15 plots estimates $\hat{\beta}_j$ against the average firm-level job destruction rate in each quintile, where we set outcome variable to be the net present value of the earning ratio ($\frac{\text{Earn}_{i,t+h}}{\text{Earn}_i}$, in green) or cumulated quarterly employment ($\text{Emp}_{i,t+h}$, in purple) over a 6-year horizon. Our estimates imply that only workers whose firms as of $t = 0$ are in the fifth quintile of job destruction experience significantly negative earnings and employment effects from being in a local market exposed to job destruction shocks. Among workers in this quintile, workers in local markets with a 1 pp higher destruction rate experience an earnings NPV loss that is around 0.625 pp (0.15 / 24 $\times$ 100 quarters) greater. In contrast, workers in the lowest quintile of job destruction experience employment and earnings spillover effects that are statistically indistinguishable from zero. These results are consistent with job search as being a key mechanisms through which spillover from elevated job loss are transmitted.

## C.5 Details on AKM estimation

We follow Card et al (2018) in estimating worker and firm fixed effects. We use the `lbdfid` definition of firm when available and use the `SEIN` when either the `lbdfid` match does not pass our quality restrictions or is missing. We winsorize the log of annual earnings of a person-firm combination at the top and bottom 0.5th percentiles, and then residualize this measure against calendar year indicators, and a cubic polynomial of age (centered at 40) interacted with sex. We estimate the firm and worker FE over a rolling six-year window

($y-5$ to $y$) on the largest connected set of workers and firms:

$$\widetilde{log(earn_i jy)} = \Psi_i + \Psi_j + \epsilon_{iy} \tag{82}$$

where $\Psi_i$ indicates the worker fixed effect and $\Psi_j$ indicates the fixed effect of the firm that employs the worker in year $y$.

## C.6 Stock-based measure of displaced workers

We describe how we construct LLM measure of aggregate search effort from displaced workers. Define the stock of aggregate search intensity for a LLM $m$ at time $t$ as $U_{m,t}$. Workers are distinguished by some group-based index $g$, and each worker in $g$ contributes $\phi_{g,t}$ of market-congesting search. Then we can write our measure of search intensity as:

$$U_{m,t} = \sum_g \phi_{g,t} u_{g,m,t} \tag{83}$$

where $u_{g,m,t}$ is the count of workers in state $g$ in market $m$ at time $t$

As in the main sample, we assign each worker's LLM $m(i)$ based on the CBSA-NAICS2 of their primary employer at the time of separation. We assign $g$ according to the quarter since the worker was last employed and let $\phi_{g,t} \geq 0$ for all workers who were separate from the job at time $t$.[77] For simplicity, we set $\phi_{g,t} = 0$ for workers with more than $\overline{g}$ quarters of nonemployment. To convert our flow measures of separation with the survival probability of nonemployment to obtain our stock measure:

$$u_{g,m,t} = S_{m,t-g} \times \Pi_{k=0}^{g} (1 - P_{m,t-k}^{(k)}) \tag{84}$$

where $S_{m,t-g}$ is the separation rate and $P_{m,t-k}^{(k)}$ is the probability that a worker separated in market $m$ who has been out of work for $k$ periods finds a job at time $t-k$. Our measure for the stock of workers is:

$$\tilde{u}_{g,m,t} = J\hat{D}R_{m,t-g} \times \Pi_{k=0}^{g} (1 - \hat{P}_{IND(m),t-k}^{(k)}) \tag{85}$$

which makes two adjustments. First, we replace the separation rate with the job destruction rate. Using net changes in employment to measure labor market search is useful to help correct for changes in employer churn. This is particularly important as our baseline

[77] We effectively set $\phi_{g,t} = 0$ for all workers who at their at time-$t$ job.

measure assigns workers based on their origin labor market – the porousness of labor markets means that gross flow measures would potentially miss replacement hiring from other sectors and bias aggregate search effort for labor markets with changing workforce compositions. Our second adjustment is to estimate to impute the job-finding hazard rate using national measures of job-finding. Using the local, measure of job-finding rate would lead to issues of reverse causality in the presence of labor market congestion, as higher levels of job destruction would reduce the job-finding probability of workers. We therefore use the industry-level job-finding rate amongst workers who have been non-employed for $k$ quarters.[78]

# D Quantitative

This section provides additional details on the estimation and solution to the quantitative model presented in Section 6.

## D.1 Moment construction

In this section, we provide a description of how we constructed simulated moments in estimating the model in Section 6. Given a vector of parameters $\Theta$, our algorithm proceeds in four steps:

1. Solve for the steady state of the model, $\overline{V}(y), \overline{g}(y)$
2. Estimating the transition dynamics of the model following a job destruction shock, $V_t(y), g_t(y)$
3. Construct all moments using a combination of analytic formulas and simulated data.
4. Evaluate the objective function $\mathcal{G}(\Theta)$ using the moments constructed from the data and the model.

The sections below provide details on each of these steps.

[78] We use the LEHD national employment file to omit workers who find employment in other states that we do not observe in our sample.

### D.1.1 Algorithm for solving the steady state

### D.1.2 Solving transition dynamics following a job destruction shock

Constructing model-implied spillover estimates requires solving the transition dynamics of the model following a job destruction shock every time we evaluate a new value of $\Theta$ from the parameter. Previous papers with heterogeneous agents typically break up the estimation procedure by sequentially fitting a subset of parameters to steady state moments and then using another, typically subset of parameters to fit dynamic moments ( e.g., time-series statistics from aggregate variables). This approach is unsuitable in our application for two reasons. First, our primary moments of interest – the worker spillover effects – reflect the response of dynamics of the labor market as it recovers from a job destruction shock. As a result, it is necessary to solve for transition dynamics when internally calibrating the model. Second, the earnings and employment effects of these spillovers cannot be cleanly separated from parameters that can be estimated in steady state, as they are impacted by the level of wage dispersion, equilibrium job-finding rate, mean job loss effects in the model. It is thefore desirable to estimate the internally calibrated paramters jointly using a combination of steady-state and dynamic moments.

We contribute a novel approach to jointly estimating both the dynamic and steady-state moments using recent advances in solving continuous-time heterogeneous agent models and high-performance numerical computing. To solve for the transition dynamics, we proceed in three steps. First, we use results from (Bilal, 2023) to construct the first-order approximation of the master equation (FAME) underlying the model. As the job destruction shocks we consider are explicitly a shift in the worker distribution (without a change in the structural parameters of the economy), computing the transition dynamics necessary for calibration only requires solving for the deterministic Impulse Value $\nu(x,x') := \frac{\partial V(x)}{\partial g(x')}(\overline{V},\overline{g})$, i.e. Frechet-derivative of the value function (at $x$) with respect to changes in the distribution (at $x'$). Solving for $\nu(x,x')$ requires knowledge of the Jacobian of of the generators $\mathcal{A}$ and $\mathcal{B}$ with respect to both the distribution and the value functions.[79] Whereas Bilal (2023) solves these functions analytically in slightly less-complex models, we instead calculate these objects computationally by automatically differentiating at the steady-state of the model using JAX (Bradbury et al., 2018).[80]

We lay out our solution of the Impulve Value in the discretized version of the model.

[79] As the flow value of job production does not depend on the worker distribution, we do not require the corresponding Jacobians of $u(\cdot)$

[80] One important benefit of JAX, relative to other open-source libraries, is its use of weak derivatives for operations commonly used to encode boundaries (e.g., `min` and `max`). As the steady state of our model requires solving the optimal stopping $x^*(h)$, this feature is essential in our implementation

We define $\tilde{\mathbf{A}}(\mathbf{V},\mathbf{g}) = \mathbf{A}(\mathbf{V},\mathbf{g})\overline{\mathbf{V}}$ to be the $N \times 1$ continuation value of the model, when the generator discretized generator of $\mathcal{A}$ is evaluated at the equilibrium $V$ and $g$. Similarly we define, $\tilde{\mathbf{B}} = \mathbf{B}(\mathbf{V},\mathbf{g})\overline{\mathbf{g}}$

The $NxN$ impulse value is given by $\nu$, where $\nu_{ij} = \frac{\partial V_i}{\partial g_j}$, satisfies solving the following linear system of equations:

$$\left[\rho\mathbf{I} - \tilde{\mathbf{A}}_V - \mathbf{A}\right]\nu + \nu\left[-\left(\mathbf{B}^T + \tilde{\mathbf{B}}_g + \tilde{\mathbf{B}}_V\nu\right)\right] = \tilde{\mathbf{A}}_g \tag{86}$$

subject to the constraint $\mathcal{R}(\nu) = 0$ that enforces the impulse value to be equal to the value at unemployment for state $\{y = (h,x,w) : x \leq x^*(h)\}$. We use $\mathbf{X_y}$ to refer to $dim(X) \times dim(y)$ the jacobian of $\mathbf{X}$ with respect to $y$ evaluated at the steady state, i.e. $X_{ij} = \frac{\partial X_i}{\partial y_j}$.

We use the fact that the bracketed terms consistute, with $\nu$, constitute a Sylvester equation to run an iterative procedure to solve for $\nu$, under the following algorithm that parallels Corrolary 1 in Bilal (2023):

1. Guess $v^0$
2. Given $\nu^{(n)}$, update $\nu^{(n+1)}$ by solving the Sylvester equation

$$\left[\rho\mathbf{I} - \tilde{\mathbf{A}}_V - \mathbf{A}\right]\nu^{(n+1)} + \nu^{(n+1)}\left[-\left(\mathbf{B}^T + \tilde{\mathbf{B}}_g + \tilde{\mathbf{B}}_V\nu^{(n)}\right)\right] = \tilde{\mathbf{A}}_g, \tag{87}$$

   and stop when $\nu^{(n+1)}$ is sufficiently close to $\nu^{(n)}$.
3. Enforce the endogenous separation conditions for infeasible productivity points by adjusting $\hat{\nu}$ from $\nu^{(n+1)}$ such that $\mathcal{R}(\hat{\nu}) = 0$.

**Perturbation** To generate model spillovers, we solve the transition dynamics following a perturbation to the steady state distribution of workers, $h(y)$,

$$g(y) = g_0(y) + \varepsilon h(y), \tag{88}$$

We consider a distributional impulse of a job destruction shock, in which $\varepsilon$ fraction of workers are separated from their jobs and sent to their (human-capital-specific) unemployment states. In implementation, we set $\varepsilon = 0.03$ and scale our estimates of spillovers proportionally.

### D.1.3 Model equilibrium with aggregate shocks

For our primary policy exercise, we consider the extension of our model to aggregate shocks in productivity $Z$. Let $\mathcal{C}(z)$ be the generator of aggregate shocks (which may depend on $z$). The first order approximation of hte model with aggreate requires knowledge of how job values change with aggregate productivity shocks. We first construct the stochastic first order appproximation of the master equation for aggregate productivity $\omega(y,z)$. The discretized version $\mathbf{w}$ is a $N \times K$ matrix, where $K$ is the number of grid points on the discretization of $\mathcal{Z}$. Similar to Section D.1.2, $\omega$ satisfies the following equation:

$$\rho\omega(x,z) = u_z(x) + \mathcal{A}_z(x)[V^{SS}] + \mathcal{A}(x)[\omega(\cdot,z)] + \int \mathcal{A}_V(x,y)[V^{SS}]\omega(y,z)d\eta(y) \tag{89}$$

$$+ \mathcal{C}(z)[\omega(x,\cdot)] + \int \nu(x,x')S(x',\omega,z)d\eta(x') \tag{90}$$

$$S(x',z,\omega) = \int \mathcal{B}_V(x',y)[g^{SS}]\omega(y,z)d\eta(y) + \mathcal{B}_z[g^{SS}] \tag{91}$$

which takes the discretized form of the $N \times K$ matrix $w$ that solves

$$\rho\mathbf{w} = \mathbf{u}_z + \tilde{\mathbf{A}}_z + \mathbf{A}\mathbf{w} + \tilde{\mathbf{A}}_\mathbf{V}\mathbf{w} + \mathbf{w}\mathbf{C}^T + +\mathbf{v}\left[\tilde{\mathbf{B}}_\mathbf{V}\mathbf{w} + \tilde{\mathbf{B}}_z\right] \tag{92}$$

where $\mathbf{C}$ is a $K \times K$ matrix and $\tilde{\mathbf{C}} = \overline{V}\iota_K^T C$, where $\iota_K$ is a vector of ones of length $K$. Rearranging, we obtain:

$$\left[\rho\mathbf{I} - \mathbf{A} - \tilde{\mathbf{A}}_\mathbf{V} + \mathbf{v}\tilde{B}_V\right]\mathbf{w} + \mathbf{w}\left[-\mathbf{C}^T\right] = \mathbf{u_z} + \tilde{\mathbf{A}}_z + \tilde{\mathbf{C}}_z + \mathbf{v}\tilde{\mathbf{B}}_z \tag{93}$$

which can be solved as a Sylvester equation, similar to the determinisic impulse value.

In our application we specify Recall that $\mathbf{S} = \tilde{\mathbf{B}}_V\omega + \tilde{\mathbf{B}}_z$

## D.2 Estimation strategy

In this section, we present details on the model estimation. Let $\Theta$ be the vector of internally calibrated parameters. We estimate the $\Theta$ via Simulated Method of Moments (SMM) under the following objective function:

$$\hat{\Theta} = \arg\min_{\Theta} \mathcal{G}(\Theta) = g(\Theta)'Wg(\Theta) \tag{94}$$

where $g(\Theta)$ is the percentage point difference between the simulated moments, $m(\Theta)$, and the moments constructed from the data, $\hat{m}$ and $W$ is a weighting matrix.[81] We use the identity matrix as the weighting matrix. In our baseline estimation, $W$ is a diagonal

[81] In implementing the GMM estimator, we ensure that all of the data moments are positive. For a given moment $k$, $g_k(\Theta) = \frac{m_k(\Theta) - \hat{m}_k}{\max(10^{-3}, \hat{m}_k)}$

matrix that is equal to the identity matrix, except for the four elements corresponding to the mean and spillover effects for on job loss for both relative earnings and employment.

We use the following procedure to estimate $\hat{\Theta}$. First, we construct a global grid search of $2^{19}$ (524,288) points over a bounded hypercube of the parameter space. We then proceed to run a series of local search among the the top 100 points following Arnoud et al. (2019), using the `NLOPT` implementation of the SUBPLEX algorithm (Johnson, 2007). The SUBPLEX performs Nelder-Mead optimization on a subspace of the parameters, which is useful for medium-dimensional optimization problems such as ours (Rowan, 1990). The global minimum from this procedure is then polished used high-tolerance local optimizer and report as $\hat{\Theta}$ in the main text.

## D.3 Details on model parameterization

**Steady-state job-finding rate** Note that we can express the job-finding rate $f(theta)$ as:

$$f(\theta) = C_m^{(1-\omega^1)k}\bar{J}^k(u + (1-u)\phi) \tag{95}$$

We directly calibrate the "effective" matching efficiency $C^{eff} = C^{(1-\omega^{-1})k}$ to ensure proper scaling of the job-finding rate.

# E Additional Tables and Figures

## Figures

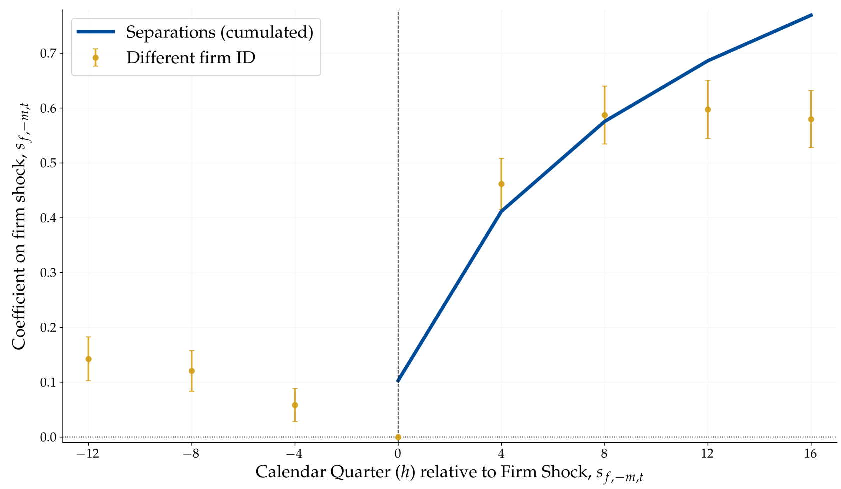


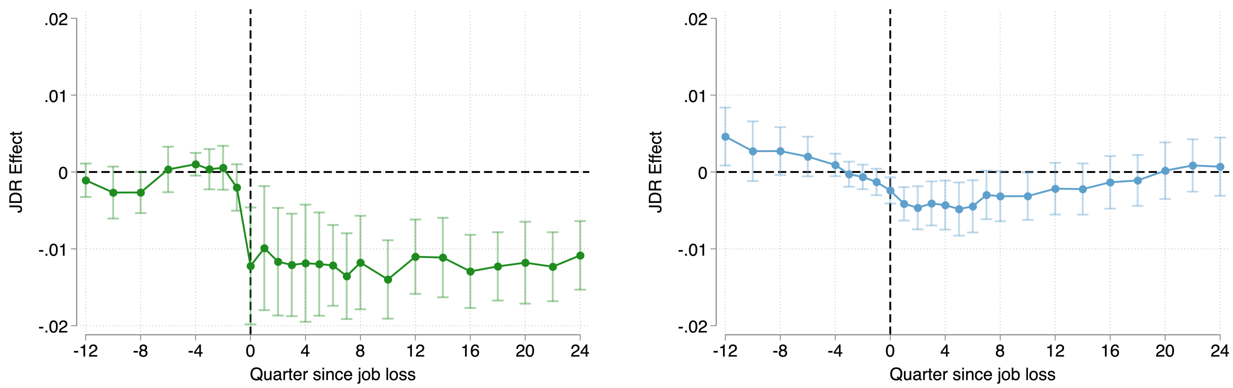

Figure 8: Cumulated Separations since firm shock

*Notes:* This figure displays the account of cumulated separations that are accounted for by separations from their primary employer at time $t$. The series "Difference firm ID" estimates coefficients $\beta^{(h)}$ from the following specification:

$$1\{f_t(i) \neq f_{t+h}(i)\} = \beta^{(h)} s_{f,-m,t} + \phi_m + +\Gamma_1^{(h)} \mathbf{X}_{i,t}^W + \Gamma_2^{(h)} \mathbf{X}_{-i,m,t}^M + \epsilon_{i,t+h}, \quad (96)$$

$1\{f_t(i) \neq f_{t+h}(i)\}$ is an indicator for whether the national firm (`lbdfid`) of the worker's primary employer at quarter $t+h$ is different than $t$. Nonemployed workers are included as having different firm identifiers. Standard errors are two-way clustered by CBSA and quarter. The series "separations (cumulated)" is the sum of coefficients from Figure 1a for $h \geq 0$. Note that, because the separation indicators $\text{Sep}_{i,t+h}$ include quality filters that may lead them to have rates lower than the observed firm-switching probability. This can arise from mergers and acquisitions, where the `lbdfid` changes without a meaningful job change for the worker.

Figure 9: Effects of market job destruction shock on earnings of job losers vs. job stayers




(a) Job losers (b) Job stayers

*Notes*: This figure shows our baseline estimates of how job destruction shocks affect the earnings of job losers (panel a) and job stayers (panel b). The job loser estimates are the same as in Figure 3. The job stayer estimates are obtained through the same specification: for a worker $i$ who at the start of quarter $t$ holds a job in local labor market (MSA-two digit NAICS pair) $m$ at firm $f$, the graphs show estimates of $\beta^{(h)}$ (along with 95% confidence intervals) from the worker-by-quarter level 2SLS regression given by

$$y_{i,t+h} = \alpha^{(h)} + \beta^{(h)}\widehat{s}_{-f,mt} + \Gamma_1^{(h)} X_{mt}^M + \delta_m + \epsilon_{imt}^h \qquad \text{(Second stage)}$$

where $\widehat{s}_{-f,mt}$ is the predicted value from the first-stage regression

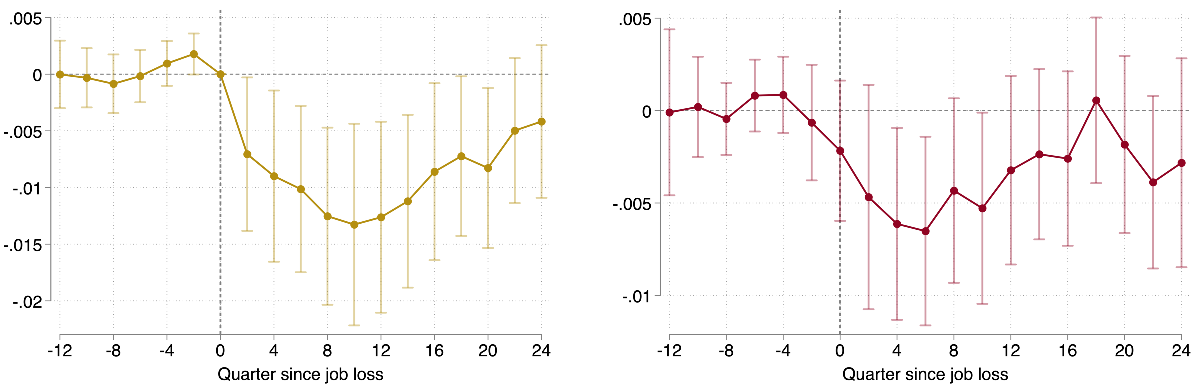
$$s_{mt} = \alpha^{fs} + \beta^{fs} s_{-f,mt}^{IV} + \Lambda_1 X_{mt}^M + \delta_m + \xi_{imt} \qquad \text{(First stage)}$$

The sample is the job stayer sample described in 4.1: workers who do not separate from their job at quarter $t$. As described in Section XX, the endogenous variable is $s_{mt}$, the local labor market-level job destruction rate. The exogenous variable is $s_{-f,mt}^{IV}$ which, as defined in (8), is a shift-share instrument constructed from the job destruction rates of national firms, leaving out the job destruction of these firms in $m$ as well as the job destruction of worker $i$'s previous firm $f$. The dependent variable $y_{i,t+h}$ is the worker's average earnings in the adjacent quarters $t+h-1$ and $t+h$, scaled by average quarterly earnings over $t-12$ to $t-1$. The vector $X_{mt}^M$ consists of the same market-level controls as in Figure 3. The regressions attach equal weight to each job loser/stayer. Standard errors are double clustered by quarter of job loss $t$ and by CBSA.

Figure 10: Changes in firm characteristics following job destruction shock: job losers vs. job stayers

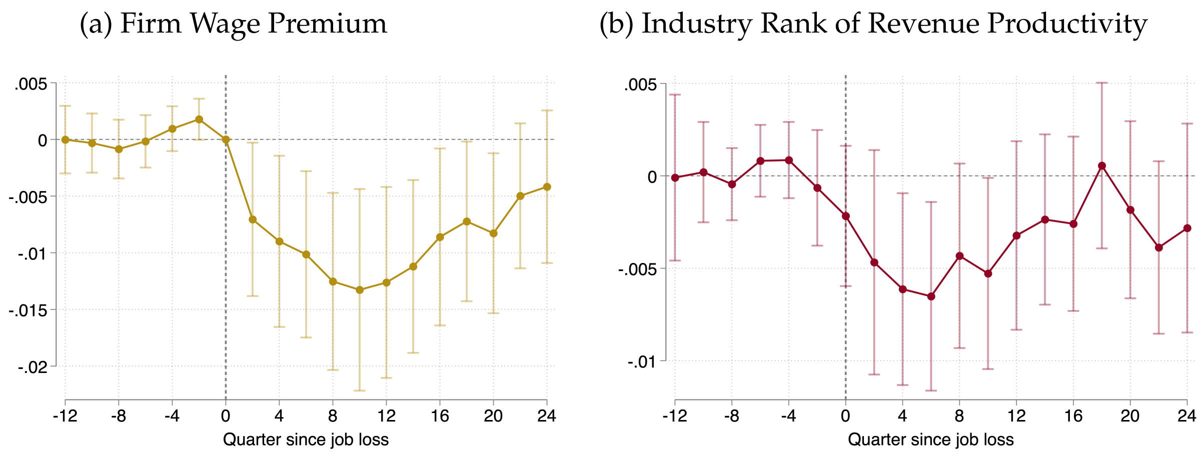
(a) Firm Wage Premium

(b) Industry Rank of Revenue Productivity




*Notes*: This figures shows estimates of the equilibrium effects of job destruction on the firm characteristics for the sample of job losers and matched control group. Both figures plot coefficients use the baseline specification described in Figure 3. Panel 10a plots estimates for the difference in the firm-wage premia between job losers and the matched control group of job stayers. We replace $y_{i,t+h}$ in (9) with $\Psi^t_{f(i),t+h} - \overline{\Psi}^t_f(i)$, which is the difference between wage premia of the worker's firm, $f(i)$, $h$ quarters after the job loss event and the average wage premia of the firm between the quarter $t-12$ to $t-1$. Firm wage premia are measured using the largest connected set of employer-workers in the five year leading up to $t$. Panel 10b presents estimates for the outcome $\overline{\text{Rank}(Y_f/N_f)}_{f(i),t+h} - \overline{\text{Rank}(Y_f/N_f)}_i$, which the difference in the within-industry rank of the employer revenue productivity (ratio of revenue to employment count), relative to the three years before the job loss event. Both figures show the difference in coefficients between job losers and job stayer, $\hat{\beta}_{JL} - \hat{\beta}_{JS}$. The regressions attach equal weight to each job loser/stayer. Estimates are scaled to a 1 pp change in the local job destruction rate. Standard errors are double clustered by quarter of job loss $t$ and by CBSA.

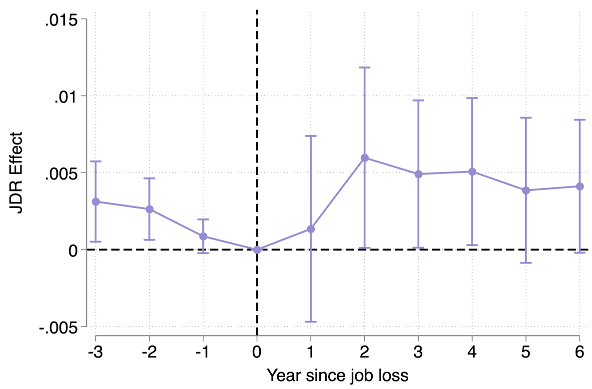
Figure 11: Changes in firm characteristics following job destruction shock: average worker



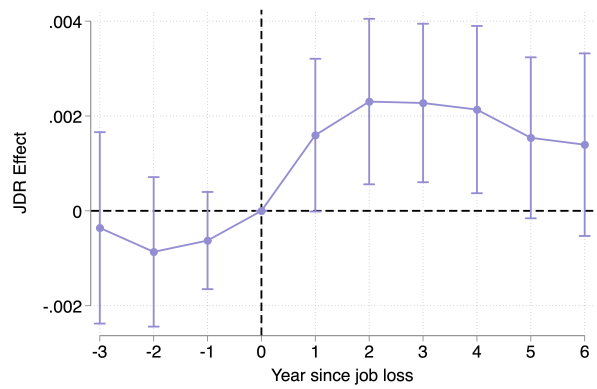

*Notes*: This figures shows estimates of the equilibrium effects of job destruction on the firm characteristics for the random sample of workers that satisfy our baseline restrictions. Both figures plot coefficients use the baseline specification described in Figure 3, and details on the outcome construction are given in Figure 10. Both figures show the coefficients for the spillover effect among the random sample of worker that satisfy our baseline restrictions. The regressions attach equal weight to each worker. Estimates are scaled to a 1 pp change in the local job destruction rate. Standard errors are double clustered by quarter of job loss $t$ and by CBSA.

Figure 12: Changes in local labor market following job destruction shock

(a) Change Industry (NAICS 2)

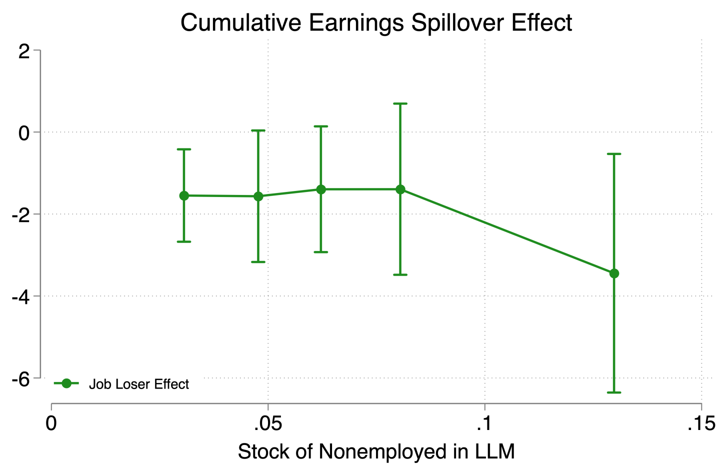



(b) Change CBSA




*Notes*: This figure shows estimates of the equilibrium effects of job destruction on the probability that workers change local labor markets. Both figures plot coefficients use the baseline specification described in Figure 3. Figure 12a plots the differences in the job stayer and job loser propensity to change the industry of employment, which we define by an indicator $1\{\text{Ind}\}_{i,t+h}$ for whether the worker's two-digit NAICS industry at $t+h$ is different from that of their primary employer at date $t$ (one year mean: 0.29). Figure 12b plots the differences in the job stayer and job loser propensity to move regions, which we define by an indicator $1\{\text{CBSA}\}_{i,t+h}$ for whether the worker's CBSA at $t+h$ is different than the one at date $t$ (one year mean: 0.10). The regressions attach equal weight to each worker. Estimates are scaled to a 1 pp change in the local job destruction rate. Standard errors are double clustered by quarter of job loss $t$ and by CBSA.

Figure 13: Heterogeneity in the spillover effects on job loss by stock of nonemployed




This figure plots the heterogeneity in job destruction spillovers by the stock of non-employed workers. We use the job flows to construct a series of recently-nonemployed workers described in Section C.6, $NE_{m,t}$. We then estimate the following extension of the baseline specification for the sample of job losers:

$$NPV\left(\sum_{h=0}^{24} \text{Earn}_{i,t+h}/\overline{\text{Earn}}_i\right) = \sum_{k=1}^{5} Q_k(NE_{m,t}) \times \left[\beta^{(k)} s_{-i,m,t} + \phi_m + \Gamma_1^{(k)} \mathbf{X}_{i,t}^W + \Gamma_2^{(k)} \mathbf{X}_{-i,m,t}^M\right] + \epsilon_{i,t} \tag{97}$$

where $Q_k(NE_{m,t})$ is an indicator for whether the labor market is in the $k$-th quintile of non-employed stock in our sample. Following our baseline specification, we similarly instrument the local job destruction with the national firm job destruction rate for each quintile. The figure plots $\beta^(k) \times \overline{NE}^k$ (y-axis) against $\overline{NE}^k$, where $\overline{NE}^k$ is the average stock of non-employed in each quintile.

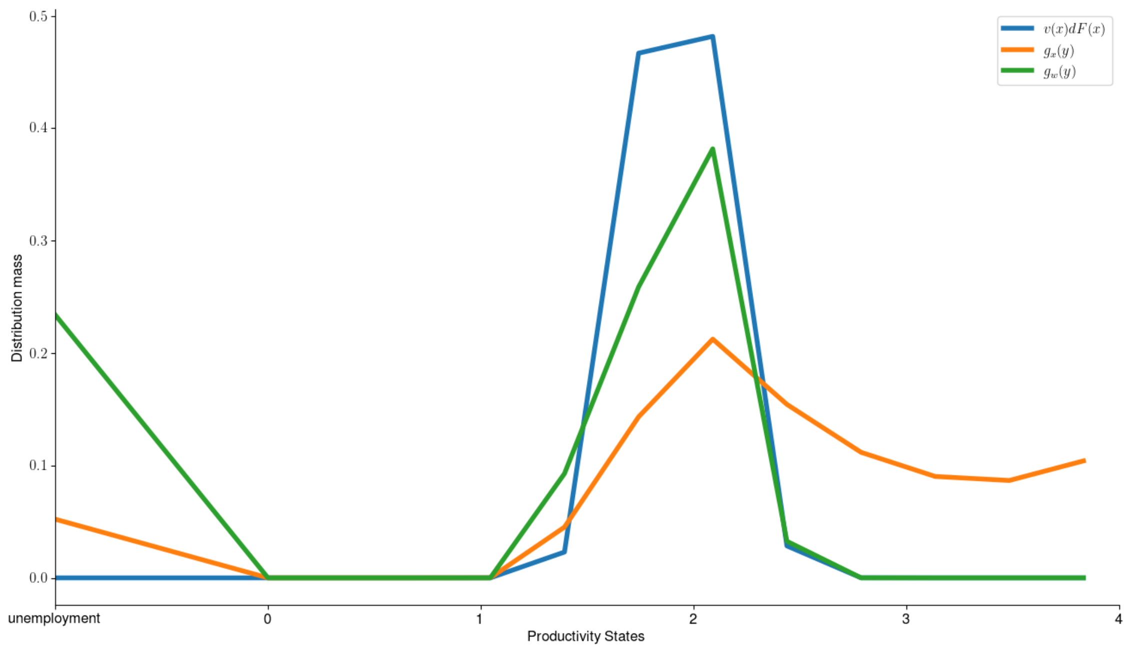



Figure 14: Worker distribution across productivity states.

*Notes*: This figure shows the distribution of employment across productivity states. $v(x)dF(x)$ refers to the distribution of new jobs (the product of vacancy effort and the exogenous firm distribution). $g_x(y)$ is the marginal distribution of job productivity. $g_y(x)$ is the marginal distribution of bargaining outside options. The first value of each series corresponds to the unemployment state.

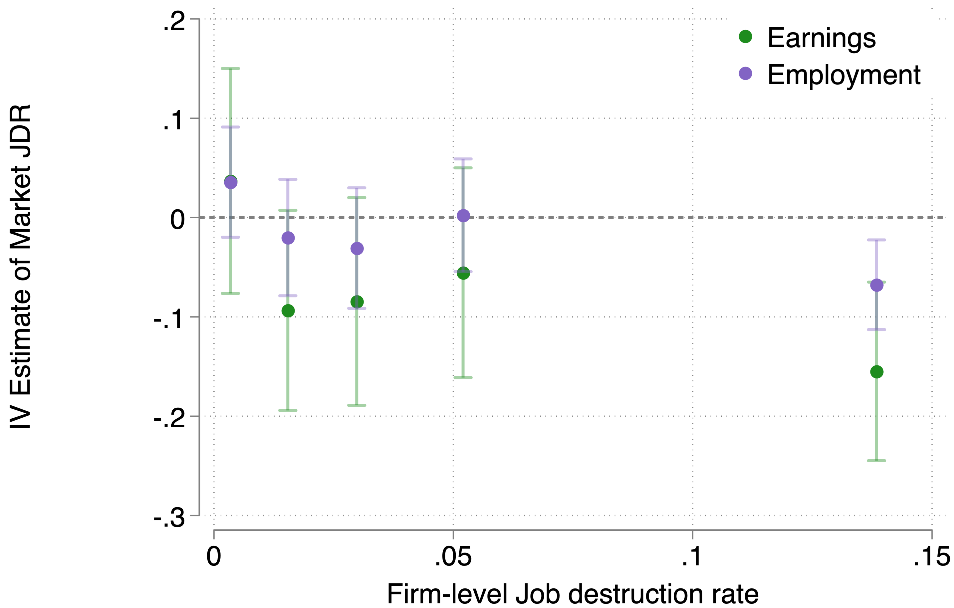



Figure 15: Effects of market job destruction shock on earnings and employment outcomes of workers, split by job destruction rate of initial job

*Notes*: This figure displays estimates of the coefficient $\beta_j$ from the following regression

$$y_{i,t} = \sum_{j=1}^{5} \left( \alpha_j + \beta_j \times s_{-f,mt} + \Gamma_j X_{it}^W + \Psi_j X_{mt}^M + \lambda_{kt} \right) \cdot Q_{f(i,t)}^{(j)} + \Phi_f + \epsilon_{it}$$

where $s_{-f,m,t}$ is the local job destruction rate excluding the worker's own firm, $Q_{f(i,t)}^{(i)}$ is the quintile of the worker's national job destruction rate, $X_{it}^M$ and $X_{it}^W$ are the market- and worker-level controls used in the baseline specification and $\phi_f$ denotes firm fixed effects. Coefficients are plotted against the average job destruction rate of the worker's employer in each quintile. The sample is restricted to workers who are employed at national firms that satisfy our baseline restrictions. Coefficients for the cumulative six-year earning ratio (green) and employment (purple) are plotted separately. Standard errors are double-clustered by CBSA and quarter.

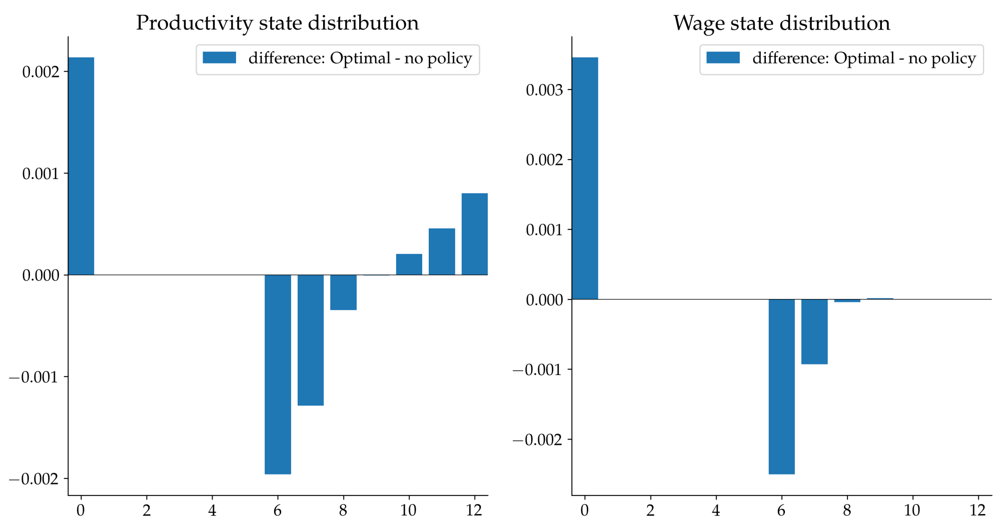



Figure 16: Changes in the distribution between no policy and steady state $\tau_0$.

*Notes:* This figure plots the differences in in the distribution in marginal job productivity (left) and outside (right) under the calibration described in Section 6.3. Differences are based on the distribution mass under the steady state subsidy, relative to the no-policy case.

## Tables

Table 4: Employment Growth Decomposition of Establishments

| Variable | (1) Variance | (2) Firm (%) | (3) Labor market | (4) Covariance | (5) Residuals |
|---|---|---|---|---|---|
| Job Destruction Rate | 0.0009232 | 31.96 | 11.12 | -10.40 | 67.27 |
| Job Creation Rate | 0.001044 | 33.7 | 9.04 | -13.99 | 67.15 |
| Net Job Creation Rate | 0.003897 | 30.64 | 9.04 | -7.92 | 69.28 |
| Job Destruction Rate (Demeaned) | 0.0007199 | 27.28 | 8.74 | 7.15 | 71.12 |

*Notes*: This table presents results from a variance decomposition of annual employment changes among establishments owned by the sample of national firms ($\mathcal{F}^N$). For each establishment-level variable $y_{f,m,t}$, we estimate:

$$y_{f,m,t} = \psi_{ft} + \phi_{mt} + \epsilon_{f,m,t} \tag{98}$$

where $\psi_{ft}$ represent firm-quarter fixed effects, $\phi_{m,t}$ are market-quarter fixed effects, and $\epsilon_{f,m,t}$ is the residual term. Column (1) reports the variance of the outcome variable. Columns (2) and (3) report the fraction of this variance explained by $\psi_{ft}$ and $\phi_{mt}$, respectively. Column (4) reports the covariance between $\psi_{ft}$ and $\phi_{mt}$, normalized by the variance. Column (5) is the residual variance unexplained by columns (2) to (4). "Job Destruction Rate" is $s_{f,m,t}$ as defined in (5); "Job Creation Rate" is the sum of positive employment growth for the establishment defined in (78); "Net Job Creation Rate" is the difference between the job creation rate and the job destruction rate; the "Job Destruction Rate (Demeaned)" is $s_{f,m,t} - \bar{s}_{f,m}$, where $s_{f,m}$ is the average establishment job destruction across all quarters in the sample.

Table 5: Summary Statistics

| Sample: | Job Loser | National Sample | Baseline restrictions |
|---|---|---|---|
| Worker | | | |
| Bachelor's degree | .2994 | .309 | .3437 |
| Born in U.S. | .7613 | .8102 | .8129 |
| Non-white | .2381 | .2344 | .1911 |
| Male | .5947 | .5335 | .5268 |
| Three-year Average earnings | 13670 | 14440 | 15390 |
| | (12550) | (13890) | (13780) |
| Three-year Average employment | .9177 | .9161 | .9508 |
| Age | | | |
| 25–29 | .1729 | .1905 | .1214 |
| 30–34 | .1933 | .1695 | .1606 |
| 35–39 | .1793 | .151 | .1726 |
| 40–44 | .1698 | .1488 | .185 |
| 45–49 | .1544 | .1519 | .1874 |
| 50–54 | .1304 | .1883 | .1729 |
| Job | | | |
| Recent CBSA switch? | .0984 | .1102 | .06851 |
| Recent industry switch? | .2928 | .2935 | .1597 |
| | | | (.3663) |
| Separate within 1 year | 1 | .3117 | .1381 |
| Tenure | | | |
| 1–3 years | .5023 | .4719 | .281 |
| 10+ years | .07571 | .09223 | .1815 |
| 3–6 years | .2808 | .2761 | .2992 |
| 6–10 years | .1412 | .1598 | .2382 |
| Missing Revenue data | .4978 | .3786 | .4377 |
| Counts | | | |
| CBSA | 450 | 450 | 450 |
| Firms | 572000 | 23500 | 939000 |
| Markets (Naics2-CBSA) | 3900 | 4400 | 6300 |
| Worker-quarter observations | 6525000 | 9972000 | 23480000 |
| Workers of parent firm | 6077000 | 8630000 | 3245000 |
| Market-quarter observations | 115000 | 169000 | 315000 |

Table 6: Impact of job destruction fluctuations on the cyclicality of job loss effects

| | (1) Actual | (2) CF | (3) Actual | (4) CF | (5) Actual | (6) CF |
|---|---|---|---|---|---|---|
| Job destruction rate | 0.582*** | 0.341*** | | | | |
| | (0.0410) | (0.0445) | | | | |
| GDP growth | | | -0.370*** | -0.277*** | | |
| | | | (0.0294) | (0.0269) | | |
| Change in unemployment rate | | | | | 0.0172*** | 0.0110*** |
| | | | | | (0.00110) | (0.000837) |
| N | 60 | 60 | 60 | 60 | 60 | 60 |
| Adjusted R2 | 0.685 | 0.415 | 0.512 | 0.513 | 0.498 | 0.358 |
| JD smoothing effect | | 0.414 | | 0.253 | | 0.362 |

*Notes:* This table shows estimates of how much the countercyclicality of the cost of job loss can be accounted for by fluctuations in job destruction, based off our causal spillover effect estimates (Table 1). Each column shows an estimate of $\gamma^{(x)}$ from the bivariate regression

$$Loss_{it}^{(x)} = \alpha^{(x)} + \gamma^{(x)} cycle_t^{(x)} + \epsilon_t$$

where $x \in \{Actual, Smooth\}$ and $cycle_t$ is some measure of the business cycle. $Loss^{(Actual)}$, the dependent variables in columns (1), (3), and (5), is the quarterly average of the 24-quarter NPV of job loss among all workers in our job loser sample described in 4.1. $Loss^{(Smooth)}$, the dependent variable in columns (2), (4), and (6), is calculated according to (14) and equals the value of this variable based off a counterfactual in which local market-level job destruction rates are set to their sample period means. See Section 5.1 for further details. The variable $cycle_t$ is set to the national job destruction rate in columns (1)-(2); the four-quarter change in real GDP in columns (3)-(4); and the four-quarter change in the unemployment rate in columns (5)-(6). The bottom row (JD smoothing effect) shows the ratio of estimates, $\gamma^{(Smooth)}/\gamma^{(Actual)}$ shows the proportional reduction in the countercyclicality of job loss effects under the smooth job destruction series. Standard errors are Newey-West using a lag of 24 quarters.

Table 7: Selection in Worker Characteristics among Job Losers

| Outcome | Mean | Instrument, $s^{IV}_{-i,m,t}$ | Local JD, $s_{-i,m,t}$ |
|---|---|---|---|
| (1) Three-year average earnings | 1.29e+04 | -33.7 | 91.5** |
| | | (85.3) | (35.6) |
| (2) Three-year average employment | 0.918 | -0.00177 | 0.002** |
| | | (0.00137) | (0.000878) |
| (3) Age | 38.7 | -0.0233 | -0.0135** |
| | | (0.0183) | (0.00688) |
| (4) Born in U.S. | 0.761 | -0.000246 | -0.000269 |
| | | (0.00121) | (0.000461) |
| (5) Non-White | 0.238 | -0.000282 | -0.000776* |
| | | (0.00116) | (0.000458) |
| (6) Tenure (Quarters) at Job Start | 16.3 | -0.132** | 0.0589** |
| | | (0.0673) | (0.0278) |
| (7) AKM FE of last employer | 0.273 | -0.00759* | 0.00529** |
| | | (0.00426) | (0.0016) |
| (8) Firm's Local Employment Share | 0.00997 | -8.12e-05 | 0.000461** |
| | | (0.0005) | (0.000195) |
| (9) Log(Firm Employment) | 4.63 | -0.028* | 0.0287** |
| | | (0.0168) | (0.00659) |
| (10) Leave LEHD States | 0.11 | 0.000323 | 0.000638** |
| | | (0.000433) | (0.000218) |
| (11) Job Separation Propensity | 0.29 | 0.00194 | -0.00364** |
| | | (0.00246) | (0.00113) |

*Notes*: This table tests for selection in the sample of job losers by estimating whether the market-level job destruction instrument predicts worker characteristics measured before event date $t$:

$$y_i = \gamma s^{IV}_{-i,m,t} + \phi_m + \Gamma \mathbf{X}^M_{-i,m,t} + \epsilon_{i,t+h} \tag{99}$$

where $\mathbf{X}^M_{-i.m,t}$ are the set of worker-firm-adjusted market-level controls and $\phi_m$ are labor market fixed effects. Column (3) presents estimates $\hat{\gamma}$ among the primary sample of job losers for various worker-level outcomes. They are as follows. Row 1 is the $\overline{\text{Earn}}_{i,t}$ base earnings in the three years before the shock event; Row 2 is the employment rate of the worker was employed during the pre-period; Row 3 is the age as measured from demographic information provided in the LEHD; Row 4 is an indicator for whether the worker was born in the United States; Row 5 is an indicator for whether the worker is recorded as non-white based on Census records; Row 6 is the number of quarters the worker has spent at their primary job as of date $t$; Row 7 is the firm wage premia of their primary employer, constructed using AKM decomposition; Row 8 is the firm's local employment share among primary jobs; Row 9 is the log of local firm employment; Row 10 is an indicator for whether the worker leaves the sample of LEHD states; Row 11 is the job separation propensity used in the matching procedure. In column (4), we present estimates for the OLS variant of (99), replacing $s^{IV}_{-i,m,t}$ $s_{-i,m,t}$.

Significance: * ($p < 0.10$); ** ($p < 0.05$). Standard errors are clustered by CBSA and observation worker. Coefficients are scaled to reflect a 1 percentage point change in the job destruction rate.