The Labor Market Spillovers of Job Destruction

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Abstract

Workers who lose their jobs during recessions face strikingly large and persistent declines in their future earnings. Using individual-level administrative data from the United States, this paper shows that an important driver of these costs is the general equilibrium effect of firms simultaneously destroying many jobs during economic downturns. To obtain variation in the job destruction rate that is unrelated to the productivity of new jobs, we exploit the differential exposure of local labor markets to the idiosyncratic shocks of large, multi-region firms. We find that job destruction fluctuations explain one-third of the difference between the average worker's cost of job loss in recessions and expansions. Accounting for additional spillover effects on employed workers, each marginal job that is destroyed imposes a total annual cost of approximately $17,000 on other workers in the same labor market. These negative spillovers could be offset by the potentially positive effects of job destruction on firm profits and the cleansing of low-quality jobs. To quantify this trade-off, we estimate a general equilibrium search model that features heterogeneous firm productivity, job-to-job mobility, endogenous separations, and state-dependent human capital accumulation. To match our reduced-form estimates, the model requires that a spike in aggregate job destruction congests the labor market, reducing workers' ability to find new jobs and limiting their human capital growth. Our results suggest that preventing the destruction of even low-productivity jobs can mitigate output losses from recessionary shocks.

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1 Introduction

Recessions in the United States are often marked by an initial burst of job destruction.[1] While workers who lose their jobs during this time experience much larger and more persistent earnings losses than in expansions (Davis and von Wachter, 2011), it is unclear to what extent these costs are caused by the concentration of layoffs in a short period of time. 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 market imperfections limit the creation of high-quality jobs, spikes in layoffs may congest the labor market by lowering the rate at which unemployed workers can find better jobs (Fujita and Ramey, 2007; Coles and Kelishomi, 2018; Mercan et al., 2024). 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. Yet, despite its importance, little work has been done to empirically quantify the size 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 preventing job loss during recessions. To estimate the causal effect of job loss on the equilibrium conditions of local labor markets, we develop a research design using granular firms and implement it using administrative employer-employee microdata from the U.S. Census Bureau. A one percentage point increase in the annual job destruction rate amplifies the earnings cost associated with job loss by 4% relative to the sample mean, leading displaced workers to lose an additional $700 in each of the following six years.[2] Factoring in spillover effects on the average employed worker, the marginal job loser imposes a total cost of approximately $17,000 per year on all other workers in the labor market, which is about 90% of the individual cost of job loss during recessions.

We calibrate an equilibrium job-ladder model with heterogeneous firm productivity, endogenous separations, and human capital depreciation during unemployment to quantitatively match these facts. The model implies that benefits to firms, through cheaper hiring and lower equilibrium wages, are less than the negative worker spillover effects we estimate. Because firms do not gain as much as workers lose, realistic job destruction shocks lead to a meaningful loss in labor market output. As a result, preventing greater job destruction can help lower the cost of recessions, which we assess by studying the transition dynamics of our model following negative aggregate productivity shocks.

We begin our analysis with a stylized model to illustrate the key channels by which job loss can impact the labor market (Section 2). We decompose the aggregate output effects of a worker layoff

[1] Following Davis and Haltwanger (1992), we define job destruction in terms of establishment-level employment contractions.

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

in terms of (i) the partial equilibrium "cleansing" effect from the destroyed job, (ii) spillovers on other workers through changes in market equilibrium, and (iii) spillovers on firm profits. Our empirical analysis is focused on estimating the second channel, while we use the enriched quantitative model to evaluate the importance of the first and third channels.

Estimating the magnitude of worker spillovers requires isolating the effects of elevated job destruction from changes to the marginal productivity of labor. This is challenging as 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 the 2007–2009 recession, the construction sector experienced a 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.

The ideal variation to identify equilibrium spillovers would be to compare the outcomes of similar workers across labor markets that vary only in the size of random job destruction shocks (i.e., deviations of the local rate relative to its level in steady-state equilibrium). We approximate this experiment by using quasi-random variation in exposure to the idiosyncratic job destruction of large, national firms across labor markets. Company-specific workforce decisions, financial constraints, and productivity shocks imply that the layoff rate among geographically distant establishments is correlated within firms. Because these companies exhibit large local employment shares, firm-specific contractions can induce granular shocks to the local job destruction rates unrelated to local market conditions. By controlling for industry-time and city-industry fixed effects, the firm-level variation we use comes from fluctuations in the job destruction rate that are orthogonal to industry loadings on the business cycle or regional differences in the long-run level of local job destruction in our sample.

In Section 3, we implement our research design using administrative data from the U.S. Census Bureau. 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 measure the exposure to national-firm job destruction activity as the average of national firms' job destruction rates in other regions, weighted by each firm's ex-ante share of total employment in the local market. We then use this measure as an instrument to estimate worker outcomes up to six years following job destruction shocks to local labor markets in our panel data.

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 local demand or labor productivity are relatively sensitive to aggregate shocks.

Two balance tests support the validity of our identifying assumption. First, under our baseline specification, the market-level instrument shows no meaningful relationship with the job destruction rates of the establishments belonging to single-region firms, which are likely sensitive to shocks to local economic conditions. Second, the national job destruction rate of the largest local employer does not predict the national job destruction rates of other firms that operate in the same labor market. Any violation of our identifying assumption must therefore result from shocks to local conditions that are correlated with the job destruction activity of a particular firm but uncorrelated with the shocks affecting other firms in the same labor market.

We apply our research design to estimate the spillover effects of job destruction on workers' short- and medium-run labor earnings (Section 4). 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 (Jacobson et al., 1993a; Flaaen et al., 2019). 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 of the job loser, relative to their pre-displacement earnings. Approximately half of the total spillover effect is driven by extended periods of nonemployment, while the remaining half is due to lower earnings upon reemployment. We show that our estimates are robust to various alternative specifications and are not primarily driven by local demand effects arising from reduced consumption following job loss.

The congestion effects that arise from job destruction are not confined to displaced workers. In Section 5, we use the same empirical design to estimate that the average employed worker in a labor market with a positive 1 percentage point (pp) job destruction shock experiences a 0.2 percentage point reduction in annual earnings growth over six years due to the decline in labor market conditions.[3] 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.[4] 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 for by inflows from separations (Shimer, 2012).

Our empirical results show that a large fraction of the total cost of job loss on workers is the result of spillovers of individual separation decisions on labor market tightness, especially during aggregate downturns. 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. However, one cannot conclude that job destruction during recessions is inefficiently high from the reduced-form results alone. This is because the earnings estimates do not capture the positive impact that job destruction may have

[3] 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.

[4] This estimate comes from averaging the spillover effects for the average worker and spillover effects for unemployed workers, under the assumption that spillovers on workers without a job are similar to those of recent job losers. Section 5 provides details on this approximation.

on firm profits, which are not measured at the same precision and frequency in U.S. administrative data as earnings. Both incumbent employers (who could dissolve low-surplus jobs) and new employers (who may find it easier to hire new workers at lower wages) could experience benefits from higher job destruction in the form of lower wages and cheaper hiring that could dominate the worker-level costs revealed by our spillover estimates.

We address this question in Section 6 by developing a structural model of labor market dynamics. Our first technical contribution in the quantitative analysis is to extend partial equilibrium job-ladder models (Jarosch, 2023; Krolikowski, 2017) to general equilibrium settings in which the worker distribution and market tightness are endogenous. To generate job destruction from recessionary shocks to the marginal product of labor, we also allow separation decisions to be endogenous to stochastic job productivity (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 the labor market becomes congested, workers struggle more to find jobs, which also erodes their human capital through scarring effects. Employed workers also experience lower earnings growth since they face greater difficulty advancing up the job ladder by switching employers and may have wages indexed to an outside option of unemployment.

Calibrating these spillovers to our empirical estimates on earnings is difficult because it requires solving for 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 the estimation of the steady-state and dynamic equilibrium, as is commonly done in past work (e.g., Audoly, 2023). Our second technical contribution is to provide a feasible approach in jointly estimating the steady-state and dynamic earnings moments for quantitatively rich job ladder models. We draw from recent advances in continuous-time heterogeneous agent models to compute the first-order transition dynamics from an impulse to the worker distribution around the steady-state equilibrium (Bilal, 2023). We find that our calibrated model is able to generate job destruction spillovers on earnings and employment that are consistent with our empirical estimates.

We then use the model to evaluate how much of the decline in worker earnings reflects a transfer to firms through lower equilibrium wages (Section 7). Our preferred calibration suggests that, following an exogenous job destruction shock, less than half of the negative spillovers on worker earnings is compensated by benefits to firms in the form of lower wages. The remaining portion represents the productive loss from labor market spillovers, driven by the persistence of unemployment; changes in the composition of available jobs; and human capital depreciation due to less time spent employed.

Finally, we apply the model to assess the value of job preservation during recession events. We consider the first-order, deterministic transition dynamics following a negative shock to aggregate productivity. To isolate the role of spillovers, we consider a policymaker who can directly set the separation rate of low-productivity jobs to offset the rise in unemployment. We find that the cumulative output loss over the transition path is 10% lower when the planner retains lower-productivity jobs. As a result, the costs of congestion prove to be stronger than the benefits of facilitating labor reallocation through unemployment. Our counterfactual exercise suggests that policymakers may find it valuable to stabilize output by directly saving jobs during recessions.

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., 1993b; Davis and von Wachter, 2011; Lachowska et al., 2020; Schmieder et al., 2023; 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 countercyclicality of earnings losses found in the data. Features such as heterogeneity in job separation rates (Krolikowski, 2017; Jarosch, 2023), worker scarring effects (Huckfeldt, 2022; 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 market-level channels of job loss (Huckfeldt, 2022), 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, 2012). Recent work, summarized in Hall and Kudlyak (2021), has emphasized how, in search models where the 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 market tightness.[5] We contribute to this work by providing causal evidence that, consistent with these models, increases in 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).[6]

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 the firm productivity distribution (Bloom et al., 2018) and higher job destruction rates

[5]Examples include models in which new hires are 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 exiting firms (Coles and Kelishomi, 2018), or heterogeneity in the productivity of job seekers that is unobservable to vacancy-posting firms (Restrepo, 2015; Engbom, 2021).

[6]Our estimates may also be useful in understanding the labor market effects of secular shocks, such as from trade normalization with China (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).

among low-productivity firms 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.[7] 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 preservation.[8]

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.

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 v 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 $\mathcal{M}(u, v)$, which is increasing in both inputs. In the terminal period $t = 2$, workers 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 zero.

We define market tightness as the ratio of available jobs per unemployed worker, $\theta := v/u$. High levels of θ 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

[7] Recent work has attempted to measure the value 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 these programs (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 helps determine whether such policies would be effective in the U.S.

[8] Some papers test for the presence of equilibrium labor market congestion following changes to the generosity of UI (Marinescu, 2017; Johnston and Mas, 2018; Lalive et al., 2018) or the availability of job placement assistance (Crépon et al., 2013). Whereas these studies focus on changes in the reservation wage of search effort of workers who already unemployed, they do not speak to the equilibrium effects of changes in the employment state of workers, which is the focus of this paper.

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: $C'(\cdot) > 0, C''(\cdot) \geq 0$. 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 (Π):

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

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

$$W_1 - U_1 = \beta S_1, \tag{1}$$

where β 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 $\xi_v = \frac{\partial \log C'(v)}{\partial \log \nu}$ be the marginal cost elasticity with respect to ν. The total effect of a job destruction shock can be expressed as:*

$$\frac{dY}{ds_i} = -\underbrace{S_1}_{\textit{Private surplus}} + \underbrace{\left[u\frac{\partial U}{\partial \log \theta} + (1-u)\frac{\partial W}{\partial \log \theta}\right]\frac{\partial \log \theta}{\partial u}}_{\textit{Worker spillover}} + \underbrace{\frac{\partial \Pi}{\partial \log \theta}\frac{\partial \log \theta}{\partial u}}_{\textit{Firm spillover}}. \tag{2}$$

where:

$$\frac{\partial U_1}{\partial \log \theta} = (1-\omega_f)f(\theta)\left[W_2 - U_2\right], \quad \frac{\partial W_1}{\partial \log \theta} = (1-\beta)\frac{\partial U_1}{\partial \log \theta}, \quad \frac{\partial \log \theta}{\partial u} = -\frac{\xi_v}{\xi_v + \omega_f}u^{-1}, \tag{3}$$

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 (2) 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.[9] 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: 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 θ), 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 (3) analytically characterizes the response of market tightness to job destruction. For job destruction to have worker spillovers, the marginal cost of creating a new job must be rising in the number of jobs. The elasticity ξ_v captures the ease by which firms can create new jobs. In standard models with free entry from fixed costs to job creation ($\xi_v = 0$), an additional job seeker has no impact on equilibrium market tightness.[10] In the case where new jobs are rationed ($\xi \to \infty$), the marginal job seeker completely crowds out another worker, with market tightness response $\frac{\partial \log \theta}{\partial u} = -\frac{1}{u}$.[11]

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 jobseekers (like recently laid-off workers) 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 and the private surplus lost, which we perform in a quantitatively enriched version 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

[9] When separations are endogenous, bilateral efficiency of the wage mechanism (1) implies that firms would only choose to terminate jobs for which $S_1 < 0$. We allow for endogenous separations in the quantitative extension.

[10] 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.

[11] 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.

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% of private-sector employment in 2015.[12] The LEHD also includes auxiliary data on demographic information (e.g., age, sex, race, and residential census tract) as well as 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.[13]

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.[14] 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.[15]

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

[13] 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.

[14] 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).

[15] 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 C.3.

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 employment 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:

$$s_{f,m,t} = \max \left[\frac{\sum_{h=0}^{3} \left(\text{Sep}_{f,m,t+h} - \text{Hire}_{f,m,t+h} \right)}{N_{f,m,t-1}}, 0 \right], \tag{4}$$

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:

$$s_{m,t} = \left(\sum_{f} N_{f,m,t-1} \right)^{-1} \sum_{f} N_{f,m,t-1} \times s_{f,m,t}. \tag{5}$$

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.[16] Using flows also helps us exclude abrupt employment changes due to corporate restructuring (e.g., mergers) from our measures.[17]

3.2.2 National firm job destruction

We construct an instrument for the local job destruction rate (5) using variation in the job destruction of *national firms*. We define the set of national firms, $\mathcal{F}^N$, as those employing more than 10

[16] 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 C.2.

[17] We favor the measure of job destruction (4) 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 (Mercan and Schoefer, 2020). As a result, gross flows are a noisier indicator of "true" job destruction. A potential drawback of our measure is that changes to (4) 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 the variation in establishment-level job destruction during our sample period is primarily driven by layoffs rather than hiring.

primary-job workers in at least two states with non-overlapping CBSAs.[18] 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 the employment-weighted average across establishments:

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

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 (5) with the national rate of its parent firm:

$$s^{IV}_{m,t} = (\sum_{f} N_{f,m,t-1})^{-1} \sum_{f\in\mathcal{F}_N} N_{f,m,t-1} \times s_{f,-m,t}, \tag{6}$$

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 (6) do not sum to one.

3.3 Estimating equation

We estimate the structural equation:

$$y_{i,t+h} = \beta^{(h)} s_{-i,m,t} + \phi_m + \Gamma_1^{(h)} \mathbf{X}^W_{i,t} + \Gamma_2^{(h)} \mathbf{X}^M_{-i,m,t} + \epsilon_{i,t+h} \tag{7}$$

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 ϕ_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 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 $s^{(IV)}_{-i,m,t}$, with the first-stage equation:

$$s_{-i,m,t} = \beta^{fs} s^{IV}_{-i,m,t} + \phi_m + \Lambda_1 \mathbf{X}^W_{i,t} + \Lambda_2 \mathbf{X}^M_{-i,m,t} + \eta_{i,t+h}. \tag{8}$$

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

3.3.1 Identification

Identifying the worker-level spillover relies on the conditional orthogonality of idiosyncratic job destruction shocks to local market conditions.[19] 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 (7) and (8) to job destruction spillovers is:

$$\mathbb{E}\left[\sum_{\forall f \in \mathcal{F}_N} s_{ft} \cdot \overline{\epsilon}^{(h)}_{ft} \middle| \overline{\mathbf{X}}^W_{ft}, \overline{\mathbf{X}}^M_{ft}\right] = 0 \tag{9}$$

where $\overline{\epsilon}^{(h)}_{ft}$, $\overline{\mathbf{X}}^W_{ft}$, and $\overline{\mathbf{X}}^M_{ft}$ 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.[20] The exogeneity condition requires that, in a given quarter, the national firms that 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 $\mathbf{X}^W_{it}$ or market-level controls $\mathbf{X}^M_{mt}$, it is reasonable to suspect that the instrument we consider does not satisfy the exogeneity condition (9). 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 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 plausibly of the identification condition relies on the following set of controls we include in our baseline specification for (7). 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.[21]

We also include a set of time-varying market-level factors. First, we control for lagged values of the instrument from the five quarters prior to t. To account for differences in the regional exposure to aggregate shocks from the local composition of industries, we include a shift-share instrument

[19] "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 (e.g., 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 rigidities from uniform national wage-setting (Hazell et al., 2021).

[20] We describe how our implementation differs from the assumptions underlying the orthogonality condition in Section D.3. In general, the differences are small in practice and are orthogonal to the key source of identifying variation conceptualized in (9). In Section B.1, we provide a formal treatment of the identification condition in an extentson of the stylized model presented in Section 2.

[21] The inclusion of the labor market fixed effect ϕ_m removes static differences in labor market reallocation by firms.

for both industry employment growth and reallocation following Chodorow-Reich (2019).

In addition. 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 (6). 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 instrument of extensive-margin variation in job destruction.

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 also 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 (8) 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 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 (8), 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 Balance tests for idiosyncratic firm shocks

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

[22]The conditional orthogonal conditions for shift-share instruments with incomplete market shares require the interaction of the employment share with all other controls (Borusyak et al., 2022). We find no change in our results when using this extended set, and therefore omit the interactions in our baseline specification.

[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 A.1, 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 A1 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.

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:

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

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 6) divided by the local employment share of national firms. Figure 2a provides estimates of $\hat{\beta}^{(q)}$ in (10) separately for establishments owned by single-region 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:

$$s^{(R)}_{f,-m,t} = \beta^{(R)} s^{(1)}_{f,-m,t} + \Gamma' X_{m,t} + \epsilon_{f,m,t}, \quad R = 2, 3, \ldots \tag{11}$$

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,

[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 (6) 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.

we find a precise lack of positive correlation between the national job destruction rate of the largest firm and that of 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 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.

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. We then apply a set of an additional data filter to ensure that we can accurately measure the worker's future jobs employment-related outcomes, which are described in Appendix C.3. 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.[27] Inspired by 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. As detailed in Appendix C.4, we pool mass layoff event from the common measurements of employment growth

[27] In search models with bilaterally-efficient bargaining, a meaningful distinction between layoffs versus quits does not exist (Shimer, 2012). 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.

used in past work. This procedure yields a sample that consists of 6.525 million job loss events (worker-quarter observations) corresponding to 6.077 million unique workers in approximately 3,900 market-quarters.[28]

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 A4). 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 (i) has a similar predicted separation propensity; (ii) is employed at a stable firm with a growth rate in the (-5%, 5%) range; and (iii) does not separate from their job for at least four quarters. We provide details on the matching procedure in Section C.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

We first construct $\text{Earn}_{i,t}$, 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 among the 12 quarters prior to the job loss event at t for which workers are employed for the full quarter.For the quarters $t+h$ after the layoff event, we take the ratio $\text{Earn}_{i,t+h}/\overline{\text{Earn}}_{i,t}$ as our primary measure of the worker's change in earnings from before the layoff to h quarters after. We

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

also estimate the dollar-value of the earnings effect by taking the difference between $t+h$ earnings and base earnings, $\text{Earn}_{i,t+h} - \overline{\text{Earn}}_{i,t}$.

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 (7) between our job loser sample and the matched controls.[29] Standard errors are two-way clustered by CBSA and the date of job loss. In panel 3a, we present estimates where the dependent variable is the earnings ratio, $\frac{\text{Earn}_{i,t+h}}{\overline{\text{Earn}}_{i,t}}$, 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.[30] In the quarter following the lay-off 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. Appendix Figure A.2 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

[29] In particular, we estimate (7) separately for job losers ($\hat{\beta}^{(h)}_{JL}$) and job stayers ($\hat{\beta}^{(h)}_{JS}$), and present the coefficients as $\hat{\beta}^{(h)} = \hat{\beta}^{(h)}_{JL} - \hat{\beta}^{(h)}_{JS}$.

[30] 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.

net present value (NPV) earnings ratio from $h = 0$ to $h = 24$, using annual interest rate of 5%.[31] 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 losers 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.

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 D.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.[32]

The fact that greater nonemployment accounts 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).[33] In

[31] 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.

[32] 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.

[33] It also may be the case that the earnings spillovers reflect are a result of differential selection out of the sample

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).[34] Row 3 shows that our estimate changes little if we follow the granular IV construction 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).[35] 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.

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.

[34] The lack of adjustments highlights the importance of estimating spillovers at the job level: without excluding the worker's own employment history, estimates of the form (28) incorporate direct productivity shocks that workers may experience through their firm.

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

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 (7) in the subsample of tradeable industries that include Oil and Gas Extraction (NAICS 21) and Manufacturing (31-33).[36] 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. With these controls, the remaining variation in job destruction would come from differences in national firm job destruction shocks across industries within a city. Row 13 of Table 2 reports that our estimates of the earnings spillovers similarly declines to -.180 (SE: 0.066).[37] The similarity between the estimates from these two alternative specifications suggests that at least 75% of the spillover effects we estimate cannot be explained by the effect of job destruction on local demand.

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 D.4, we consider an alternative design where, instead of conditioning on job loss, we estimate the heterogeneity in spillovers among workers with different levels of future separation risk, which we proxy 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 A.8). In comparison, there are no spillovers for workers firms with the lowest level of future separation risk.

[36]We use 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.

[37]We omit CBSA-quarter fixed effects in our baseline design due to the possibility 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.

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 fraction of worker earnings reduction that are implicit transfers to firms.[38] 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.[39]

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, Ψ^t_f using rolling five-year windows prior to job loss date t.[40] We then estimate (7) 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 A.3a 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 premia 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., 2023). 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.[41] For our measure of labor productivity, we use the rank of the firm's revenue per worker within their the primary

[38] 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.

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

[40] Details are provided in Section D.5.

[41] 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.

four-digit NAICS industry. As a result, our 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 A.3b, we find that higher job destruction leads job losers to join 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 we instead consider the changes in firm composition for the *average* employed worker in the labor market, we get a somewhat different picture. Appendix Figure A.4 plots the same outcomes of changes to firm wage premia (A.4a) and rank labor productivity (A.4b) 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 to the earnings effect of job loss 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 earnings loss estimates:

$$\text{Loss}_{i,t}^{(Smooth)} := \text{Loss}_{i,t}^{(Est)} - \hat{\beta} \times (s_{-i,m,t} - \bar{s}_m) \tag{12}$$

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 (12), 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.[42]

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.[43] 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 of job loss by estimating the following relationship:

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

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 A3 shows this estimate under three different cyclical indicators.[44] 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)-

[42] 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 A.5 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 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).

[43] 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.

[44] 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.

(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 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.[45]

5.2 Spillovers on the average worker

Next, 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 destruction:

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

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.[46]

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.[47] Using equation (2) from Section 2, we can express

[45]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 (3)). Appendix Figure A.6 shows that the total earnings spillovers are larger when the stock of recently nonemployed is high, which suggests that the amplifying force prevails.

[46]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.

[47]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.

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, $\frac{ds}{d \text{ job loser}}$

$$\text{Spillover Cost of Job Lost} = \frac{ds}{d \text{ job loser}} \times N_m \left[\underbrace{\frac{dW}{ds}}_{\text{1. Effect on employed}} + \underbrace{u \times \left(\frac{dU}{ds} - \frac{dW}{ds} \right)}_{\text{2. Rel. effect on the unemployed}} \right], \tag{13}$$

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 (13) 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 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).[48] 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 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:

$$\frac{1}{1 - 0.061} \times [0.050 \times \$15,490 + 0.061 \times 0.2618 \times \$13,390] \times 100 = \$105,000.$$

Annually, our estimates suggest that the marginal job loss 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 employed, 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.

[48] 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.

Our data and research design is not well-suited to measure the spillover effects of job destruction on firm profits, the third term in (2). 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.

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 begin to answer these questions by estimating a quantitative labor market model using our evidence on job destruction spillovers. In Section 7, we apply this model to determine the overall welfare effects and the implication for employment subsidies in the presence of aggregate shocks.

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 ρ. 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 for existing jobs, and the job acceptance decisions of workers. Worker are heterogeous heterogeneity 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 these idiosyncratic states by $y := (h_y, x_y, r_y) \in \mathcal{Y}$ and the distribution of worker 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 $b(h) > 0$. When workers exit the labor force, they do so permanently and receive flow income that is normalized 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:

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

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.[49] We define the set of productivity states as $\mathcal{X} = \{b\} \cup [\underline{x}, \overline{x}]$, where $[\underline{x}, \overline{x}]$ is the bounded interval of employed productivity states and, with slight abuse of notation, we use b to denote production during unemployment.

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 $z \in \mathbb{R}_+$. Job productivity evolves stochastically according to the diffusion:

$$dx = \mu(x)dt + \sigma(x)d\mathcal{W}_x \tag{14}$$

where $\mathcal{W}_x$ is a Wiener process and $\mu(x) \in \mathbb{R}$, $\sigma(x) > 0$ 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 $\psi_u(h)$.

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.[50] The distribution of new jobs for which firms can recruit is exogenous and denoted

[49] The constant returns to scale 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 that firm size plays an important role in labor market dynamics and our research design, 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 (e.g., Bilal, 2022). 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.

[50] 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 reflected in job creation low productivity matches which are only available following declines in the value of unemployment. Engbom (2021)

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 $C'(\cdot) > 0$, $C''(\cdot) \geq 0$. They set the advertising intensity to maximize expected profits

$$\Pi_t(x) = \max_{v \geq 0} q(\theta_t) E_t[J_t(y)|x_y = x] - \mathcal{C}(v), \tag{15}$$

where $E_t[J_t(y)|x_y = x]$ is the firm's expected surplus, given the current distribution of workers.

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 ϕ 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. Aggregate recruiting intensity, which we refer to as vacancies, is given by $\nu_t = \int_x v_t(x) dF(x)$. 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 $M_t = M(\nu_t, e_t)$, where the matching function $M(\cdot, \cdot)$ is weakly increasing in both arguments and exhibits constant returns to scale.

6.1.5 Wages

Wages are set according to the sequential-auction-with-bargaining mechanism of Cahuc et al. (2006), modified to allow for renegotiation by mutual consent (Postel-Vinay and Turon, 2010). For a worker $y = (h_y, x_y, r_y)$, we define the expected present value of production as $V_t(h_y, x_y) := W_t(y) + J_t(y)$, the value of unemployment as $U_t(h_y)$, and total job surplus as $S_t(h, x) = V_t(h, x) - U_t(h)$. Importantly, the production value and job surplus does not depend on the worker's bargaining threat point $r \in \mathcal{X}$.[51] Wages $w_t(y)$ are set to satisfy:

$$W_t(y) - U_t(h_y) = S_t(h_y, r_y) + \beta \left(S_t(h_y, x_y) - S_t(h_y, r_y) \right) \tag{16}$$

and the firm surplus is the remaining value $J_t(y) = S_t(h, x) - W_t(y) - U_t(h)$. .[52] Worker who are hired out of unemployment (where $S_t = 0$) have a threat point of $r = b$ which reduces to the standard Nash bargaining protocol.

There are two ways in which the bargaining threat point of workers change. First, they make contact with new job offers. When a worker in state y meets a new job with productivity x',

studies this type of mechanism in a setting where elevated separation rates deteriorate match quality through the additional applications that unemployed workers may send.

[51] We prove the independence of V in Section E.1.3.

[52] We provide the recursive representation of worker value in Section E.1.2. In contrast to Cahuc et al. (2006), the wage is updated continuously due to stochastic movements in job productivity.

one of three situations may arise. If $x' \leq r_y$, then the worker rejects the job match and remains in state y. If $r_y < x' \leq x_y$, then worker will use the incoming offer as the new threat point, allow them to bargain up her wage at the existing firm. This leads to an updated worker state of $y' = (h_y, x_y, x')$. If $x' > x$, the worker will switch to the more productive job and use the previous firm's productivity as the threat point for the new match. In this case, the updated worker state is $y' = (h_y, x', x_y)$. [53] Second, the worker may agree to renegotiate the wage if the firm's value $J_t(y)$ falls below their reservation value of 0, but the job surplus remains positive. In this case, the wages are set so that the worker retains all of the job surplus, which is done from setting the threat point to the current job productivity, $W_t((h_y, x_y, x_y) = V_t(h_y, x_y)$. This type of wage renegotiation implies that the bargaining threat point moves in lock-step with job productivity only when $x < r$ and $dx < 0$:

$$dr = (\mu(x)dt + \sigma(x)d\mathcal{W}_x) \cdot 1\{x \leq r\} \cdot 1\{dx < 0\}, \tag{17}$$

where $\mathcal{W}_x$ is the identical Wiener process as in (14) and we omit the Poisson jumps associated with job transitions for clarity.

6.1.6 Separations

Existing jobs can be terminated in one of four ways. First, workers permanently exit the labor market at an exogenous rate κ, 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 δ, which leaves workers in unemployment and firm owners with a scrap value that we normalize to 0.[54] Third, workers may quit to a new job with higher productivity

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 the 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:

$$V_t(h, x_t^*(h)) = U_t(h) \tag{18}$$

This form of endogenous job destruction reallocates workers to productive matches when search effort on the job is lower than when unemployed ($\phi < 1$), as workers have a higher chance to match to new jobs post-separation.

[53]Succinctly, the wage bargaining mechanism implies that the worker state is updated after a job meeting to $\tilde{y} = (h_y, \tilde{x}, \tilde{r})$, where $\tilde{x} = \max\{x_y, x'\}, \tilde{r} = \max\{\min\{x_y, x'\}, r_y\}$. Since workers only accept job offers if it increases their expected lifetime earnings, this characterization relies on the fact that the production value is monotonic in job productivity x, which is shown in Section E.1.4.

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

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.

Proposition 6.1. *Let $\mathcal{M}_x(x)[\cdot]$ be the infinitesimal generator encode the job productivity diffusion (14); $\mathcal{M}_h^j(h)[\cdot]$ encode the human capital diffusion, for $j = e,u$; $\mathcal{M}_r(y)[\cdot]$ encode the bargaining threat point diffusion (17); $\eta(x)$ be the base measure of the worker state space $\mathcal{Y}$; and $dH_t(x) := \frac{v_t(x)}{\nu_t}dF(x)$ be the base measure of the distribution of available jobs. Also, let $\mathcal{B}^*$ denote the adjoint of some operator $\mathcal{B}$. The recursive equilibrium of the labor market is defined by the following conditions:*

1. *the vacancy policy for new jobs, $v_t(\cdot)$, is determined by the solution (15);*
2. *worker surplus share, $W_t(\cdot)$, is determined from the bargaining equation (16);*
3. *firm surplus is given by $J_t(y) = V_t(h_y, x_y) - W_t(y)$;*
4. *market tightness θ_t is the ratio of aggregate recruiting intensity $\nu_t = \int_x v_t(x)dF(x)$ to aggregate search intensity $e_t = u_t + (1-u_t)\phi$;*
5. *the separation threshold $x_t^*(h)$ is determined by the bilateral efficiency condition (18);*
6. *the sequence of value functions $V_t : \left[\underline{h}, \overline{h}\right] \times \mathcal{X} \to \mathbb{R}$*

$$
\begin{aligned}
\rho V_t(h,x) &= p(h,x,z) + \mathcal{M}_x(x)[V] + \mathcal{M}_h^{(e)}(h)[V] - \kappa V_t(h,x) - \delta\left(V_t(h,x) - U_t(h)\right) \quad (19)\\
&\quad + \phi f(\theta)\beta \int_x^{\overline{x}} \left(V_t(h,x') - V_t(h,x)\right) dH_t(x') + \frac{\mathbb{E}_t\left[dV(h,x)\right]}{dt}, \quad x \geq x_t^*(h)\\
V_t(h,x) &= U_t(h), \quad x \leq x_t^*(h)\\
\rho U_t(h) &= b(h) + \mathcal{M}_h^{(u)}(y)[U_t] - (\kappa+\kappa_u)U_t(h) + \frac{\mathbb{E}_t\left[dU_t(h)\right]}{dt}\\
&\quad + f(\theta)\beta \int_{x^*(h)}^{\overline{x}} \left(V((h,x)) - U_t(h)\right) dH_t(x)
\end{aligned}
$$

7. *the worker distribution $g_t : \mathcal{Y} \to \mathbb{R}$ for $t \geq 0$ that satisfy the following set of equations, for the productive states follows, for $x > x_t^*(h)$:*

$$
\frac{dg_t(y)}{dt} = \mathcal{IN}(y) + \mathcal{M}_r^*(y)[g_t] + \mathcal{M}_x^*(x)[g_t] + \mathcal{M}_h^*(h)[g_t] - (\delta + \kappa + \phi f(\theta)(1 - H_t(x_y)))g_t(y),
$$

with employment inflows:

$$\mathcal{IN}(y) = \begin{cases} q(\theta_t)\phi \cdot dH_t(r) \int_{y' \in \mathcal{Y}} 1\left\{h_{y'} = h_y, x'_{y'} = x_y, r_{y'} \leq r_y\right\} g_t(y')\, d\eta(y') \\ \quad + dH_t(x) \int_{y' \in \mathcal{Y}} 1\left\{h_{y'} = h_y, x'_{y'} = r_y\right\} g_t(y')\, d\eta(y'), & \text{if } r_y > b, \\ dH_t(x) q(\theta_t) u_t(h), & \text{if } r_y = b, \end{cases}$$

and, for $x = b$:

$$\frac{du_t(h)}{dt} = (\delta + \kappa)\left(\overline{g}_t^{(h)} - u_t(h)\right) - f(\theta_t)u_t(h) + \frac{\sigma(x_t^*(h))^2}{2}\partial_x g_t(y_t^*(h)) - \mathcal{M}_x^*(y_t^*(h))[g_t] \tag{20}$$

where $u_t(h) := g_t((h,b,b))$ and $\overline{g}_t^{(h)} := \int_y 1\{h_y = h\}\, g_t(y) d\eta(y)$ are the unemployment rate and worker mass for a given human capital level, respectively.

8. *the worker distribution additionally satisfies the boundary condition:*

$$g_t(y) = 0 \text{ for } \left\{y \in \mathcal{Y} : \underline{x} \leq x_y \leq x_t^*(h) \text{ or } r_y > x_y\right\}.$$

The HJB (19-6) and KF (7-20) equations, provide a complete characterization of the dynamics of the labor market – all other endogenous features of the economy depend only on the functions $\{V_t(\cdot), U_t(\cdot), g_t(\cdot)\}$. Section E.2 provides greater details and the proof for Proposition 6.1.

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.[55] We make the following parametric assumptions to estimate the steady state of the model. Worker production when employed is set to be $p(h, x, \overline{z}) = \overline{z} + hx$. 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

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

capital accumulation and unemployment scarring are both constant drift rates in h: $\psi^e(h) = \psi_e$ and $\psi^u(h) = \psi_u$. We parameterize the matching function as a Cobb-Douglas production function $M(e_t, v_t,) = C_m e_t^{\omega} v_t^{1-\omega}$ where $1 - \omega$ is the elasticity of the job-finding rate with respect to market tightness $\theta_t = \frac{v_t}{e_t}$ and $C_m \geq 0$ is the matching efficiency. On the firm side, we set the cost function to take the form: $\mathcal{C}(v) = \frac{C_v}{1+\xi} v^{1+\xi}$ 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 $C_v = 1$. The distribution of new jobs $dF(x)$ is parameterized as Beta(a_β, b_β) over $[\underline{x}, \overline{x}]$, where a_β and b_β are positive.

6.3.2 External calibration

We estimate the model at the monthly frequency. Following the literature, we set the discount rate ρ to target an annual interest rate of 5%. The labor force exit rate κ is set to match an expected career length of 35 years. We also allow for the unemployed to exit at an added rate κ_u that is set to be half of the employed worker's exit rate. The matching elasticity to market tightness ω is set to 0.5 following Moscarini and Postel-Vinay (2021).

6.3.3 Internal estimation

The remaining parameters $\Omega = \{b, C_m, \beta, a_\beta, b_\beta, \mu_x, \sigma_x, \psi_e, \psi_u, \phi, \xi, \delta, z\}$ are internally calibrated to three sets of moments. 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).[56] 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 that are often used when estimating 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.

[56] 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.[57] 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 E.6.

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.[58] This is made apparent in Appendix Figure A.7, 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, 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 cumulative job loss effects for both earnings and employment, it is useful to assess whether the dynamic of these effects are consistent

[57] 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.

[58] 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).

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 implications of these spillovers during recessions in Section 7.2, where we study the counterfactual output loss when low-productivity jobs are retained to completely offset an increase in the unemployment rate. 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 is as follows:

$$\begin{aligned} \text{SWF} &= \int_y W(y)g(y)dy + \int_y J(y)g(y)dy + \int_h U(y)\overline{g}_h(h)dh + \int_x \Pi(x)dF(x) \\ &= \frac{1}{\rho}\left[\int_y p(y)g(y)dy - \int_x C(v(x))dF(x)\right], \end{aligned} \tag{21}$$

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 (21), where we decompose PDV of the first-order effect of the job destruction shock dS:

$$\frac{d\text{SWF}_0}{dS} = \int W_0(y)\partial_S g(y)\,dy + \int J_0(y)\partial_S g(y)\,dy \tag{22}$$
$$+ \int \partial_S W_0(y)\,dG(y) + \int_0^\infty e^{-\rho t}\left[\int_h \partial_S U_t(y)\overline{g}_h(h)dh\right]$$
$$+ \int \partial_S J(y)\,dG(y) + \int_0^\infty e^{-\rho t}\left[\int_x \partial_S \Pi_t(x)dF(x)\right]$$

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 $\Pi_t(x)$ with $q(\theta)\overline{J}_t(x) = q(\theta)\int_{y:x_y<x} J(y)g(y)dy$ in the third line of (22).

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 Limiting job loss after negative productivity shocks

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 imply that policymakers should limit the rate of job loss? While mitigating labor market spillovers is valuable, the jobs that are destroyed are relatively less productive than the ones that survive. Retaining these workers limits labor reallocation, which can generate the dispersion in the marginal product of labor across firms (Hopenhayn and Rogerson, 1993). Assessing the value of these job transfers relies on understanding whether it would be better to mitigate spillovers or facilitate reallocation during recessions.

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 limiting job loss. We consider an exercise in which a policymaker can directly influence the separation rate of low productivity jobs. We then consider the counterfactual output effects of setting policy to keep the unemployment rate constant, given the realization of a perfect foresight "MIT" shock to aggregate productivity. We make three remarks on the counterfactual exercise we consider.

First, adjusting the low-productivity separation rate is not equivalent to solve for the optimal job-retention subsidy. In particular, assumptions on the financing, eligibility, and targeting are important in setting the optimal employment subsidy. These subsidies can influence additional channels, including job creation, inefficient separations, and the fiscal externality of unemployment insurance, which are beyond the scope of the current paper.

Second, we set the primal instrument to maximize an ad hoc objective function (the unemployment gap relative to steady state) that differs from welfare. Since we solve for transition dynamics in the first-order linearization of the quantitative model, the model does not capture second-order nonlinearities that may limit the effectiveness of the nonparametric instrument in reducing output. Instead, our policy exercise shows the consequences of limiting congestion that results from a rise in unemployment.

Third, additional workers that are "retained" as a result of reducing the low-productivity separation rate may extend beyond those that endogenously separate. Following a productivity shock, unemployment can increase due to both a reduction in outflows (from lower job creation) as well as an increase in inflows. The policy we consider aims to neutralize both of these margins. In doing so, we are implicitly allow the policymaker to reduce separations *below* the steady state level to keep unemployment unchanged.

7.2.1 Aggregate shock

We consider an aggregate shock to the growth rate of job productivity, μ_x, which reduces aggregate output through a lower mass of highly productive jobs in the future. We consider an autoregressive aggregate shock of the form: $d\mu_x(t) = e^{-\rho_\mu t} d\mu_x(0)$. We set the persistence such that the $d\mu_x(t)$ is 5% its impact value after 3 years. We then set $\mu_x(0)$ to a target 3% decline in net output in the first year following the shock. Appendix Figure A.9a plots the drift rate in the first 12 years.

7.2.2 Separation response

We consider the separation from low productivity job: $S_t(y) = s_t \cdot \left(1 - R(x_y)\right)^k$, where $R(\cdot)$ is the rank of job productivity between 0 ($\underline{x}$) and 1 ($\overline{x}$) and $\overline{s} := 0$ in steady state. The shape parameter

k controls the loading of the separation shock on low productivity jobs: higher values of k means that the separation policy loads more on low-productivity firms. We present results for a moderately large $k = 4$, which leads to significant loading and lower-productivity jobs. We then solve for the path separation adjustments $\{s_t\}_{t \geq 0}$ that minimizes deviations of the unemployment rate from steady state,

$$\mathcal{L} = \frac{1}{2} \int_{t=0}^{\infty} e^{-\rho t} \left(u(t) - \overline{u}\right)^2 \tag{23}$$

where $u(t)$ is the unemployment following the aggregate shock to productivity and separations. Because $\mathcal{L}$ is quadratic, the discretized version of (23) admits a closed-form solution, $s^*(t)$, in the linearized version of the economy (McKay and Wolf, 2023).[59]

7.2.3 Transition dynamics

Figure 8 presents the transition dynamics following the aggregate shock. In panel (a), we plot the unemployment rate following the exogenous productivity shock in both the case without policy (No policy) and under the unemployment-stabilizing policy path (Policy, no congestion). In our calibrated model, the aggregate productivity shock leads to an approximate 0.5 percentage point increase in the peak unemployment rate. When we set the low-productivity separations to minimize (23), the unemployment rate is kept at its steady state value. Panel (b) shows the policy path, $s^*(t)$, that minimizes $\mathcal{L}$. To counteract the rise in unemployment, the policy path leads to a pro-cyclical decline in the separation rate of low-productivity jobs that matches the counterfactual rise in unemployment.

Panel (c) shows the deviation of expected output for both the labor market without policy intervention and the labor market without congestion effects. Reducing low-productivity separations reduces the loss at the trough of the output. As a result, output recovers more quickly than the case without policy. Reducing the low-productivity separation rate reduces the net-present-value of output loss by 10% compared to the case without policy.

The output effects we capture have two components. The first component comprises of the general equilibrium effects of lowering the separation rate, which is the sum of the spillovers on worker earnings and firm profits discussed in Section 7.1. The second component features the partial equilibrium effect: as some jobs on the margin are weakly positive surplus, reducing their separation rate directly boosts output. Implicit in this channel is the fact that there are gains from the planner preventing bilaterally inefficient separations. While not formally estimated, the presence of bilaterally inefficient separations may result from the fact that the substantial negative spillovers of job destruction lower the marginal productivity threshold $x^*(h)$, which helps counteract the rise in separations. To match the fluctuations in job destruction we observe in the data, it is therefore likely that some of fraction of separations that occur during recessions may be bilaterally inefficient. The presence of such separations would be consistent with countercyclical innovations in the separation rate from the aggregate time series (Mercan et al., 2024).

[59] We provide details of the solution in Appendix E.7.

The reduced output loss suggests the congestion effects from job destruction outweigh the benefits of reallocation through unemployment. Panel (d) helps characterizes this difference by comparing the aggregate cost of vacancy posting between the shocked labor market and the one with the counterfactual policy response. In the absence of changes in the aggregate search effort, a negative productivity shock reduces aggregate vacancy creation. However, when the unemployment rate fluctuates, we see that firms post more vacancies during the recovery than they would during steady state. Due to the convex costs of vacancy posting (ξ), this increased hiring is insufficient to offset the rise unemployment, leading to a decline in market tightness (Appendix Figure A.9).

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 countercyclicality of the costs of job loss. The strength of spillovers suggests a motive to slow down the rate of job destruction during recessions. As a result, the estimates of worker costs we provide can help inform the design of effective fiscal policy measures that mitigate household exposure to 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 change the optimal mix of fiscal policy between unemployment insurance expansions and job support programs during recessions. The relative value of these two types of policies may depend on the effectiveness of employment subsidies in preventing layoffs during recessions, which has been the subject of recent work but not formally examined in this paper (Autor et al., 2022). Second, it is important to better document the firm response to 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).

References

Abadie, Alberto and Guido W. Imbens, "Large Sample Properties of Matching Estimators for Average Treatment Effects," *Econometrica*, 2006, *74* (1), 235–267. 79

Abowd, John M., Francis Kramarz, and David N. Margolis, "High wage workers and high wage firms," *Econometrica*, 1999, *67* (2), 251–333. 22

_ , _ , and Sébastien Roux, "Wages, Mobility and Firm Performance: Advantages and Insights from Using Matched Worker–Firm Data," *The Economic Journal*, 2006, *116* (512), F245–F285. 10

Abraham, Katharine G. and Susan N. Houseman, "Short-time compensation as a tool to mitigate job loss? Evidence on the U.S. Experience during the recent recession," *Industrial Relations*, 2014, *53* (4), 543–567. 7

Acemoglu, Daron and Pascual Restrepo, "Robots and Jobs: Evidence from US Labor Markets," *Jounal of Political Economy*, 2020. 6

Achdou, Yves, Jiequn Han, Jean-Michel Lasry, Pierre-Louis Lions, and Benjamin Moll, "Income and Wealth Distribution in Macroeconomics: A Continuous-Time Approach," *The Review of Economic Studies*, 2022, *89* (1), 45–86. 34, 94

Audoly, Richard, "Firm Dynamics and Random Search over the Business Cycle," *Working Paper*, 2023, pp. 1–51. 5

Autor, David, David Cho, Leland Crane, Mita Goldar, Lutz Byron, Joshua Montes, William Peterman, David Ratner, Daniel Villar Vallenas, and Ahu Yildirmaz, "The $800 Billion Paycheck Protection Program: Where Did the Money Go and Why Did It Go There?," 2022. 39

Autor, David H., David Dorn, and Gordon H. Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168. 9

_ , _ , _ , and Jae Song, "Trade Adjustment: Worker-Level Evidence," *The Quarterly Journal of Economics*, 09 2014, *129* (4), 1799–1860. 6

Bailey, Keith A. and James R. Spletzer, "A New Way to Impute Multiple Jobholding in the US Economy," *CES Working Paper Series*, 2020, (20-26). 76

Barlevy, Gadi, "The sullying effect of recessions," *Review of Economic Studies*, 2002, *69* (1), 65–96. 28

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis, "COVID-19 Is also a reallocation shock," *SSRN Working paper*, 2020. 7

Beraja, Martin and Nathan Zorzi, "Inefficient Automation," *The Review of Economic Studies*, 02 2024, p. rdae019. 6

Bertheau, Antoine, Edoardo Maria Acabbi, Cristina Barceló, Andreas Gulyas, Stefano Lombardi, and Raffaele Saggio, "The Unequal Consequences of Job Loss across Countries," *American Economic Review: Insights*, September 2023, *5* (3), 393–408. 6

Bilal, Adrien, "The geography of unemployment," *Quarterly Journal of Economics*, 2022. 28

_ , "Solving Heterogeneous Agent Models with the Master Equation," *Working paper*, 2023, pp. 1–59. 5, 34, 84, 92, 93, 94, 95

— **and Esteban Rossi-Hansberg**, "Anticipating Climate Change Across the United States," 2023. 96

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry, "Really Uncertain Business Cycles," *Econometrica*, 2018, *86* (3), 1031–1065. 6

Boeri, Tito and Herbert Bruecker, "Short-time work benefits revisited: Some lessons from the Great Recession," *Economic Policy*, 2011, *26* (68), 697–765. 7

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-Share Research Designs," *The Review of Economic Studies*, 06 2022, *89* (1), 181–213. 3, 13, 14

Bradbury, James, Roy Frostig, Peter Hawkins, Matthew James Johnson, Chris Leary, Dougal Maclaurin, George Necula, Adam Paszke, Jake VanderPlas, Skye Wanderman-Milne, and Qiao Zhang, "JAX: composable transformations of Python+NumPy programs," 2018. 95

Burdett, Kenneth, Carlos Carrillo-Tudela, and Melvyn Coles, "The Cost of Job Loss," *Review of Economic Studies*, 2020, *87* (4), 1757–1798. 6

Caballero, Ricardo J. and Mohamad L. Hammour, "The Cleansing Effect of Recessions," *American Economic Review*, 1994, *84* (5), 1350–1368. 7

Cahuc, Pierre, Fabien Postel-vinay, and Jean marc Robin, "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, 2006, *74* (2), 323–364. 27, 29, 84

— **, Francis Kramarz, and Sandra Nevoux**, "The Heterogeneous Impact of Short-Time Work: From Saved Jobs to Windfall Effects," *IZA Discussion Paper*, 2021, (14381). 7

Cattaneo, Matias D., Richard K. Crump, Max H. Farrell, and Yingjie Feng, "On Binscatter," *American Economic Review*, May 2024, *114* (5), 1488–1514. 15

Chodorow-Reich, Gabriel, "Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?," *American Economic Journal: Economic Policy*, 2019, *11* (2), 1–34. 14, 24

— **and Johannes Wieland**, "Secular Labor Reallocation and Business Cycles," *Journal of Political Economy*, 2020, *128* (6), 2245–2287. 7

— **and Loukas Karabarbounis**, "The Cyclicality of the Opportunity Cost of Employment," *Journal of Political Economy*, 2016, *124* (6), 1563–1618. 33

— **, Plamen Nenov, and Alp Simsek**, "Stock Market Wealth and the Real Economy: A Local Labor Market Approach," *American Economic Review*, 2021, *111* (5), 1613–1657. 21

Coles, Melvyn G. and Ali Moghaddasi Kelishomi, "Do job destruction shocks matter in the theory of unemployment?," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 118–36. 2, 6

Crépon, Bruno, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora, "Do labor market policies have displacement effects? Evidence from a clustered randomized experiment," *Quarterly Journal of Economics*, 2013. 7

Crouzet, Nicolas and Neil R. Mehrotra, "Small and Large Firms over the Business Cycle," *American Economic Review*, 2020, *110* (11), 3549–3601. 15

Davis, Steven and John Haltwanger, "Gross Job Creation , Gross Job Destruction , and Employment Reallocation," *Quarterly Journal of Economics*, 1992, *107* (3), 819–863. 2, 6, 11, 77

Davis, Steven J. and Till von Wachter, "Recessions and the costs of job loss," *Brookings Papers on Economic Activity*, 2011, (2), 1–72. 2, 6, 16, 19, 78

_ , R. Jason Faberman, and John Haltiwanger, "Labor Market Flows in the Cross Section and Over Time," *Journal of Monetary Economics*, 2012, *59* (1), 1–18. 11

Elsby, Michael W. L., Ryan Michaels, and Gary Solon, "The Ins and Outs of Cyclical Unemployment," *American Economic Journal: Macroeconomics*, January 2009, *1* (1), 84–110. 6

Engbom, Niklas, "Contagious Unemployment," 2021. 6, 28, 33

Flaaen, Aaron, Matthew D. Shapiro, and Isaac Sorkin, "Reconsidering the consequences of worker displacements: Firm versus worker perspective," *American Economic Journal: Macroeconomics*, 2019, *11* (2), 193–227. 4, 16, 78, 79

Fujita, Shigeru and Garey Ramey, "Job matching and propagation," *Journal of Economic Dynamics and Control*, 2007, *31* (11), 3671–3698. 2, 6

_ and Giuseppe Moscarini, "Recall and unemployment," *American Economic Review*, 2017, *107* (12), 3875–3916. 79

Gabaix, Xavier and Ralph S. J. Koijen, "Granular Instrumental Variables," *SSRN Electronic Journal*, 2019. 20

Gathmann, Christina, Ines Helm, and Uta Schönberg, "Spillover Effects of Mass Layoffs," *Journal of the European Economic Association*, 2020, *18* (1), 427–468. 6

Gertler, Mark and Simon Gilchrist, "Monetary policy, business cycles, and the behavior of small manufacturing firms," *Quarterly Journal of Economics*, 1994, *109* (2), 309–340. 15

Giroud, Xavier and Holger M. Mueller, "Firms Internal Networks and Local Economic Shocks," *American Economic Review*, 2019, *109* (10), 3617–3649. 13

Giupponi, Giulia and Camille Landais, "Subsidizing Labour Hoarding in Recessions: The Employment and Welfare Effects of Short-time Work," *The Review of Economic Studies*, 12 2022, *90* (4), 1963–2005. 7

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen, "Do Credit Market Shocks Affect the Real Economy? Quasi-experimental Evidence from the Great Recession and "Normal" Economic Times," *American Economic Journal: Economic Policy*, February 2020, *12* (1), 200–225. 15

Hall, Robert E. and Marianna Kudlyak, "Why Has the US Economy Recovered So Consistently from Every Recession in the Past 70 Years?," *NBER Macroeconomics Annual 2021*, 2021, pp. 01–48. 6

Haltiwanger, John C, Henry R Hyatt, Erika McEntarfer, and Matthew Staiger, "Cyclical Worker Flows: Cleansing vs. Sullying," *NBER Working Paper*, 2021, (28802). 6

Haltiwanger, John C., Henry R. Hyatt, Lisa B. Kahn, and Erika McEntarfer, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85. 6

Hazell, Jonathon, Christina Patterson, Heather Sarsons, and Bledi Taska, "National Wage Setting," 2021, (November). 13

Hershbein, Brad and Lisa Kahn, "Do Recessions Accelerate Routine-Biased Technological Change ? Evidence from Vacancy Postings," *American Economic Review*, 2018, *108* (7). 7, 39

Hopenhayn, Hugo and Richard Rogerson, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, 1993, *101* (5), 915–938. 37, 100

Huckfeldt, Christopher, "Understanding the Scarring Effect of Recessions," *American Economic Review*, April 2022, *112* (4), 1273–1310. 6

Ilut, Cosmin, Matthias Kehrig, and Martin Schneider, "Slow to Hire, Quick to Fire: Employment Dynamics with Asymmetric Responses to News," *Journal of Political Economy*, 2018, *126* (5), 2011–2071. 7

Imbens, Guido W., "Matching Methods in Practice: Three Examples," *The Journal of Human Resources*, 2015, *50* (2), 373–419. 79

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan, "Earnings Losses of Displaced Workers," *The American Economic Review*, 1993, *83* (4), 685–709. 4

_ , _ , and _ , "Earnings Losses of Displaced Workers," *American Economic Revie*, 1993, *83* (4), 685–709. 6

Jarosch, Gregor, "Searching for Job Security and the Consequences of Job Loss," *Econometrica*, 2023, *91* (3), 903–942. 5, 6, 19, 27, 33, 34

Johnson, Steven G., "The NLopt nonlinear-optimization package," 2007. 97

Johnston, Andrew C. and Alexandre Mas, "Potential unemployment insurance duration and labor supply: The individual and market-level response to a benefit cut," *Journal of Political Economy*, 2018, *126* (6), 2480–2522. 7

Koenders, Kathryn and Richard Rogerson, "Organizational dynamics over the business cycle: a view on jobless recoveries," *Review*, 2005, *87* (Jul), 555–580. 30

Kopp, Daniel and Michael Siegenthaler, "Short-Time Work and Unemployment in and after the Great Recession," *Journal of the European Economic Association*, 01 2021, *19* (4), 2283–2321. 7

Kroft, Kory, Fabian Lange, and Matthew J. Notowidigdo, "Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment," *The Quarterly Journal of Economics*, 2013, *128* (3), 1123–1167. 19

Krolikowski, Pawel, "Job Ladders and Earnings of Displaced Workers," *American Economic Journal: Macroeconomics*, April 2017, *9* (2), 1–31. 5, 6, 27

Lachowska, Marta, Alexandre Mas, and Stephen A. Woodbury, "Sources of Displaced Workers' Long-Term Earnings Losses," *American Economic Review*, October 2020, *110* (10), 3231–66. 6

Lalive, Rafael, Camille Landais, and Josef Zweimüller, "Market Externalities of Large Unemployment Insurance Extension Programs," *American Economic Review*, 2018, *105* (12), 3564–3596. 7

Landais, Camille, Pascal Michaillat, and Emmanuel Saez, "A macroeconomic approach to optimal unemployment insurance: Applications," *American Economic Journal: Economic Policy*, 2018, *10* (2), 182–216. 7

_ , _ , and _ , "A macroeconomic approach to optimal unemployment insurance: Theory," *American Economic Journal: Economic Policy*, 2018, *10* (2), 152–181. 7

Lehr, Nils Haakon and Pascual Restrepo, "Optimal Gradualism," December 2022, (30755). 6

Marinescu, Ioana, "The general equilibrium impacts of unemployment insurance: Evidence from a large online job board," *Journal of Public Economics*, 2017, *150*, 14–29. 7

McKay, Alisdair and Christian K Wolf, "Optimal Policy Rules in HANK," 2023. 38

Mercan, Yusuf and Benjamin Schoefer, "Jobs and Matches: Quits, Replacement Hiring, and Vacancy Chains," *American Economic Review: Insights*, March 2020, *2* (1), 101–24. 11

_ , _ , and Petr Sedláček, "A Congestion Theory of Unemployment Fluctuations," *American Economic Journal: Macroeconomics*, January 2024, *16* (1), 238–85. 2, 6, 38

Mian, Atif and Amir Sufi, "What Explains the 2007-2009 Drop in Employment?," *Econometrica*, 2014, *82* (6), 2197–2223. 21

Mortensen, Dale T. and Christopher A. Pissarides, "Job creation and job destruction in the theory of unemployment," *Review of Economic Studies*, 1994, *61* (3), 397–415. 5, 6, 7, 27

Moscarini, Giuseppe and Fabien Postel-Vinay, "On the Job Search and Business Cycles," *SSRN Electronic Journal*, 2021, pp. 0–54. 33, 55

Nakamura, Emi and Jón Steinsson, "Fiscal Stimulus in a Monetary Union: Evidence from US Regions," *American Economic Review*, 2014, *104* (3), 753–792. 21

Pierce, Justin R., Peter K. Schott, and Cristina Tello-Trillo, "To Find Relative Earnings Gains After the China Shock, Look Upstream and Outside Manufacturing," Technical Report, NBER Working Paper 2024. Accessed: 2024-10-30. 6

Postel-Vinay, Fabien and Hélène Turon, "On-the-job search, productivity shocks, and the individual earnings process," *International Economic Review*, 2010, *51* (3), 599–629. 29

Restrepo, Pascual, "Skill Mismatch and Structural Unemployment," *Working Paper*, 2015. 6

Rowan, Thomas Harvey, "Functional stability analysis of numerical algorithms." PhD dissertation, Department of Computer Science, University of Texas at Austin, Austin, TX 1990. 97

Schmieder, Johannes F., Till von Wachter, and Jörg Heining, "The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany," *American Economic Review*, May 2023, *113* (5), 1208–54. 6, 22

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 2005, *95* (25-49). 33

_ , "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 2012, *15* (2), 127–148. 4, 6, 16

Stokey, Nancy L., *The Economics of Inaction: Stochastic Control Models with Fixed Costs*, Princeton, NJ: Princeton University Press, 2009. 86

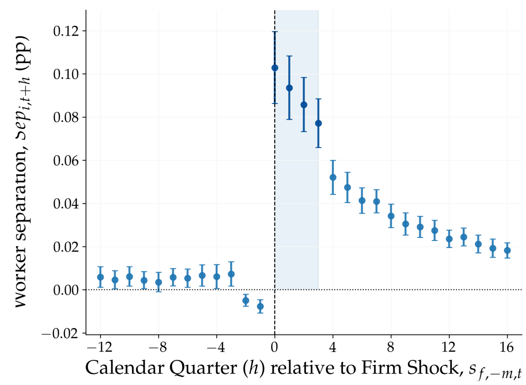
von Wachter, Till, "Lost Generations: Long-Term Effects of the COVID-19 Crisis on Job Losers and Labour Market Entrants, and Options for Policy*," *Fiscal Studies*, 2020, *41* (3), 549–590. 7

_ , "The Persistent Effects of Initial Labor Market Conditions for Young Adults and Their Sources," *Journal of Economic Perspectives*, November 2020, *34* (4), 168–94. 17

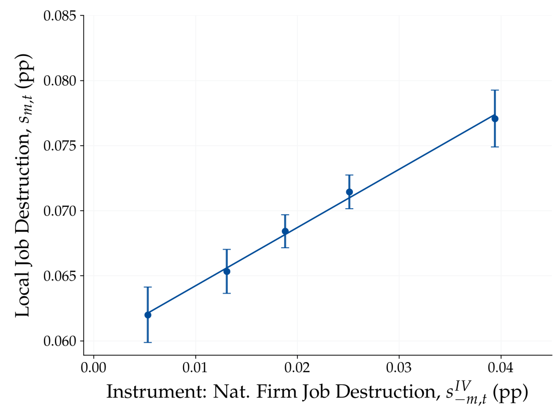
Figures and Tables

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

(a) Worker separation at shocked firms



(b) Market-level job destruction

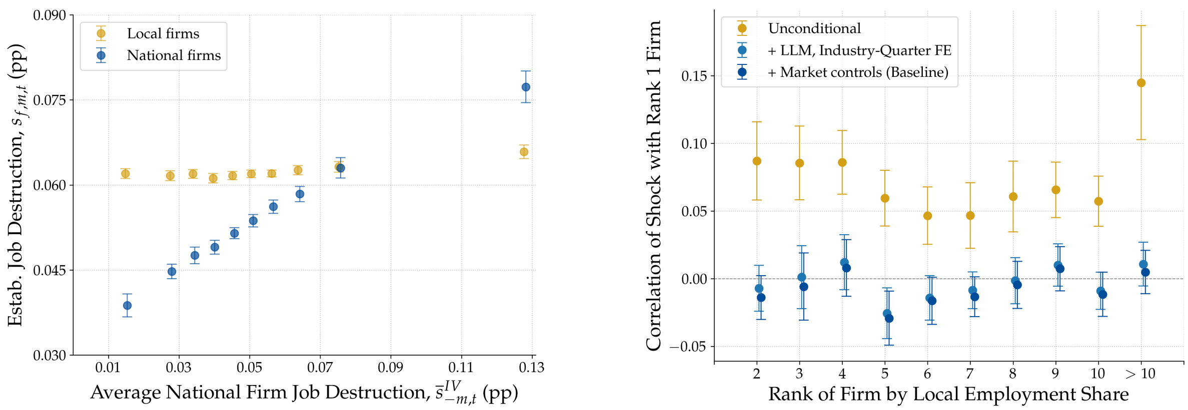


Notes: This figure displays the relationship between national firm and local job destruction. Panel 1a plots coefficients from estimating $S_{i,t+h} = \beta s_{f(i),-m(i),t} + \phi_m + \Gamma_1^{(h)} \mathbf{X}_{i,t}^W + \Gamma_2^{(h)} \mathbf{X}_{m,t}^M + \epsilon_{i,t+h}$ for $h = -12, \ldots, 16$ 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 $s_{m,t} = \sum_{k=1}^{5} \beta^k Q_k(s_{mt}^{IV}) + \phi_m + \mathbf{X}_{-i,m,t}^M + \epsilon_{i,t}$, where $Q_k(s_{mt}^{IV})$ 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 (8) 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.

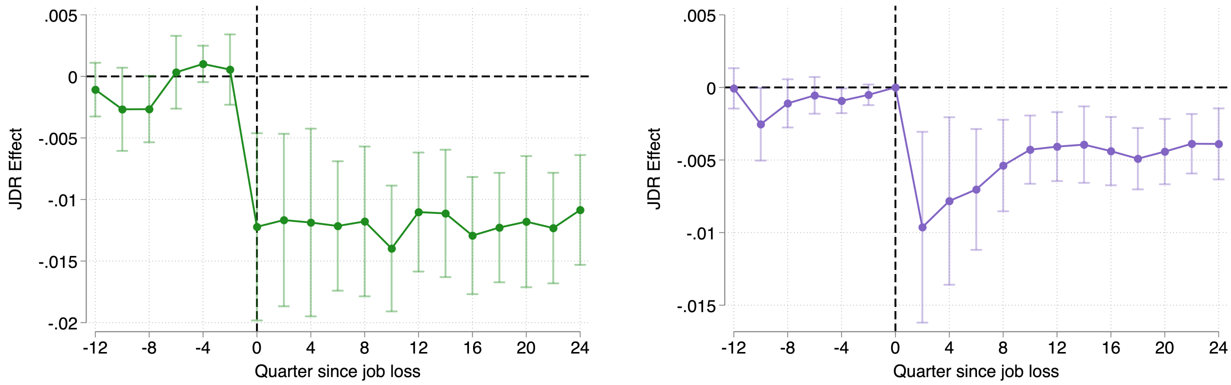
(a) Between local and national firms

(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 (10), 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 $\hat{\beta}^{(R)}$ (11) 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 of job losers



(a) Earnings

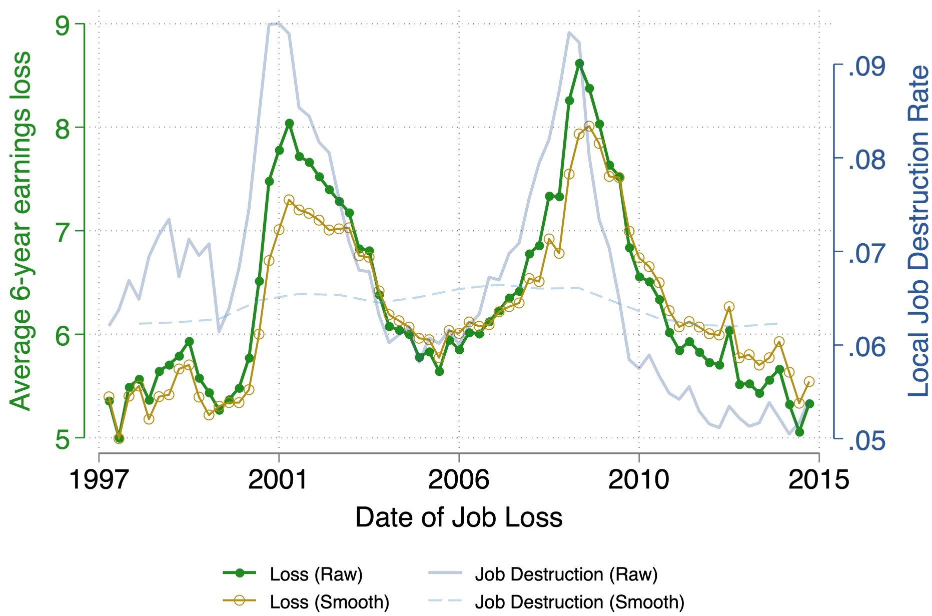
(b) Employment

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 ($\hat{\beta}_{JL}^{(h)}$) and job stayer ($\hat{\beta}_{JS}^{(h)}$) from (7) under our baseline specification, reproduced below:

$$y_{i,t+h} = \beta_k^{(h)} s_{-i,m,t} + \phi_m + \Gamma_1^{(h)} \mathbf{X}_{i,t}^W + \Gamma_2^{(h)} \mathbf{X}_{-i,m,t}^M + \epsilon_{i,t+h}$$

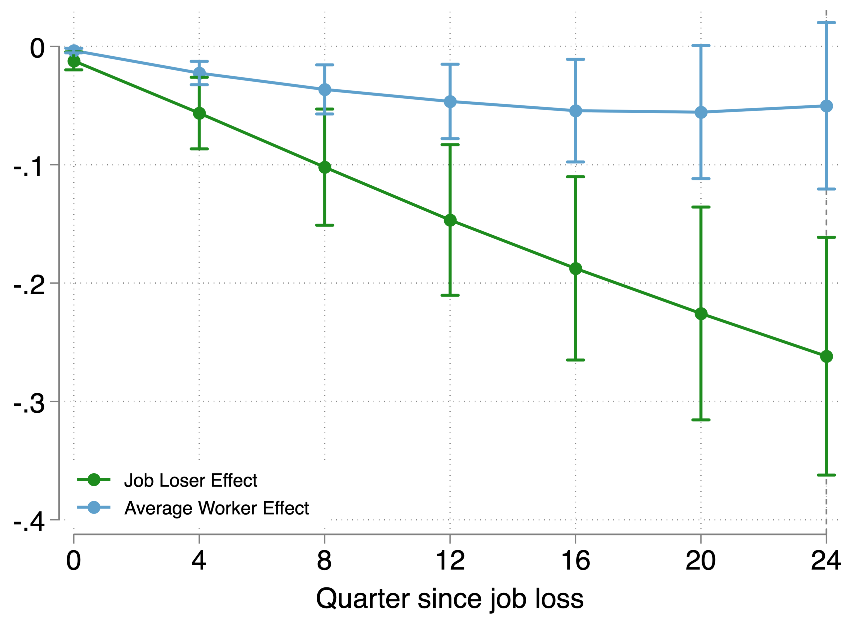
for $k = JL, KS$, h is the quarter relative to the job loss event (t). Coefficients estimates are scaled to reflect a 1 pp increase in the local job destruction rate, $s_{-i,m,t}$. Panel (a) shows estimates when $y_{i,t+h}$ is the worker's average earnings in the adjacent quarters $t+h-1$ and $t+h$, 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 C.5. The vector X_{mt}^M 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 $s_{-f,mt}^{IV}$, the shift-share job creation instrument (from quarters $t-8$ to t) given by (D.1.1), 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 ϕ_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



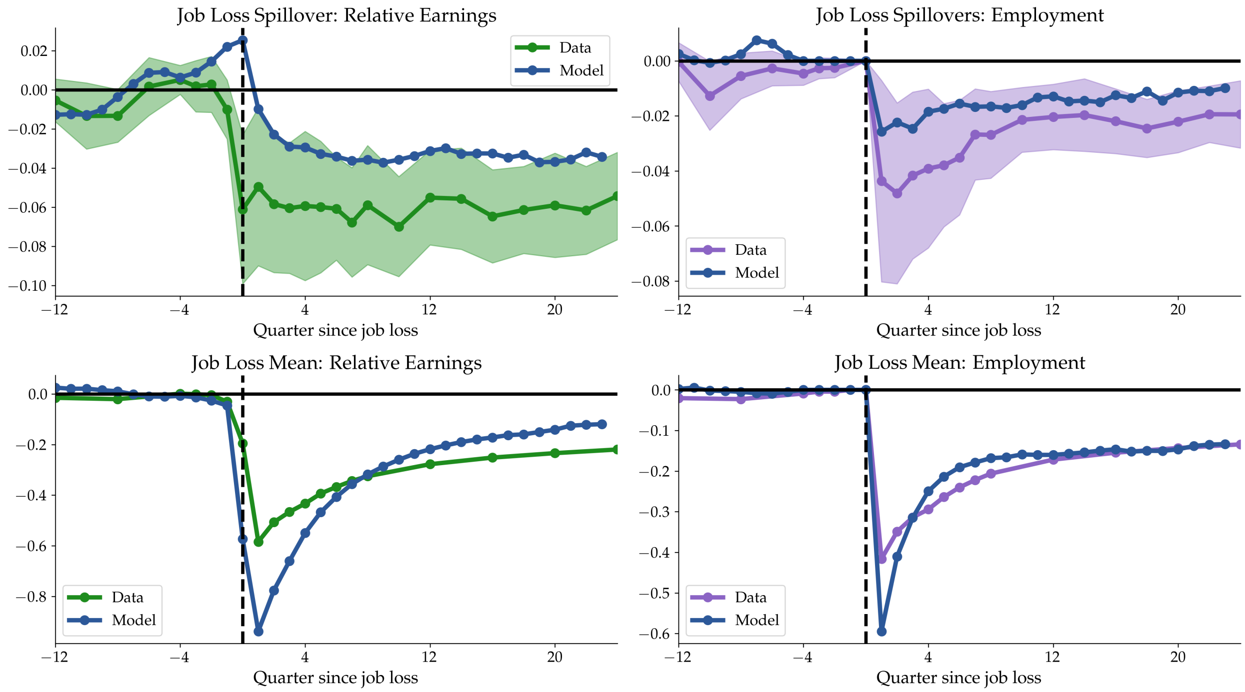
Notes: This figure shows the aggregate means of the cost of job loss and job destruction rates for each quarter in our sample. The green-closed circle line,$\text{Loss}_{i,t}^{(Est)}$, is the NPV of the difference between the average six-year earnings of job losers and matched control sample. The yellow-open circle line is this variable under the counterfactual of a constant local job destruction rate, $\text{Loss}_{i,t}^{(Smooth)}$, defined in (12). 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 earnings effect of job destruction shock, job loss vs. average employer worker.



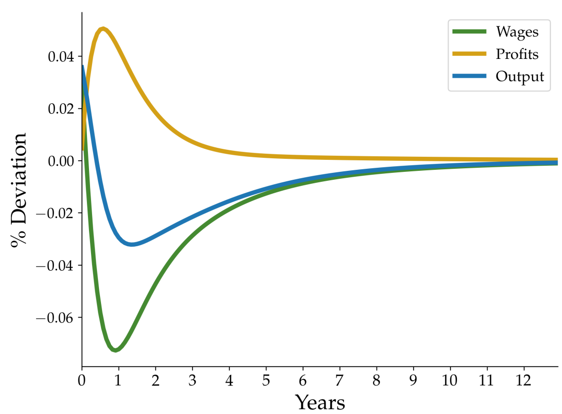
Notes: This figures plots estimates of the cumulated earnings spillovers for the average worker and job loser. The average worker effect (blue) consists of coefficients $\beta^{(h)}$ from the two-stage least-square estimation of (7), using national firm job destruction as the excluded instrument and 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 controls 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.

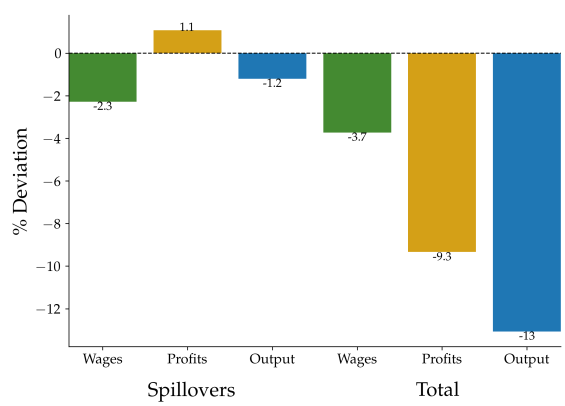


Notes: Estimates correspond to the respond of earnings and employment from a 3 percentage point increase in the job destruction rate. Model-based measures of relative earnings are constructed in the same manner as the empirical measurements using simulated earnings data at the quarterly for 100,000 workers.

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



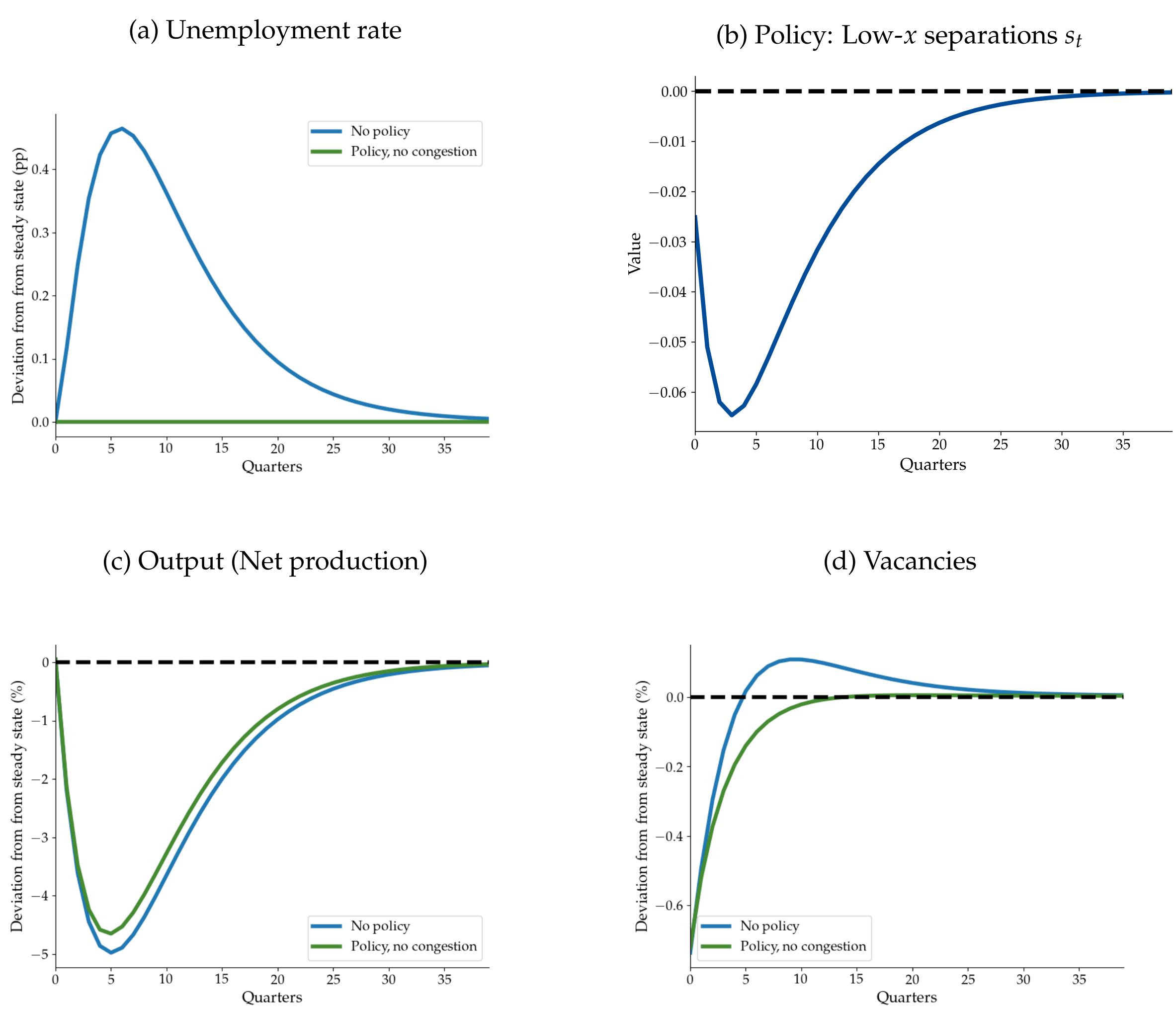
(a) Welfare decomposition of Job destruction shock



(b) Net production

Notes: This plots shows the simulated effects of a 1 percentage 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.

Figure 8: The first-order effects of a negative aggregate productivity shock.



(a) Unemployment rate

(b) Policy: Low-x separations s_t

(c) Output (Net production)

(d) Vacancies

Notes: These figures show the response of equilibrium variables following a negative aggregate productivity shock. The no policy line refers to the first-order transition dynamics around the steady-state equilibrium, following a negative shock to the job productivity growth rate calibrated to last 3 years and reduces net output by 3% in the first year. See Section 7.2 for details.

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 (7):

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

where $\widehat{s}_{-f,mt}$ is the predicted value from the first-stage regression (8), 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			
ρ	Discount Rate	0.00407	Annual Interest Rate	-	0.05	-
ω	Matching Elasticity	0.5			-	Moscarini and Postel-Vinay (2021)
κ_u	Labor force exit	0.00245		-	-	
κ_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
δ	Exogenous Job Destruction	0.0147	EU rate	0.025	0.0148	CPS
ϕ	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
β	Wage Bargaining	0.533	Job loss effect: Earnings when employed	0.142	0.162	LEHD
μ_x	Log Productivity Drift (-)	0.039	Job loss effect: Earnings	6.55	7.77	LEHD
σ	Log Productivity Volatility	0.166	Job loss effect: Employment	4.8	4.58	LEHD
(a^{β}, b^{β})	Beta Distribution	(32.6,26.8)	Wage Dispersion (P50/P10, P90/P50)	(0.5,0.52)	(0.42,0.354)	LEHD
ψ_e	HC: job experience	0.205	Annual wage growth	1.02	1	LEHD
ψ_u	HC: scarring (-)	0.221	Spillover effect: Earnings	0.707	0.713	LEHD
ξ	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).

Appendices

A Additional Tables and Figures

Figures

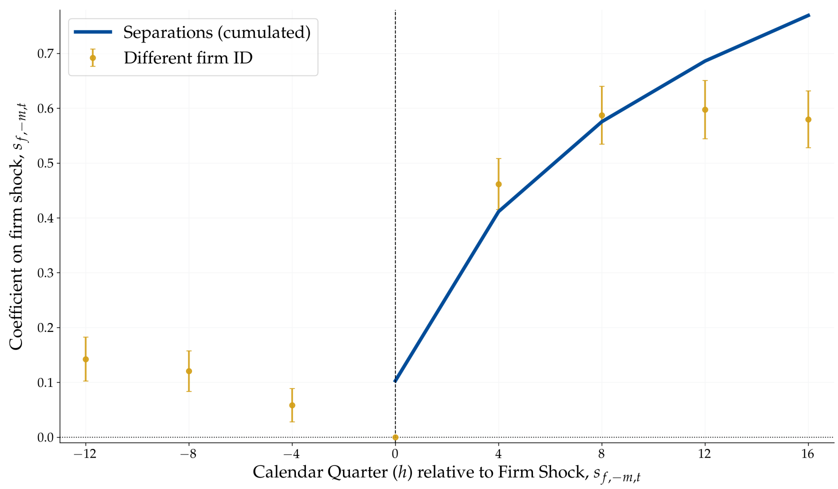


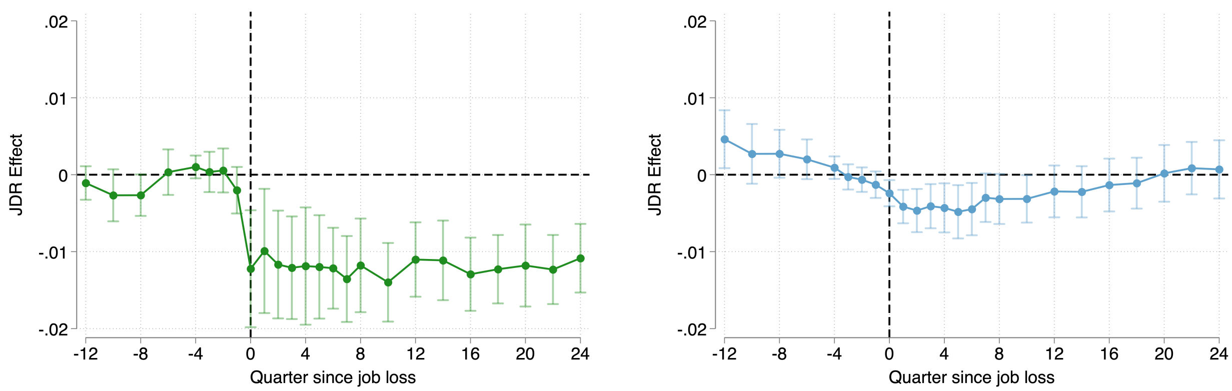
Figure A.1: Cumulated Separations since firm shock

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:

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

$1\{f_t(i) \neq f_{t+h}(i)\}$ 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 A.2: 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

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

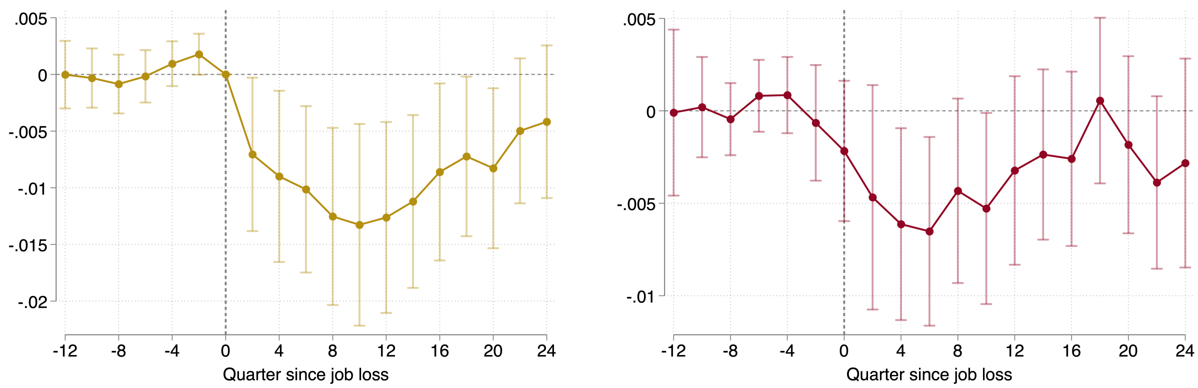
where $\widehat{s}_{-f,mt}$ is the predicted value from the first-stage regression

$$s_{mt} = \alpha^{fs} + \beta^{fs} s_{-f,mt}^{IV} + \Lambda_1 X_{mt}^M + \delta_m + \xi_{imt}$$

The sample is the job stayer sample described in 4.1: workers who do not separate from their job at quarter t. 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 (6), 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 A.3: Changes in firm characteristics following job destruction shock: job losers vs. job stayers

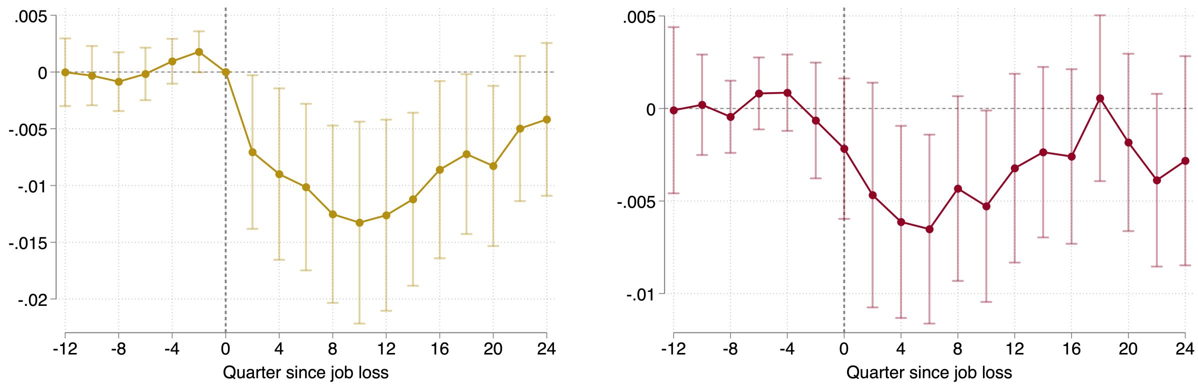
(a) Firm Wage Premium (b) Industry Rank of Revenue Productivity



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 A.3a 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 (7) 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 A.3b 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 A.4: Changes in firm characteristics following job destruction shock: average worker

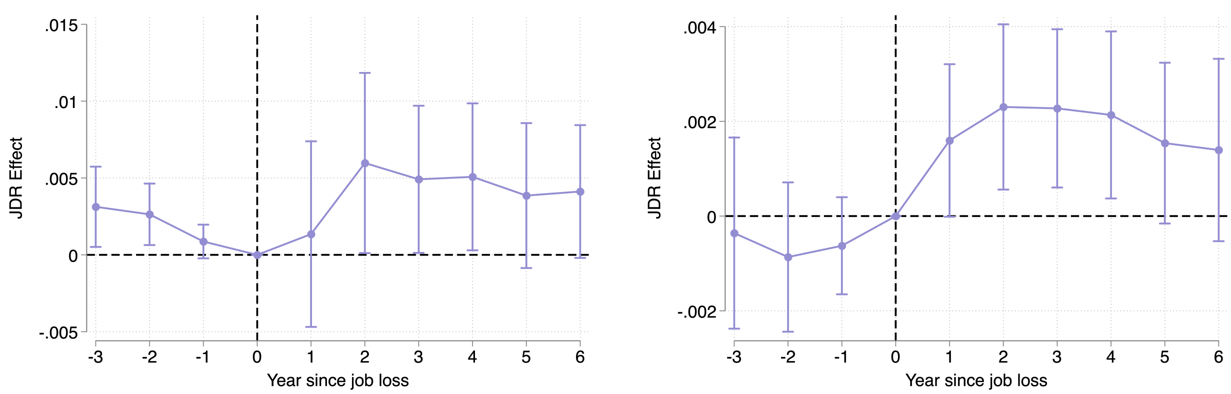
(a) Firm Wage Premium (b) Industry Rank of Revenue Productivity



Notes: This figures shows estimates of the equilibrium effects of job destruction on the firm characteristics for the 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 A.3. 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.

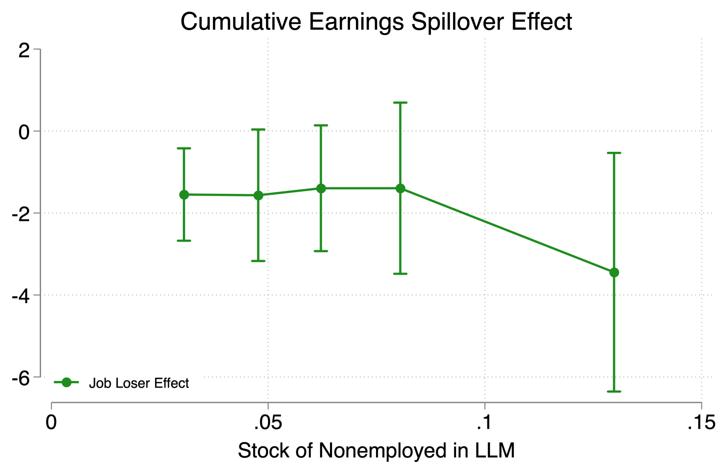
Figure A.5: Changes in local labor market following job destruction shock

(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 A.5a 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 A.5b 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 A.6: 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:

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

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.

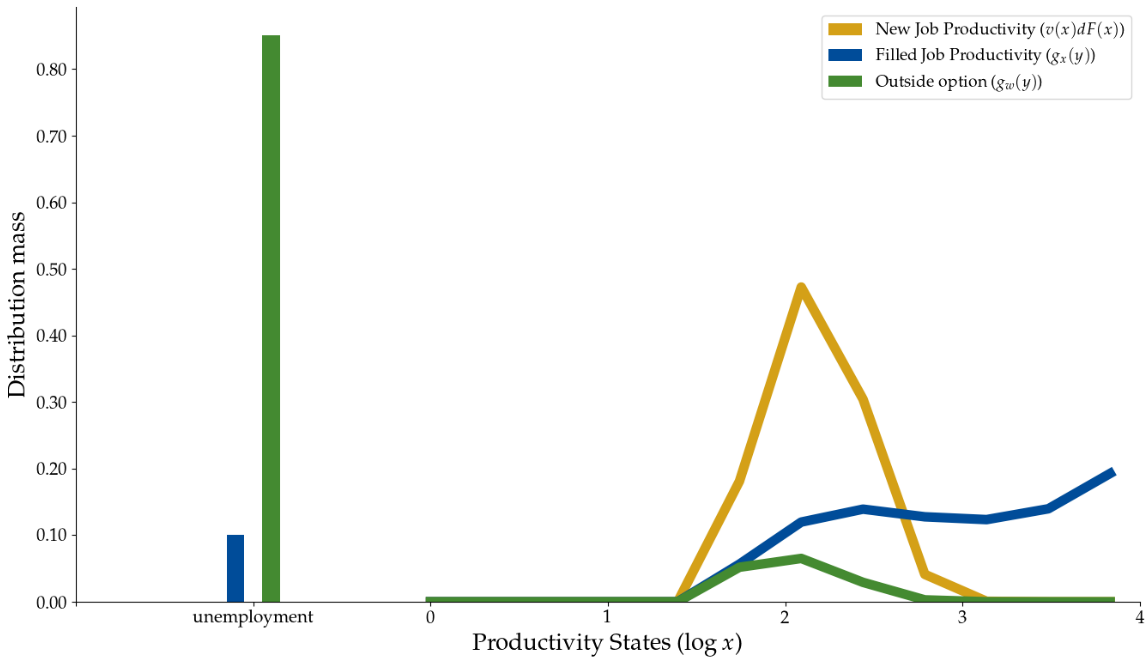


Figure A.7: Worker distribution across productivity states.

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.

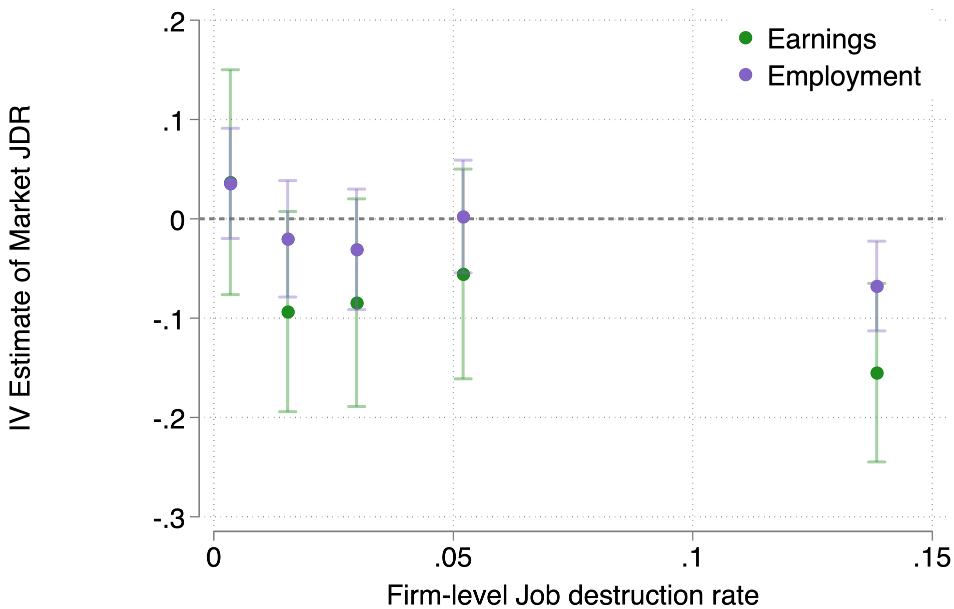


Figure A.8: Effects of market job destruction shock on earnings and employment outcomes of workers, split by job destruction rate of initial job

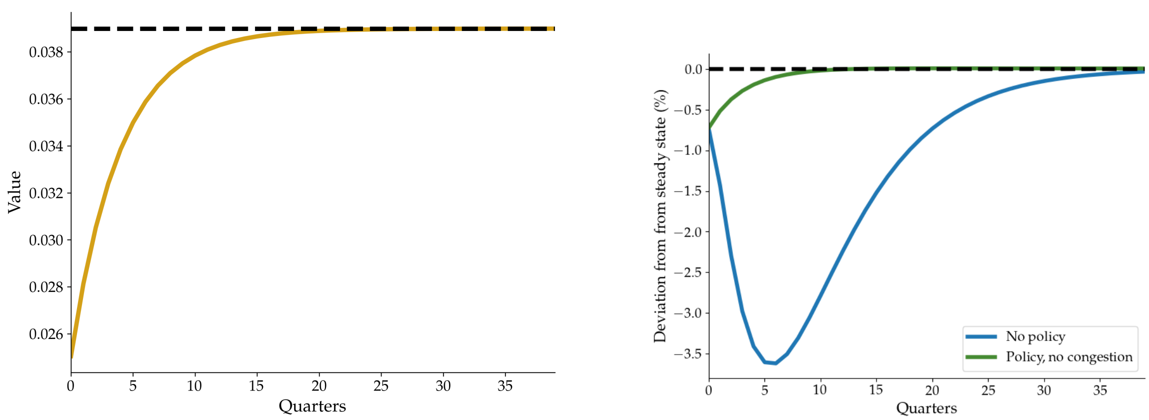
Notes: This figure displays estimates of the coefficient β_j from the following regression

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

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 ϕ_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 A.9: Additional Transition Dynamics: Negative Aggegate Productivity Shock

(a) Aggregate shock ($\mu_x(t)$) (b) Market tightness



Notes: This figure plots additional impulse functions for the primary transition dynamics exercise. See Section 7.2 for details.

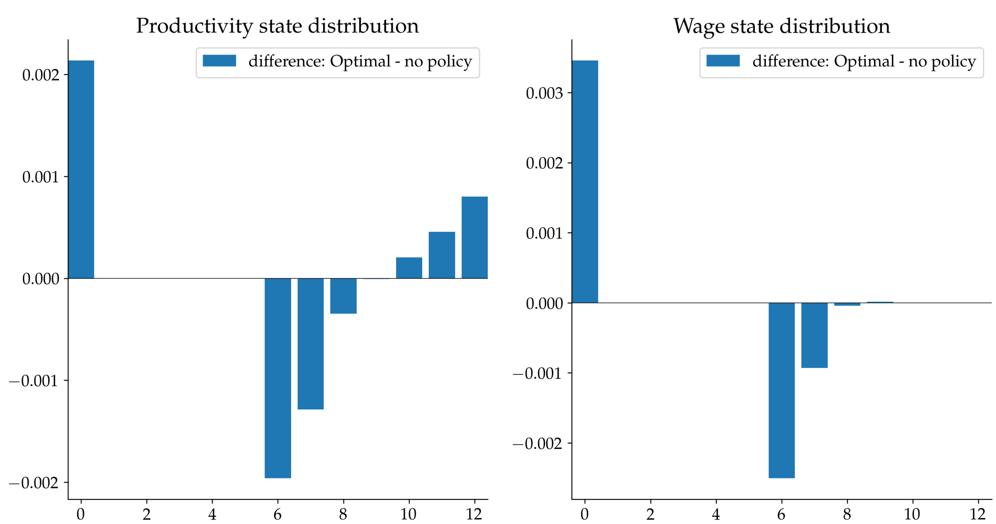


Figure A.10: Changes in the distribution between no policy and steady state τ_0.

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. Section E.8 provides the details of this exercise.

Tables

Table A1: 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:

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

where ψ_{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 ψ_{ft} and ϕ_{mt}, respectively. Column (4) reports the covariance between ψ_{ft} and ϕ_{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 (4); "Job Creation Rate" is the sum of positive employment growth for the establishment defined in (33); "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 A2: 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 A3: 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 (12) 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 A4: 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:

$$y_i = \gamma s^{IV}_{-i,m,t} + \phi_m + \Gamma \mathbf{X}^{M}_{-i,m,t} + \epsilon_{i,t+h} \tag{26}$$

where $\mathbf{X}^{M}_{-i.m,t}$ are the set of worker-firm-adjusted market-level controls and ϕ_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 (26), 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.

B Theory

B.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 (7). 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:

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

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 η_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 η_i, we assume that p_i is independent across establishments. The firm-level shocks take the form:

$$q_f = u_f + a_f' z$$

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.[60] The market-level shocks are similarly given by:

$$r_m = v_m + b_m' z$$

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:

$$y_i = \beta s_{m(i)}^{(M)} + \Gamma_y' \mathbf{x}_i + \gamma^{(p)} p_i + \gamma^{(f)} q_{f(i)} + \gamma^{(m)} r_{m(i)} + \epsilon_i,$$

where $s_{m(i)}^{(M)}$ is the market-level job destruction rate (s_{mt} in the main text), and β captures the spillover effects of job destruction. Unobserved productivity shocks $\left\{p_i, q_{f(i)}, r_{m(i)}\right\}$ can impact

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

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., ξ_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:

$$s = \Gamma_s' \mathbf{X} + \alpha^{(i)} p + \alpha^{(f)} Oq + \alpha^{(m)} Lr + \eta \tag{27}$$

$$y = \beta s^{(M)} + \Gamma_y' \mathbf{X} + \gamma^{(p)} p + \gamma^{(f)} Oq + \gamma^{(m)} Lr + \epsilon \tag{28}$$

$$q = u + A'z$$

$$r = v + B'z$$

In what follows, we use Ω 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 $N^{(M)} = L'n$.[61] We define the market shares of each establishment as Λ^M, where $\Lambda_{im}^M = \frac{n_i}{N_{m(i)}^M}$. We similarly define Λ^F to be the matrix containing the share of firm employment at each establishment, i.e. $\Lambda_{if}^F = \frac{n_i}{N_{f(i)}^F}$.

Recall that the national firm job destruction rate, leaving out market m, is $s_{f,-m} = \sum_{i:f(i)=f, i\neq i'} \frac{n_i}{N_{m(i)}^M - N_{i'}} s_i$ 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 $\widetilde{\Lambda}^F$:

$$\widetilde{\Lambda}^F = D_{-e}^F \left(O \Lambda^{F\prime} - D_e^F \right) \tag{29}$$

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

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, δ as:

$$\delta := \widetilde{\Lambda}^F s \tag{30}$$

Due to the leave-out correction, δ 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 $\widetilde{\Lambda}^M$:

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

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

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 B.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: $E\left[s_{f,-m,t} \middle| \{\phi_m\}, \{\lambda_{kt}\} \mathbf{X}_{mt}\right] = \mu c_{f,t}$ *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:*

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

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

To prove Proposition B.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*

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

where $\widetilde{\omega}_{\cdot}$ 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:

$$\begin{aligned} Cov[x, T(x)] = E[x'T(x)] &= E\left[x_i \sum_{\substack{j:\, m(i)=m(j),\\ f(i)\neq f(j)}} \widetilde{\omega}_k^M \sum_{\substack{k:\, m(j)\neq m(k),\\ f(j)=f(k)}} \widetilde{\omega}_k^F x_k \right] \\ &= \sum_{\substack{j:\, m(i)=m(j),\\ f(i)\neq f(j)}} \widetilde{\omega}_k^M \sum_{\substack{k:\, m(j)\neq m(k),\\ f(j)=f(k)}} \widetilde{\omega}_k^F E\left[x_i x_k\right] \end{aligned} \tag{31}$$

1. $E[p_i p_k] \neq 0$ if and only if $i = k$. However, inspecting the summation terms (31), 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 (31). 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 (31). 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 (31). 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 (32). Consider the structural equation (28), residualized against observable **X**:

$$y^{\perp} = \beta \widetilde{\Lambda}^M s^{\perp} + \gamma^{(p)} p^{\perp} + \gamma^{(f)} O q^{\perp} + \gamma^{(m)} L r^{\perp} + \epsilon^{\perp}$$

Expanding the covariance of the worker outcome with the instrument:

$$\begin{aligned} Cov(y^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp}) = \beta Cov(\widetilde{\Lambda}^{M}s^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp}) + \gamma^{(p)}Cov(p^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp}) + \gamma^{(f)}Cov(Oq^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp}) \\ + \gamma^{(m)}Cov(Lr^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp}) + Cov(\epsilon^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp}) \end{aligned}$$

We consider each term:

A: $Cov(\widetilde{\Lambda}^{M}s^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp})$ is recovered from the first stage equation (32).

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

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

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

where in the first line we use the definition of the firm shocks (30), we use the specified data-generating process for s in (27), 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:

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

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 $Cov(Oq^{\perp}, \widetilde{\Lambda}^{M}\delta^{\perp})$:

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

where the last line uses Lemma (2).

Combining these terms,

$$Cov(\widetilde{\Lambda}^M y^\perp, \widetilde{\Lambda}^M \delta^\perp) = \beta Cov(\widetilde{\Lambda}^M s^\perp, \widetilde{\Lambda}^M \delta^\perp) \\ + Cov\left[\left(\gamma^{(f)}OA + \gamma^{(m)}LB\right)z^\perp, \widetilde{\Lambda}^M\widetilde{\Lambda}^F\left(\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^\perp\right)\right]$$

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

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

□

B.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 β.

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

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

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:

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

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

$$\begin{aligned} Cov(P_R'\delta^\perp, P_1'\delta^\perp) &= Cov\left[P_R'\widetilde{\Lambda}^F s^\perp, P_1'\widetilde{\Lambda}^{F\prime} s^{\perp\prime}\right] \\ &= Cov\left[P_R'\widetilde{\Lambda}^F\left(\alpha^{(f)}Oq^\perp + \alpha^{(m)}Lr^\perp\right), P_1'\widetilde{\Lambda}^{F\prime}\left(\alpha^{(f)}Oq^\perp + \alpha^{(m)}Lr^\perp\right)\right] \\ &= Cov\left[P_R'\widetilde{\Lambda}^F\left(\alpha^{(f)}Oq^\perp + \alpha^{(m)}Lr^\perp\right), P_1'\widetilde{\Lambda}^{F\prime}\left(\alpha^{(f)}Oq^\perp + \alpha^{(m)}Lr^\perp\right)\right] \\ &= Cov\left[P_R'\widetilde{\Lambda}^F\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^\perp, P_1'\widetilde{\Lambda}^F\left(\left(\alpha^{(f)}OA + \alpha^{(m)}LB\right)z^\perp\right)\right] \\ &+ Cov\left[P_R'\widetilde{\Lambda}^F\alpha^{(m)}Lv, P_1'\widetilde{\Lambda}^F\alpha^{(m)}Lv\right] \end{aligned}$$

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:

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

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:

$$s_L = \psi \cdot \widetilde{\Lambda}^M\delta + \Gamma'_{fs}\widetilde{\Lambda}^M\mathbf{X} + \nu \tag{32}$$

for the set of I_L that have single establishments. Recall that, under (29), $\delta_f = 0$ for these sets of firms and so $\widetilde{\Lambda}^M\delta = \Lambda^M\delta$ in (32). 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 δ are dijoint:

$$\begin{aligned}
Cov(s_L^{\perp},\delta^{\perp}) &= Cov\left(s_L^{\perp},\widetilde{\Lambda}^F s^{\perp}\right)\\
&= Cov\left(\left(\alpha^{(i)}p^{\perp}+\alpha^{(f)}Oq^{\perp}+\alpha^{(m)}Lr^{\perp}+\eta^{\perp}\right),\widetilde{\Lambda}^F\left(\alpha^{(i)}p^{\perp}+\alpha^{(f)}Oq^{\perp}+\alpha^{(m)}Lr^{\perp}+\eta^{\perp}\right)\right)\\
&= Cov\left(\left(\alpha^{(f)}OAz^{\perp}+\alpha^{(m)}LBz\right)_L,\widetilde{\Lambda}^F\left(\alpha^{(f)}OAz^{\perp}+\alpha^{(m)}LBz\right)\right)
\end{aligned}$$

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.

C Data and Measurement

C.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.

C.2 Measuring job flows

C.2.1 Firm and job definitions

Jobs We define a job as a unique relationship between a worker identifier ('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.[62]

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.[63] 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.[64]

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 cross-

[62]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.

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

[64]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,

walk to link individuals to parent firm identifiers from the LBD ('lbdfid'). This is the notion of firm used in the main text.

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).

C.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) 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.[65] These serve as denominator from which we measure job flows.[66] 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 establishment j , we define the cumulated job separation rate s^c_{jq} and hiring

[65]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 Spletzer, 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.

[66]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.

rate h^c_{jq} as

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

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:

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

where we define the job creation rate symmetrically 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. This 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 identifiers (lbdfid) are not fully longitudinal.

C.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;[67] (iv) is not employed in the following industries at t: Agriculture (11) Other Services (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`

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

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.

C.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 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 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.[68]

[68] Note that some theoretical ambiguity in the expected direction of the selection bias. If separations by incumbent

C.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 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 covariates 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.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:

$$U_{m,t} = \sum_{g} \phi_{g,t} u_{g,m,t}$$

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

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., 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.

was last employed and let $\phi_{g,t} \geq 0$ for all workers who were separate from the job at time t.[69] 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:

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

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:

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

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 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.[70]

D Empirical Results: Details and Extensions

D.1 Details on baseline specification

D.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:

$$c_{f,m,t} = \max\left[\frac{\sum_{h=0}^{3}\left(\text{Hire}_{f,m,t+h} - \text{Sep}_{f,m,t+h}\right)}{N_{f,m,t-1}}, 0\right]. \quad (33)$$

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

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

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

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

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:

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

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.

D.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).[71] 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.[72]

[71] Precisely, if β_h is the coefficient estimate from (7) 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 $t+h$).

[72] 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 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,

D.3 Spillover identification

Definition of market-weighted residuals

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

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

Difference between implementation and assumptions for (9) 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.

D.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.[73]. The national firm job destruction rate provides a measure of worker's separation risk that, when leaving out the worker's own LLM and conditional on market-level controls, is not endogenous to the characteristics of either the worker or market conditions.

We estimate the following extension of (7):

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

where $Q_{f(i,t)}^{(j)}$ denotes the quintile of the national separation rate of the worker's firm. By including

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.

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

quintile-specific time-by-sector fixed effects (λ_{jkt}), the coefficients β_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 $Q^{(j)}_{f(i,t)}$ 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, ψ_f, to account for potential sorting of workers across with varying employment dynamism.

Figure A.8 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.

D.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:

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

where Ψ_i indicates the worker fixed effect and Ψ_j indicates the fixed effect of the firm that employs the worker in year y.

E Quantitative Model Details and Estimation

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

E.1 Derivations/Expressions

Notation Let $\partial_q F(q,\cdot) = \frac{\partial F}{\partial q}(q,\cdot)$ generically denote the partial derivative of a function with respect to some variable q. We use $\mathbb{D}_d(\cdot)$ to denotes the Dirac measure at d. Unless otherwise noted, we use $y = (h, x, r) \in \mathcal{Y}$ to refer to the idiosyncratic states of workers, where $\mathcal{Y} := \left[\underline{h}, \overline{h}\right] \times \mathcal{X} \times \mathcal{X}$.[74] We also define the set of employed worker states for some human capital level h as $\mathcal{Y}_E(h) := \left\{y \in \mathcal{Y} : x_y \neq b, h_y = h\right\}$ Following Bilal (2023), we define the worker distribution with respect to base measure $\eta(y) := \eta((h, x, r))$ as the product of marginal measures, with mass points located at states of unemployment and the boundary points of each state:

$$d\eta(y) := \left(dh + \mathbb{D}_{\underline{h}} + \mathbb{D}_{\overline{h}}\right) \otimes \left(dx + \mathbb{D}_b + \mathbb{D}_{\underline{x}} + \mathbb{D}_{\overline{x}}\right) \otimes \left(dr + \mathbb{D}_b + \mathbb{D}_{\underline{x}} + \mathbb{D}_{\overline{x}}\right)$$

where $\otimes$ denotes the tensor product of measures,and b is an index denotes the unemployed state and which we set to $b < \underline{x}$ and r share the same domain $\mathcal{X} = \{b\} \cup [\underline{x}, \overline{x}]$.[75] The index for unemployment, b, should not be confused with the flow value of unemployment.

Productivity diffusion Denote the infetesimal generator associated with the productivity diffusion process x_t in (14) as $\mathcal{M}_x(y)[\cdot]$, which encodes the expectations of changes to a function over the internal $[t, t + dt)$. We define the diffusion generator for some value function V as

$$\mathcal{M}_x(y)[V] = \partial_x V(y)\mu(x) + \frac{\sigma^2(x)}{2}\partial_{xx}V(y) \tag{34}$$

Similarly, define the generator for human capital $\mathcal{M}_h(y)[\cdot]$ such that:

$$\mathcal{M}_h(y)[V] = \begin{cases} -\psi_u(h)\partial_h V(y), & \text{if } x = b \text{ (unemployed)} \\ \psi_e(h)\partial_h V(y), & \text{if } x \neq b \text{ (employed)} \end{cases}$$

where $\psi_u(h)$ and $\psi_e(h)$ are the drift rates of human capital in unemployment and employment respectively.

E.1.1 Incorporating mutual consent

As job productivity evolves stochastically it is possible that, at a given wage $w_t(y)$ negotiated according to Cahuc et al. (2006), the surplus share of the firm falls below their outside option of zero. To maintain bilateral efficiency, we therefore extend the bargaining mechanism to allow for renegotiation under mutual consent. We do so by allowing firms to renegotiate a wage such that their surplus share is equal to zero. As a result, the worker resets their outside option r to be equal to the current value of productivity. An implication of this form renegotiation that

[74] Recall from Section 6.1 that $\mathcal{X} = [\underline{x}, \overline{x}] \cup \{b\}$.

[75] Note that the distribution of vacancies does not contain any mass points. We therefore use $dH_t(\cdot)$ as the distribution, which implicitly uses dx as the base measure.

the worker's outside option is never greater than the job productivity. Formally, we define the diffusion generator for the outside option as in (17).

Importantly, the outside option diffusion is only active if productivity is equal to the outside option *and* the diffusion will enter negative firm-surplus space ($dx < 0$). In this case, the worker's outside option moves lock-step with productivity, as guaranteed by the fact that the diffusion is the same as that (14) including the identical Wiener process, $\mathcal{W}_x$. We therefore define $\mathcal{M}_r(y)[\cdot]$ as the generator of the diffusion corresponding to (17).

E.1.2 Firm/Worker HJB equations

$$\rho W_t(y) = w(y) + \mathcal{M}_x(y)[W_t] + \mathcal{M}_h(y)[W_t] - \kappa W_t(y) - \delta\left(W_t(y) - U_t(h)\right) + \frac{\mathbb{E}_t\left[d_t W_t(y)\right]}{dt} \tag{35}$$
$$+\phi f(\theta)\left[\int_r^x \left(W((h,x,x')) - W(y)\right) dH_t(x') + \int_x^{\overline{x}} \left(W((h,x',x)) - W(y)\right) dH_t(x')\right]$$

subject to

$W_t(y) \geq U_t(h)$ (Individual rationality)

where $w(y)$ is the wage defined by (16) and we use the notation $y = (h, x, r)$. The first line includes state transitions unrelated to job-finding, including time-dependent changes to the worker value $\frac{\mathbb{E}_t[d_t W_t(y)]}{dt}$. The second line are changes to the value function as a result of contact with new jobs, with occurs at Poisson rate $\phi f(\theta)$. Jobs of productivity x' that are between worker's outside option and current firm productivity $r \leq x' < x$ lead to bargaining, while jobs of productivity $x' \geq x$ lead to the worker quitting and starting the new job.[76]

The unemployed worker's HJB equation is similarly:

$$\rho U_t(h) = b(h) + \mathcal{M}_h(y)[U_t] - (\kappa + \kappa_u)U_t(h) + \frac{\mathbb{E}_t\left[d_t U_t(h)\right]}{dt}$$
$$+ f(\theta)\int_{x^*(h)}^{\overline{x}} \left(W((h,x,b)) - U_t(h)\right) dH_t(x)$$

where unemployed workers are allowed to have a different labor market exit rate and accept offers from jobs with PDV that is greater than their separation threshold $x^*(h)$.[77]

[76] Under the wage mechanism, contact from new jobs of productivity $x \leq r$ are ignored by the worker.

[77] By definition, these are the set of jobs that are more valuable than unemployment. Firms of jobs $x \leq x^*(h)$ cannot commit to an individually rational wage offer that would be accepted by the worker.

Similarly, the firm HJB equation is:[78]

$$\rho J_t(y) = p(h,x,z) - w(y) + \mathcal{M}_x(y)[J_t] + \mathcal{M}_r(y)[J_t] + \mathcal{M}_h(y)[J_t] - (\kappa+\delta)\, J_t(y) + \frac{\mathbb{E}_t\left[d_t J_t(y)\right]}{dt} \tag{36}$$
$$+\phi f(\theta)\left[\int_r^x \left(J(y) - J((h,x,x'))\right) dH_t(x')\right] - \phi f(\theta)(1-H_t(x))J(h,x,x')$$

subject to

$J_t(y) \geq 0$ (Individual rationality).

Incumbent firms whose workers are poached get zero-normalized scrap value if their worker separates in either of the four ways (quit, endogenous layoff, exogenous separation, or retirement). Workers that bargain up their wages lower the firm's surplus (second line of 36).[79]

From (36), we can derive the expected value of firms that post new jobs, $J_t^N(x)$:

$$J_t^N(x) = \int_{\underline{h}}^{\overline{h}} \int_{x' \in \{b\} \cup [\underline{x}, x]} \int_{x \in \mathcal{X}} J_t((h,x,x')) d\eta((h,x',r)) \tag{37}$$

We first show that the value function of a given employment state is not dependent on the on the outside option of the worker, $r \in \mathcal{X}$. For conciseness, we assume that the value functions reflect is ex post of the decision to remain in the match.

E.1.3 Surplus independence of rent division

In describing the wage-bargaining mechanism (16), we express the production value (V) and surplus (S) of solely in terms of the productivity components of the worker's state, (h,x). We present the formal derivation below.

Lemma 3. *The production value $V(y) = J(y) + W(y)$ and surplus $S(y) = V(y) - U(h)$ of a worker in state $y := (h,x,r)$ are independent of the outside option r.*

Proof. First, add (35) and (36) and use the definition $S(y) = J(y) + W(y) - U(h)$ to write:

$$\rho V(y) = p(h,x,z) + \mathcal{M}_x(y)[V] + \mathcal{M}_h(y)[V] + \mathcal{M}_r(y)[V] - \kappa V(y) - \delta\left(V(y) - U(h)\right) + \frac{\mathbb{E}_t\left[d_t V(y)\right]}{dt} \tag{38}$$
$$+\phi f(\theta)\int_r^x \left(V((h,x,x')) - V(y)\right) dH_t(x') + \phi f(\theta)\int_x^{\overline{x}} \left(W((h,x',x)) - V(y)\right) dH_t(x')$$

[78]In sequential, the firm value of job y is given by:

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

where the profits $\pi(y_s) := p(x(y_s), z_s) - w(y_s)$ is the flow production net of worker wages and $\overline{J}_{t+T(y_t)}(y_{T(y_t)})$ is a potential transfer to the firm at the end of the job's duration, $y_{T(y_t)}$, where $T(y_t)$ is the duration of the match conditional on the worker's state. Note that the match duration is itself a stochastic variable and reflects the "optimal stopping" of the job as a result hitting the lower boundary or poaching by other firms. See of state y_t. See Stokey (2009) for details.

[79]Note that $J_t(y) = 0$ for $y \in \mathcal{Y} - \mathcal{Y}_E$.

Subtracting $U_t(h)$ from both sides and using $\mathcal{M}_x(y)[U] = 0$:

$$\begin{aligned}\rho S(y) &= p(h,x,z) - b(h) + \mathcal{M}_x(y)[S] + \mathcal{M}_h(y)[S] - (\kappa+\delta)S + \frac{\mathbb{E}_t\left[d_t S(y)\right]}{dt} \\ &\mathcal{M}_r(y)[S] + (S(h,x,b) - S(h,r,b))(1-\beta) + \phi\beta f(\theta)\int_r^x \left(S((h,x,x')) - S((h,x,r))\right) dH_t(x') \\ &+ \phi f(\theta)\beta \int_x^{\overline{x}} \left(S(h,x',b) - S(h,x,b)\right) dH_t(x') - f(\theta)\beta\int_{x^*(h)}^{\overline{x}} S(h,x,b)dH_t(x) \\ &+ (\Psi_u(h)[U] - \Psi_e(h)[U] - \kappa_u U_t(h))\end{aligned} \tag{39}$$

where we substitute (16) in the third line, include $U_t(h) - U_t(h)$ in the integral terms, and use the fact that $S((h,b,b)) = 0$.[80] We conjecture that the suplus does not depend on the outside option. Under this assumption, then the second line (39) is zero. Next note that the first line does not depend directly on the outside option r and the fourth line is only a function of $U_t(h)$. Finally, under the assumption that the surplus is independence of division rents, then the third line does not depend on r. As a result, it is confirmed that the right hand side of the surplus is independent of the outside option r, and we re-express the surplus as:

$$\begin{aligned}\rho S((h,x)) &= p(h,x,z) - b(h) + \mathcal{M}_x((h,x))[S] + \mathcal{M}_h((h,x))[S] - (\kappa+\delta)S + \frac{\mathbb{E}_t\left[d_t S((h,x))\right]}{dt} \\ &+ \phi f(\theta)\beta\int_x^{\overline{x}} \left(S(h,x') - S(h,x)\right) dH_t(x') - f(\theta)\beta\int_{x^*(h)}^{\overline{x}} S(h,x'')dH_t(x'') \\ &+ (\Psi_u(h)[U] - \Psi_e(h)[U] - \kappa_u U_t(h))\end{aligned} \tag{40}$$

This automatically implies that $V_t((h,x,r))$ is independent of r as $V_t((h,x)) = S_t((h,x)) + U_t(h)$. Under bilateral efficiency of the wage bargaining, we combine the individual rationality conditions to obtain:

$$V_t(h,x) \geq U_t(h)$$

□

E.1.4 Monotonicity of value functions

Next, we confirm that the value functions are monotonic in the productivity state x, which allows us to define the separation contour $x^*(h)$

Lemma 4. *The production value function $V(h,x)$ is monotonic in x for all h.*

Proof. Suppose not: there exists some (h,x) such that $\partial_x V(h,x) = \partial_x S(h,x) < 0$. Then, using (40) and considering the first-order terms, we get the following expression after rearranging terms:

$$(\beta\phi f(\theta)\mathcal{P}_A(x) + \rho + \kappa + \delta)\partial_x S((h,x)) = \partial_x p(h,x,z)$$

[80] Note also that $W((h,x',x)) - W(y) = (S(h,x,b) - S(h,r,b))(1-\beta) + \beta(S(h,x',b) - S(h,x,b))$.

where $\mathcal{P}_A(x) := \int_{x'} 1\{S(h,x') \geq S(h,x)\} \, dH_t(x)$ is the measure of new jobs that a worker with state (h,x) would accept. expected surplus gain from accepting new jobs, with $(Y)_+ := \max[Y,0]$. On the right-hand side, the first term $\partial_x p(h,x,z)$ by definition of the production function $p(h,\cdot,z)$, which contradicts $S_x(h,x) < 0$ as $\beta\phi f(\theta)\mathcal{P}_A(x) + \rho + \kappa + \delta > 0$.

□

An implications of the monotonicity of the value functions is that we can conveniently define the separation contour $x^*(h)$, which is used in equilibrium definition (Proposition 6.1).

Corollary E.0.1. *For every $h \in [\underline{h}, \overline{h}]$, there exists a unique $x^*(h)$ such that $V(h, x^*(h)) = U(h)$.*

E.2 Proof of Proposition 6.1

Proof. We proceed in two parts. First, we show that the HJB and KF equations defined in Proposition 6.1 describe the worker distribution and values of all agent states. Second, we show that all other endogenous variables can be treated as static conditional on $\{V(\cdot), g(\cdot)\}$.

HJB equation. From (38), we use Lemma 3 to re-express the second line as:

$$
\begin{aligned}
\rho V_t(h_y, x_y) = {} & p(h_y, x_y, z) + \mathcal{M}_x(h_y, x_y)[V] + \mathcal{M}_h(h_y, x_y)[V] - \kappa V_t(h_y, x_y) \\
& - \delta\left(V_t(h_y, x_y) - U_t(h)\right) + \frac{\mathbb{E}_t\left[d_t V(h_y, x_y)\right]}{dt} \\
& + \phi f(\theta)\beta \int_x^{\overline{x}} \left(V_t((h, x')) - V_t(h, x)\right) dH_t(x')
\end{aligned}
\tag{41}
$$

where (41) coincides with (19). Next, we also subsitute out the worker value functions in the unemployment HJB to obtain:

$$
\begin{aligned}
\rho U_t(h) = {} & b(h) + \mathcal{M}_h^{(u)}(y)[U_t] - (\kappa + \kappa_u)U_t(h) + \frac{\mathbb{E}_t\left[d_t U_t(h)\right]}{dt} \\
& + f(\theta)\beta \int_{x^*(h)}^{\overline{x}} \left(V((h,x)) - U_t(h)\right) dH_t(x)
\end{aligned}
$$

which coincides with the value of unemployment in (19). Finally, the boundary condition $V_t(h,x) = U_t(h)$ is a direct result of combining the bilateral efficiency of separations with Corollary E.0.1.

KF equation. Next consider the law of motion for workers. We first consider employment dynamics. Workers in employed state y exogenously separate at rate δ and exit the labor market at rate κ. In addition, they meet new jobs at rate $\phi f(\theta)$. As a worker would only accept a job if its production value is greater than its current job, the probability of accepting a job is $1 - H_t(x_y)$, where x_y is the productivity corresponding to employment state y. Next, consider inflows to

y, $\mathcal{IN}(y)$ which can come from hiring or wage adjustments (e.g., bargaining). The inflows into $y = (h_y, x_y, r_y)$ are given by:

$$\mathcal{IN}(y) = \begin{cases} q(\theta_t)\phi \cdot dH_t(r) \int_{y' \in \mathcal{Y}} 1\left\{h_{y'} = h_y, x'_{y'} = x_y, r_{y'} \le r_y\right\} g_t(y')\, d\eta(y') \\ \quad +dH_t(x) \int_{y' \in \mathcal{Y}} 1\left\{h_{y'} = h_y, x'_{y'} = r_y\right\} g_t(y')\, d\eta(y'), & \text{if } r_y > b, \\ \\ dH_t(x) q(\theta_t) u_t(h), & \text{if } r_y = b. \end{cases}$$

where $u_t(h) = g_t((h, b, b))d\eta(y)$ is mass of workers of human capital h in unemployment to denote the total search effort among workers with human capital h. For jobs where the outside option is not unemployment ($r_y \neq b$), then inflows consist of two terms. The first term captures the mass workers flowing into y as a result of bargaining without quits. For workers at job productivity x_y with outside options lower than r_y, meeting a firm posting jobs productivity r_y allows them to increase their threatpoint during bargaining. This is scaled by the frequency of job-r_y contacts, which is $q(\theta_t)dH_t(r_y)$. The second term captures the mass of workers who flow into y due to hiring. Firms already at jobs with productivity r_y will quit when they meet a job-x_y vacancy, which occurs with rate $q(\theta_t)dH_t(x_y)$. States where the outside option is unemployment can only hire workers out of unemployment.

Next, we consider movements in productivity. Define $\mathcal{M}^*_x(y)[\cdot]$ to be the adjoint operator of $\mathcal{M}_x(y)[\cdot]$ defined in (34) with respect to the base measure $\eta(x)$. Similarly, define $\mathcal{M}^*_h(y)[\cdot]$ to be the adjoint operator of the human capital diffusion $\mathcal{M}^*_h(y)[\cdot]$ and $\mathcal{M}^*_r(y)[\cdot]$ to be the adjoint of $\mathcal{M}^*_r(y)[\cdot]$. Combining these terms yields the following KF equation for unemployed workers on the interior of the distribution:

$$-\frac{dg_t(y)}{dt} = -(\delta + \kappa + \phi f(\theta)(1 - H_t(x_y)))g_t(y) + \mathcal{M}^*_x(y)[g_t] + \mathcal{M}^*_h(y)[g_t] \\ + \mathcal{IN}(y) + \mathcal{M}^*_r(y)[g_t], \quad \text{for } \{y \in Y_E\}$$

Unemployment dynamics are characterized by worker separations as well as a re-injection of workers from labor market exit. Let us define $g_t^{(h)} = \int_{y:h_y=h} g_t(y)d\eta(y)$ as the distribution of workers with human capital h. The KF equation for unemployed workers is:

$$\partial_t u_t(h) = (\delta + \kappa)\left(g_t^{(h)} - u_t(h)\right) - f(\theta_t)u_t(h) + \frac{\sigma(x^*_t(h))^2}{2}\partial_x g_t(y^*_t(h)) - \mathcal{M}^*_x(y^*_t(h))[g_t]$$

where $y^*_t(h) = (h, x^*_t(h), x^*_t(h))$ is the employment state corresponding to the separation threshold for h. The first term captures unemployment inflows arising from exogenous separation shocks or re-injection of workers from labor market exit. Workers leave unemployment if they find a job at rate $f(\theta_t)$. Similar to employed workers, human capital also involves during unemployment but according to a different diffusion process. Finally, the fourth term captures the inflow of workers due to endogenous separations at the separation boundary, which corresponds to the mass of workers that leave the non-separated employment states at time t.[81]

Finally, we describe the boundary conditions implied by the model. From endogenous separations we have no mass below the separation contour:

$$g_t(y) = 0, \quad \text{for } \{y \in \mathcal{Y}_E : \underline{x} \le x_y \le x_t^*(h)\}$$

Due to renegotiation under mutual consent, we similarly have that workers cannot have outside options greater than their current job productivity:

$$g_t(y) = 0, \quad \text{for } \{y \in \mathcal{Y} : r_y > x_y\}$$

This concludes the first part of the derivation.

Sufficiency. Next, we show that all other endogenous variables can be treated as static functions only of $\{U_t(\cdot), V_t(\cdot), g_t(\cdot)\}$ for fixed t. First, we obtain $x_t(\cdot)$ immediately from its (18). Next, the firm and worker value functions are immediately given by the wage bargaining equation (16) for $W_t(\cdot)$, and for $J_t(\cdot)$:

$$J_t(y) = V_t(h(y), x(y)) - W_t(y) - U_t(h(y)).$$

for all $y \in \mathcal{Y}_E$. As a result, the expected value of a new job, $J^N(x)$ in (37), is also determined. For every new job of productivity x, vacancies $v_t(x)$ are determined such that:

$$\mathcal{C}_t'(v_t(x)) \ge q(\theta) J_t^N(x) \tag{42}$$

which holds with equality for $v_t(x) > 0$. Define the implied solution to (42) as $v_t(x;\theta)$. Similarly, define aggregate recruiting intensity as $\nu_t(\theta) := \int_x v_t(x) dF(x)$. Aggregate search effort is obtained immediately from knowledge of the worker distribution:

$$e_t = \phi \int_{y \in \mathcal{Y}_E} g_t(y) d\eta(y) + \int_{y \in \mathcal{Y} \mathcal{Y}_\mathcal{E}} g_t(y) d\eta(y)$$

The relationship for tightness is:

$$\theta_t = \frac{\nu_t(\theta_t)}{e_t}$$

Conditional the value functionals and distribution, this is equation is one unknown and implicitly defines θ. Since θ is a function of $\{U_t(\cdot), V_t(\cdot), g_t(\cdot)\}$, $v_t(x)$ in (42) is as well, along with $dH_t(x) := v_t(x) dF(x)$. □

[81] Note that there is zero mass at the separation boundary, $g(y_t^*(h)) = 0$.

E.3 The Master equation

We state the Master Equation corresponding to the quantitative model in Section 6. Relative to the equilibrium described in Propoisition 6.1, we make two modifications for conciseness. First, we express the value function $V_t(\cdot)$ over the worker state space (including unemployment), by defining $V_t(y) := V_t(h_y, x_y)$ if the worker is employed and ($x_y \neq b$), and $V_t(y) = U_t(h)$ if the worker is unemployed.[82] Second, we replace the boundary condition governing endogenous separations with a Poisson process that depends on the difference between the value at y and unemployment $S(U_t(h_y) - V_t(y))$, where $S(\cdot)$ is a logistic function scaled to ensure separation with high probability if $V_t(y) < U_t(h)$.[83] To compress notation, we define the generator $\mathcal{A}[\cdot]$ as encoding the conditional expectations of the HJB equations. We therefore express (19-6) in the shortened form:

$$\rho V_t(y) = p(h_y, x_y) + \mathcal{A}(y)[V] + \frac{E_t[dV_t(y)]}{dt}, \tag{43}$$

where $\mathcal{A}(y)[V] =$

$$\begin{cases} \mathcal{M}_x(x_y)[V] + \mathcal{M}_h^{(e)}(h_y)[V] - \left(\delta + S(U_t(h_y) - V_t(h_y))\right)\left(V_t(y) - U_t(h_y)\right) - \kappa V_t(y) \\ \quad +\phi f(\theta)\beta \int_{x_y}^{\overline{x}} \left(V_t(h_y, x') - V_t(y)\right) dH_t(x'), \text{if employed} \\ \mathcal{M}_h^{(u)}(h_y)[V] - (\kappa + \kappa_u)V_t(y) + f(\theta)\beta \int_{x^*(h_y)}^{\overline{x}} \left(V_t(h_y, x') - V_t(y)\right) dH_t(x'), \text{if unemployed} \end{cases}$$

Similarly, we define $\mathcal{B}[\cdot]$ to be the operator encoding the law of motion from the KF equations (7-20), which lets us write:[84]

$$\frac{dg_t(y)}{dt} = \mathcal{B}(y)[g_t] \tag{44}$$

Importantly, $\mathcal{B}$ is not the adjoint of $\mathcal{A}$ due to the presence of mass points and because the production value does not depend on the worker's outside option.

The Master Equation substitutes the KF equation (44) into the HJB equation (43) to index the value functions by the distribution of worker across states and stochastic aggregate productivity, z. In particular, we re-express $V_t(y)$ as $V_t(y, g_t, z)$ where now the value function only depends on t through nonstochastic changes in the model parameters Ω_t. We then use the chain rule to express the time-varying component of the HJB equation in terms of these aggregate state variables, which lead to the Master Equation:

$$\rho V_t(y, g, z) = p(h_y, x_y, z) + \mathcal{A}(y)[V] + \int_{y'} \frac{\partial V_t(y)}{\partial g_t(y')} \mathcal{B}(y')[g_t] d\eta(y') + \mathcal{Q}(z)[V_t] + \frac{\partial V_t}{\partial t} \tag{45}$$

where $\mathcal{Q}(z)$ is an operator that encodes changes in the continuation value from aggregate risk. The

[82] Similarly, we define $p(h, x) = b(h)$ for unemployment states.

[83] Quantitatively, replacing the boundary condition with a softmax operator makes little difference, but simplifies the solution to the transition dynamics.

[84] Consistent with our modification, we replace $\frac{\sigma(x_t^*(h))^2}{2} \partial_x g_t(y_t^*(h))$ with $\int_y \{h = h_y\} S(U_t(h_y) - V_t(y)) g_t(y) d\eta(y)$ in (20).

third term encodes how the value function changes with changes to the equilibrium distribution of workers across states, where we use (44) to substitute for $\frac{dg_t}{dt}$. The final term reflects the value function response to perfect foresight changes to the economy. Note that, in the steady state of the model without aggregate shocks, the last three terms are set to zero.

E.4 FAME

An explicit solution to the Master Equation (45) is difficult in our context due to its dependence on the distribution function of workers. To compute transition dynamics, we instead perform a first-order approximation of the Master equation (FAME) following Bilal (2023). We proceed in two parts. First, we derive the deterministic impulse value , ν^D, which is the operator that encodes the Frechet derivative of the value function with respect to perturbations in the distribution, evaluate at the deterministic steady state $(\overline{V}, \overline{g})$: $\nu^D(y, y') := \frac{\partial V(y)}{\partial g(y)}|_{V=\overline{V}, g=\overline{g}}$. Then, we solve for the impulse value that captures deterministic transition dynamics for some $d\Omega_{tt\geq 0}$, ν^t. In what follows, we consider the model with aggregate risk, and therefore ignore $\mathcal{Q}(z)$.

E.4.1 Deterministic impulse value

Consider an impulse to the steady state worker distribution, h, of magnitude ϵ: $\overline{g} \mapsto \overline{g} + \epsilon h$. To simplify notation, we denote $\overline{\mathcal{A}}_V(y)[\overline{V}]$ to be Frechet derivative of the conditional expectation operator at the steady state value function.[85] We define $\overline{\mathcal{A}}_g[\overline{V}]$, $\overline{\mathcal{B}}_V[\overline{g}]$, and $\overline{\mathcal{B}}_g[\overline{g}]$ similarly.

Proposition E.1. *Deterministic FAME The first-order approximation to the Master equation following a perturbation of the distribution , ν^D, around the steady state solves the following recursive equation:*

$$\rho\nu^D(y, y') = \int \overline{\mathcal{A}}_V(y, w)[\overline{V}]\nu^D(w, y')d\eta(w) + \mathcal{A}(y)\left[\nu^D(\cdot, y')\right] + \overline{\mathcal{A}}_g(y, y')[\overline{V}] + \mathcal{B}^*(y')[\nu(y, \cdot)] + \int_w \nu^D(y, w)\mathcal{G}(w, y')d\eta(w) \quad (46)$$

where $\mathcal{G}(w, y') = \{\overline{\mathcal{B}}_g(w, y')[\overline{g}] + \int_\ell \overline{\mathcal{B}}_V(w, \ell)[\overline{g}]\nu^D(\ell, y')d\eta(\ell)\}$.

Proof. We follow the proof for Theorem 1 of Bilal (2023). We lienearize each term of the Master equation (45). First, note that flow production $p(y)$ is not dependent on V and g. Next, consider the continuation value: Linearizing (45) around the steady state, we obtain:

$$\int \rho\nu^D(y, y')h(y')d\eta(y')d\left[\mathcal{A}(y)[V]\right] = \int\int \overline{\mathcal{A}}_V(y, w)[\overline{V}]\nu^D(w, y')d\eta(w)h(y')d\eta(y') + \int \mathcal{A}(y)\nu^D(\cdot, y')h(y')d\eta(y') + \int \overline{\mathcal{A}}_g(y, y')[\overline{V}]h(y')d\eta(y')$$

[85] As we will see in the numerical implementation, if we discretize the worker state space over N grid points, then we can write If we consider the discretized version of the value function, $\mathbf{V}$, and the operator, $\mathbf{A}$, then $\overline{\mathcal{A}}_V(y)[\overline{V}]$ correspond to the matrix $\overline{A}$, where $\overline{A}_{V,ij} = \sum_{k=0^N} \frac{\partial A_{ik}}{\partial V_j} V_k$.

Next consider the third term that encodes the dependence on the value function based on the worker distribution. Differentiating the generator for the worker law of motion:

$$d\left[\mathcal{B}(w)[\overline{g}]\right] = \mathcal{B}(w)[\overline{g}] + \mathcal{B}(w)[\overline{h}] + \int_{y'} \overline{\mathcal{B}}_g(w,y')[\overline{g}]h(y')d\eta(y') + \int_{y'}\int_{\ell} \overline{\mathcal{B}}_V(w,\ell)[\overline{g}]\nu^D(\ell,y')h(y')d\eta(\ell)d\eta(y') \tag{47}$$

Note that by definition of steady state, $\mathcal{B}(w)[\overline{g}] = 0$. Next, let $\mathcal{B}^*$ be the adjoint operator of $\mathcal{B}$. Then we can rewrite the second term in (47):

$$\int_{y'} \nu^D(y,y')\mathcal{B}(y')[\overline{h}]d\eta(y') = \int_{y'} \mathcal{B}^*(y')[\nu(y,\cdot)]h(y')d\eta(y') + \overline{Q}$$

where, following Bilal (2023), $\overline{Q}$ is an integral over some measure $\overline{\eta}$ that only loads on the mass points of $\mathcal{Y}$. We can therefore write:

$$d\left[\int_{y'} \frac{\partial V_t(y)}{\partial g_t(y')}\mathcal{B}(y')[g_t]d\eta(y')\right] = \int_{y'} \mathcal{B}^*(y')[\nu(y,\cdot)]h(y')d\eta(y')$$
$$+ \int_{y'}\int_{w} \nu^D(y,w)\left\{\overline{\mathcal{B}}_g(w,y')[\overline{g}]h(y')d\eta(y') + \int_{\ell}\overline{\mathcal{B}}_V(w,\ell)[\overline{g}]\nu^D(\ell,y')h(y')d\eta(\ell)\right\}d\eta(w)d\eta(y') + \overline{Q}$$

where use the definition $\frac{\partial \overline{V}(y)}{\partial \overline{g}(y')} = \nu^D(y,y')$ and ignore the linearization in the of $d\nu^D(\cdot,\cdot)$ in the third term because it consists of terms greater than first order. We ignore the final two terms of (45) at the deterministic steady state. Combining the three terms with the linearization of the left-hand side, $\rho\int_{y'}\nu(y,y')h(y')d\eta(y')$, we obtain the deterministic FAME in E.1:

$$\rho\int_{y'}\nu(y,y')h(y')d\eta(y') = \int\int \overline{\mathcal{A}}_V(y,w)[\overline{V}]\nu^D(w,y')d\eta(w)h(y')d\eta(y')$$
$$+ \int \mathcal{A}(y)\nu^D(\cdot,y')h(y')d\eta(y') + \int \overline{\mathcal{A}}_g(y,y')[\overline{V}]h(y')d\eta(y') + \int_{y'} \mathcal{B}^*(y')[\nu(y,\cdot)]h(y')d\eta(y')$$
$$+ \int_{y'}\int_{w} \nu^D(y,w)\mathcal{G}(w,y')d\eta(w)h(y')d\eta(y') + \overline{Q}$$

where $\mathcal{G}(w,y') = \left\{\overline{\mathcal{B}}_g(w,y')[\overline{g}] + \int_{\ell}\overline{\mathcal{B}}_V(w,\ell)[\overline{g}]\nu^D(\ell,y')d\eta(\ell)\right\}$. Equating coefficients, we drop the $h(y')d\eta(y')$ to obtain (46).

□

E.5 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 Θ, 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.

E.5.1 Algorithm for solving the steady state

To solve for the steady state of the model, we implement a standard finite difference scheme following Achdou et al. (2022).

E.5.2 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 Θ 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 therefore desirable to estimate the internally calibrated parameters 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 the generators $\mathcal{A}$ and $\mathcal{B}$ with respect to both the distribution and the value functions.[86] 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).[87]

We lay out our solution of the Impulve Value in the discretized version of the model. 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 ν, where $\nu_{ij} = \frac{\partial V_i}{\partial g_j}$, satisfies solving the following linear system of equations:

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

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 ν, constitute a Sylvester equation to run an iterative procedure to solve for ν, 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

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

   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, $h(y)$,

$$g(y) = g_0(y) + \varepsilon h(y),$$

We consider a distributional impulse of a job destruction shock, in which ε 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.

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

[87] 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

E.5.3 Stochastic FAME

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 the model with aggregate requires knowledge of how job values change with aggregate productivity shocks. We first construct the stochastic first order approximation 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 E.5.2, ω satisfies the following equation:

$$\begin{aligned}\rho\omega(x,z) &= u_z(x) + \mathcal{A}_z(x)[V^{SS}] + \mathcal{A}(x)[\omega(\cdot,z)] + \int \mathcal{A}_V(x,y)[V^{SS}]\omega(y,z)d\eta(y) \\ &\quad + \mathcal{C}(z)[\omega(x,\cdot)] + \int \nu(x,x')S(x',\omega,z)d\eta(x') \\ S(x',z,\omega) &= \int \mathcal{B}_V(x',y)[g^{SS}]\omega(y,z)d\eta(y) + \mathcal{B}_z[g^{SS}]\end{aligned} \tag{48}$$

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

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

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

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

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

E.5.4 Deterministic shocks with FAME

The deterministic FAME ν^D captures the response of the production value functions following an impulse to the worker distribution. To solve for the perfect foresight transition shocks,ν^t, we must account for the fact that impulse response may change due to changes in the structural parameters of the model. The solution of the FAME following an MIT shock $d\Omega(t)$ to the model parameters satisfies a version of the FAME equation that accounts for the potential for the HJB and KF generators to be time-varying. We follow the construction outlined in Proposition 3 of Bilal and Rossi-Hansberg (2023), which can also be seen as constructing a stochastic FAME $\omega(x,z)$ in (48) by replacing the aggregate states $\mathcal{Z}$ as $\mathbb{R}_+$ and the generator $\mathcal{A}(x)$ as a detemrinistic drift term to track the path of $d\Omega(t)$ over time.

E.5.5 Discretized FAME equations

$$\rho\mathbf{V}^D = \overline{A}_g + \overline{\mathbf{A}}_V\mathbf{V}^D + \mathbf{A}\mathbf{V}^D + \mathbf{V}^D\left(\mathbf{B} + \overline{\mathbf{B}}_g + \mathbf{B}_V\mathbf{V}^D\right)$$

$$(\Delta)^{-1}(\mathbf{h}_{t+1} - \mathbf{h}_t) = \left(\mathbf{B} + \overline{\mathbf{B}}_g + \overline{\mathbf{B}}_V \mathbf{V}^D\right)\mathbf{h}_t + B_\Omega d\Omega_t + \overline{\mathbf{B}}_V \mathbf{v}^t$$

for time step Δ, around the steady state equilibrium.

$$\rho \mathbf{v}^t = u_\Omega d\Omega_t + \mathbf{A}\mathbf{v}^t + \overline{\mathbf{A}}_\Omega d\Omega_t + \overline{\mathbf{A}}_V \mathbf{v}^t + \mathbf{V}^D\left(\overline{B}_\Omega d\Omega_t + \overline{B}_V v^t\right) + (\Delta)^{-1}\left(\mathbf{v}^{t+1} - \mathbf{v}^t\right)$$

E.6 Estimation strategy

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

$$\hat{\Theta} = \arg\min_{\Theta} \mathcal{G}(\Theta) = g(\Theta)' W g(\Theta)$$

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.[88] We use the identity matrix as the weighting matrix. In our baseline estimation, W is a diagonal 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 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.

E.7 Transition dynamics and separation response to aggregate shocks

In this section, we provide details on the transitions dynamics following an "MIT" shock to aggregate productivity in Section 7.2. We provide details for the discretized problem, where the state space $\mathcal{Y}$ is discretized into N points.

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

E.7.1 Planner's problem

We solve the planner's response to a perfect foresight MIT shock in the discretized form. We let τ^* be an arbitrary policy, which can include the low-productivity separation rate s. We solve for the time-truncated separation policy $\{\tau^*\}_{t=0,\ldots,T_M}$, where we set the number of months T_M to be large. In matrix form, the planner's problem is:

$$\widetilde{SWF}(d\Omega) = \max_{\boldsymbol{\tau}\in\mathbb{R}^{T_M}} \frac{1}{2}\hat{\mathbf{y}}(d\Omega, d\tau)'\hat{\mathbf{y}}(d\Omega, d\tau) - \frac{1}{2}\widehat{\mathbf{C}}(v(d\Omega, d\tau))'\widehat{\mathbf{C}}(v(d\Omega, d\tau)) + \mu d\tau,$$

where $\hat{\mathbf{y}}(\cdot,\cdot)$ is the T_M-length vector of the output gap in each period, $\widehat{\mathbf{C}}(\cdot)$ is the gap in vacancy costs and μ is the constraint on the policy deviation. Under regularity conditions, the optimal policy $d\tau^*$ is given by the solution to the following linear system (suppressing the arguments for brevity):

$$\hat{\mathbf{y}}'\mathbf{J}_{y,\tau} + \widehat{\mathbf{C}}\mathbf{J}_{C,\tau} = -\mu$$

where $\mathbf{J}_{y,\tau}$ is the Jacobian of the output gap with respect to the policy, i.e. $\mathbf{J}_{y,\tau}(i,j) = \frac{\partial y_i}{\partial \tau_j}$, and similarly for $\mathbf{J}_{C,\tau}$. To compute the Jacobian of the output gap, let $h_t := g_t - g_{ss}$ and note that $y_t = p_t' dg_t$, where p_t is the N_y-length vector of flow production at time t. Then, using the fact that the separation policy has no direct effect on real production ($\partial_{\tau_j} p_t = 0$), we $\frac{\partial d\mathbf{y}_i}{d\tau_j} = p'\partial_{\tau_j} h_i$ which gives results in the Jacobian:

$$\mathbf{J}_{y,\tau} = \mathbf{H} \times_1 p$$

where $\mathbf{H}$ is the $N_y \times T_M \times T_M$ matrix encoding the change in the distribution for each time-specific policy: $\mathbf{H}(i,j,k) = \partial_{\tau_k} h_j(i)$. Relative to the first-order approximation of the transition dynamics, $\mathbf{H}$ is the Hessian matrix corresponding to the cross-partial derivative of the mass at state i with respect to the aggregate shock at period j and the value of τ at period k. To solve for $\mathbf{H}$, use the stochastic partial differential equation (56)

$$\frac{dh_t(x)}{dt} = Bh_t + \tilde{B}_g + \tilde{B}_V v^D + \tilde{B}_t + \tilde{B}_V v^{(t)} \tag{56}$$

Recall that, from the impulse response function, the transition dynamics of the worker distribution follow a law of motion that depends on the deviation of the impulse value at each time period. In matrix form, the law of motion can be expressed as the Sylvester equation:

$$\mathbf{J}_{y,\tau} = \mathcal{H} \times_2 p, \text{ where } \mathcal{H}_{tis} = \frac{\partial h_{ti}}{\partial \tau_s}$$

$$h_{t+1} = h_t + \mathbf{G}h_t + \mathbf{B}_\Omega \Omega_t + \mathbf{B}_\tau \tau_t + \overline{\mathbf{B}}_V v^t, \text{ where } G = \mathbf{B} + \overline{\mathbf{B}}_g + \overline{\mathbf{B}}_V \mathbf{V}^D$$

$$(\rho I + I)\mathbf{v}^t = u_\Omega d\Omega_t + u_\tau \tau_t + \mathbf{A}\mathbf{v}^t + \overline{\mathbf{A}}_\Omega \Omega_t + \overline{\mathbf{A}}_\tau \tau_t + \overline{\mathbf{A}}_V \mathbf{v}^t + \mathbf{V}^D \left(\overline{B}_\Omega \Omega_t + \overline{B}_\tau \tau_t + \overline{B}_V v^t\right) + \mathbf{v}^{t+1}$$

Define the TxT difference operator D such that the i-th row of D consists of $D_{ij} = -1$, $D_{i,j+1} = 1$, and 0 elsewhere for $i = 1, \ldots, T-1$. The last row consists of 0s.

Recall that $y = \mathbf{H}p$, where $\mathbf{H}$ is the $N \times T$ matrix of distribution deviation from steady state. Let $\mathbf{\Omega}$ be the $K \times T$ deviation of structural parametesrs (length K) from steady state, and τ to be the $T \times 1$ policy vector. Also let $\mathbf{V}^T$ be the NxT matrix of time-dependent deviations of the value function. We rewrite the IRF and trend FAME as:

$$\mathbf{HD}' = \mathbf{GH} + \mathbf{B}_\Omega \mathbf{\Omega} + \mathbf{B}_\tau \tau + \overline{\mathbf{B}}_V \mathbf{V}^T, \text{ where } G = \mathbf{B} + \overline{\mathbf{B}}_g + \overline{\mathbf{B}}_V \mathbf{V}^D$$

$$\rho \mathbf{V}^T = \mathbf{u}_\Omega \mathbf{\Omega} + \mathbf{u}_\tau \tau + \mathbf{A}\mathbf{V}^T + \overline{\mathbf{A}}_\Omega \mathbf{\Omega} + \overline{\mathbf{A}}_\tau \tau + \overline{\mathbf{A}}_V \mathbf{V}^T + \mathbf{V}^D \left(\overline{B}_\Omega \mathbf{\Omega} + \overline{B}_\tau \tau + \overline{B}_V \mathbf{V}^T \right) + \mathbf{V}^T \mathbf{D}'$$

For any τ_s, where $s = 1, \ldots, T$, we can differentiate these equations to obtain:

$$\mathbf{H}_{\tau_s} \mathbf{D}' = \mathbf{G}\mathbf{H}_{\tau_s} + \mathbf{B}_\tau 1_{\tau_s} + \overline{\mathbf{B}}_V \mathbf{V}^T_{\tau_s}$$
$$\rho \mathbf{V}^T_{\tau_s} = \mathbf{u}_\tau 1_{\tau_s} + \mathbf{A}\mathbf{V}^T_{\tau_s} + \overline{\mathbf{A}}_\tau 1_{\tau_s} + \overline{\mathbf{A}}_V \mathbf{V}^T_{\tau_s} + \mathbf{V}^D \left(\overline{B}_\tau 1_{\tau_s} + \overline{B}_V \mathbf{V}^T_{\tau_s} \right) + \mathbf{V}^T_{\tau_s} \mathbf{D}'$$

where 1_{τ_s} is a vector that is 0 everywhere except for the $s-th$ element, which is tau_s.

To solve for $\mathbf{V}^T_{\tau_s}$, we rearrange the differentiated equation to obtain the following Sylvester equation.

$$\left(\rho \mathbf{I} - \mathbf{A} - \overline{\mathbf{A}}_V - \mathbf{V}^D \overline{\mathbf{B}}_V \right) \mathbf{V}^T_{\tau_s} + \mathbf{V}^T_{\tau_s} \mathbf{D}' = \mathbf{u}_\tau 1_{\tau_s} + \overline{\mathbf{A}}_\tau 1_{\tau_s} + \mathbf{V}^D \overline{B}_\tau 1_{\tau_s}$$

Given $\mathbf{V}^T_{\tau_s}$, then we can solve for $\mathbf{H}_{\tau_s}$ by backward iterating from $t = T$. Since $\mathcal{H}_{\cdot\cdot s} = \mathbf{H}_{\tau_s}$, this gives us $\mathcal{H}$.

Next,

$$\mathbf{J}_{c,\tau} = MC(\mathbf{vac}) * \mathbf{J}_{vac,\tau}$$

where $MC(vac) = \partial_{vac} C(vac)$. Note that $\mathbf{J}_{vac,\tau}$ is a $N_x \times T$ matrix. Because vacancies are flows, then we can write:

$$\frac{\partial c_{it}}{\partial \tau_s} = C'(vac_{it}) \left(\frac{\partial vac_{it}}{\partial V_{it}} \frac{\partial V_{it}}{\partial \tau_s} + \frac{\partial vac_{it}}{\partial g_{it}} \frac{\partial g_{it}}{\partial \tau_s} \right)$$

Combining these terms gives us a closed-form solution to the FOC that we solve to obtain τ^*.

E.8 Steady state solution for linear employment subsidy.

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

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

where SWF(τ) is the modified social welfare function (21) with the employment subsidy.[89] Because agents are forward-looking, job creation is also impacted by τ 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 0.29% 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 A.10, 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.[90] At the same time, the steady state unemployment rate increases by 3% as a result and the worker share of total production declines significantly.

[89]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.

[90]The loss of low-productivity jobs also leads to a decline in the bargaining threat points as shown in right panel of Appendix Figure A.10.