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LABOR MARKET DYNAMICS AND GEOGRAPHICAL REALLOCATION

by Gaetano Basso*, Salvatore Lo Bello* and Francesca Subioli**

Abstract

We study how local labor demand shocks affect internal migration using the universe of labor market flows for Italy. First, we document two novel facts: i) large and systematic differences between gross and net job and internal migration flows arise both across space and over time; ii) each gross flow is an important driver of the net growth rates. We estimate the causal impact of different-sign labor demand shocks on internal migration flows using as instrumental variable plausibly exogenous large mass hire and layoffs events. Our estimates reveal that job creation has a strong effect on the in-migration rate, whereas job destruction has a much milder effect on the out-migration rate. Crucially, we document that the large responsiveness of in-migration does not work through an increase in the number of relocating workers, but rather through changes in their chosen destination alternatives. We also find that the effects of job creation on in-migration flows have a much larger geographical reach than those of job destruction, as out-migration flows are locally concentrated.

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1 Introduction

Understanding the responsiveness of the geographical allocation of workers to local labor market dynamics is a first-order issue in the economic literature. Indeed, it has long been argued that migration is a major mechanism to absorb labor demand variations and that people move across regions (Blanchard and Katz, 1992) or change their commuting behavior (Monte et al., 2018) in response to employment opportunities. There is evidence of such empirical regularities in many contexts. However, labor market flows are correlated across space and time and so do migration flows, posing challenges to the identification of the causal nexus. For this reason, most of the literature focuses on specific labor demand events such as mass layoffs (Gathmann et al., 2020; Foote et al., 2019), disruptions due to international trade (Autor et al., 2013), major construction events (Carrington, 1996) or the Great Recession (Monras, 2018), often taking a reduced form approach that hardly allows to generalize the results.[1] Moreover, the literature largely overlooks whether the migration responses to positive and negative demand variation are symmetric, often as a consequence of the identification strategies adopted.[2]

In this paper, we try to overcome these limitations by jointly estimating the causal impact of both positive and negative local labor demand shocks on internal migration flows. To do so, we exploit plausibly exogenous variation stemming from mass events at the establishment level. Our estimates reveal important effects of both job creation and job destruction on net migration, with the former being much larger than the latter. In particular, job creation strongly stimulates the in-migration rate, whereas job destruction has a milder effect on the out-migration rate, which appears as a less responsive margin of adjustment. Moreover, the two margins have a different geographical reach, with outflows being much more locally concentrated than inflows. Overall, our findings highlight the importance of separately assessing the contemporaneous impact of different-sign labor demand shocks on migration patterns.

Our study uses administrative data on the universe of labor market transitions in Italy for the period 2010-2018. The high quality of the data allows us to precisely identify mass events at the micro level and to track their effects on aggregate migration flows via job creation and job destruction – defined as the sum of job flows net of establishment-level churning.[3] Our results are particularly interesting if one considers that they apply to an

[1] The literature on the response of migration to labor demand shocks is vast and it is not fully reported here. A subset of the literature also looks at international migration responses (Beyer and Smets, 2015; Basso et al., 2019). For the Italian case, see Ciani et al. (2019). For an overview of internal migration and of the related literature, see Molloy et al. (2011).

[2] Notable exceptions are Ciani et al. (2019) and Notowidigdo (2020).

[3] As the focus of our analysis is labor demand, we adopt the classical definition of Davis and Haltiwanger (1992); Davis et al. (1998, 2006), that has been shown to capture well business cycle dynamics.

economy with sluggish labor market dynamics.[4] Surprisingly, we uncover a large amount of labor market dynamism, in line with Citino et al. (2023), and a substantial degree of responsiveness of internal migration to employment opportunities, more than previously estimated for Italy (Ciani et al., 2019) and in line with estimates from the US (Basso and Peri, 2020; Monras, 2018; Coen-Pirani, 2010).

We contribute to the existing literature in two ways. First, we account for both job creation and job destruction when estimating adjustments to demand shocks, ensuring identification by instrumenting both margins of labor market dynamism. The literature, instead, typically takes a reduced-form approach, such as estimating region-level mass-layoffs (Gathmann et al., 2020), or focuses on one margin at a time (Carrington, 1996; Monras, 2018). We show that both margins of labor demand, properly instrumented, matter in explaining gross and net migration flows. Second, we uncover that net migration adjustments are stronger for positive than for negative variations in labor demand, in line with the evidence on the US (Notowidigdo, 2020) and differently from what previously shown for Italy (Ciani et al., 2019). We find that this asymmetry is mainly due to the greater amount of inflows generated by job creation than the outflows (or reduced inflows) spurred by job destruction.

In the first part of the paper, we use the detailed microdata to document novel facts on labor market flows and internal migration rates at the local labor market (LLM) level, roughly equivalent to a US commuting zone.[5] In particular, in a symmetric fashion for job and migration flows, we find that: i) the magnitude of gross flows dwarfs that of net flows, implying a large degree of excess turnover, both at the aggregate and at the local level; ii) gross and net flows feature systematic differences across space and over time; iii) both gross job creation and job destruction (in-migration and out-migration) are important determinants of over-time fluctuations in the employment growth (net in-migration) rate.

More precisely, we find that the average excess turnover rate – the sum of gross flows over the absolute value of net flows – is 36.2 (71.5) for job (internal migration) flows at the local labor market-year level. To fix ideas, this implies for instance that when a location experiences a unit increase in employment in one year, total gross job flows (i.e. job creation plus job destruction) amount to about 36, on average. This highlights the existence of marked differences in the magnitude of gross and net flows, suggesting that it is important to study them separately. Moreover, we document that gross flows are especially concentrated in regions where net flows are relatively small, and that their

[4]As documented by Elsby et al. (2013), in Italy the probability of flowing into and out of employment is the smallest, among OECD countries.

[5]There are 610 LLMs as defined by ISTAT. We also test the robustness of the results at the level of province (more coarse) and municipality (more disaggregated), reported in the Appendix.

dynamics over time are quite different. Importantly, very similar patterns arise for both job flows and internal migration, suggesting a link between the two. Finally, we decompose the variance of net flows (migration) into separate components attributable to the opposite-sign gross flows. We find that, on average, each gross flow rate accounts for roughly half of the aggregate fluctuations in net rates over time. Consistently, in the estimation part of our paper we focus our attention separately on gross and net flows, and explore potential differences between the effects on internal migration of positive and negative labor demand shocks.

When we relate internal migration to labor market dynamism, our objective is to analyze the contemporaneous effects of both job creation and job destruction. Simple OLS regressions indicate that job flows are highly correlated with migration flows: a 1 percentage point increase in the job creation rate (job destruction rate) is associated with an increase (decrease) in the net migration rate of 0.21 (0.14) percentage points. To overcome plausible endogeneity and identify causal effects (as the causality nexus between migration flows and job creation and destruction is not a priori determined), we then turn to an instrumental variable identification strategy.

We exploit changes in labor demand spurred by mass hire and layoff events at the establishment level, which we identify directly from the administrative data. We define as mass events those that involve more than 500 workers (robustness with thresholds at 250 and 750 workers are reported in Appendix C and D). Even though the Italian labor market is characterized by institutions aiming at preserving employment relations (e.g., short-time work schemes) and delaying layoffs, we show that such events are quite salient (they involve between 0.04 and 12 percent of the yearly local labor market employment) and spread across the country (depending on the threshold, they occur in 30 to 241 local labor markets over the sample period). Most importantly, regression results indicate that they are unanticipated both at the establishment and at the local labor market level, a major condition for exogeneity to hold, and have strong predictive power on aggregate job flows. Moreover, there are negligible cross-effects (mass layoff on job creation rate and mass hire on job destruction rate), indicating that we are able to separately identify job creation and job destruction.

The 2SLS estimates provide further interesting evidence. First, the magnitude of the job creation effect on net migration is about 40 percent larger than in the OLS estimates (a 1 percentage point increase in the job creation rate leads to a 0.23 percentage points increase in the in-migration rate), whereas that of job destruction is reduced by more than two thirds (-0.04, not statistically significant). These differences can be traced back to the specific gross flows involved in the adjustment, as job creation is able to generate more migration flows than job destruction. Second, similarly to the literature on US and

Germany (Gathmann et al., 2020), our evidence shows that movements out of a region are muted relative to inflows: however, we still find outflows to be non-negligible following negative shocks in labor demand, differently to what was found in previous papers (Monras, 2018; Notowidigdo, 2020). Moreover, we show that the timing of the effects varies, with the response of in-migration to job creation shocks being contemporaneous, against a more delayed response of out-migration to job destruction shocks. Finally, we also study the geographical reach of the effects. Binning the migration flows by distance, we show that the out-migration rate responds only locally to a change in job destruction rate (up to 100 km) and it decays quickly farther away, while in-migration flows increase in response to job creation rate with a much larger reach, though with a decaying intensity over space. This is a relevant finding that speaks directly to the consequences of shocks on spatial inequality. Indeed, the welfare gains brought about by positive shocks are shared with relatively large inflows of migrants, who cover about 30 percent of new jobs and act as a counteracting equilibrium force. In addition, our results provide useful insights into the extent to which labor markets are actually local as opposed to perfectly integrated, in the spirit of Manning and Petrongolo (2017).

We further demonstrate the absence of systematic differences between mass layoff and mass hire events, both in terms of the geographical and sectoral distribution as well as of the population involved (except for a difference in the average age of workers directly affected by such shocks). In any case, we rule out that these differences may explain more than twenty percent of the asymmetric response of migration flows to job creation and destruction. Thus, we inspect the mechanics of the in-migration reaction by decomposing the overall inflow into two separate terms. The first one is a measure of *potential in-migrants*, i.e. the sum of workers relocating from all other locations, while the second one captures how attractive a given location is relative to all other competing destinations. By running separate regressions, we document that job creation rate shocks do *not* cause more individuals to relocate, but rather they cause relocating individuals to revise their ranking over possible destination alternatives. We see this as a very important finding for a number of reasons. First, this is a crucial piece of information to correctly model the reaction of migration choices to labor demand shocks. Second, this implies the existence of negative externalities of region-specific shocks to other competing regions, which work by altering their relative attractiveness. Third, we claim that this sheds a fundamental light on the asymmetry between the effect of positive shocks on in-migration – i.e., very large – and that of negative ones on out-migration – i.e., much smaller. Our evidence points to the fact that the effect of positive shocks on in-migration operates through a margin – the relative attractiveness of the location – that, by construction, does not exist for out-migration.

We conclude the paper by laying out the policy implications of our results. Given the evidence at our disposal, policy makers may want to act more aggressively against negative labor demand shocks – as internal migration does not help much at absorbing them – in order to mitigate the potential short-run increase in cross-regional disparities. On the contrary, the consequences of job creation are already largely shared across space due to the strong and quick reaction of in-migration even at long distances. Hence, they contribute to a lesser extent to generating spatial inequality.

2 Descriptive Evidence

In this Section, we use highly detailed microdata to compute aggregate labor market flows at the local level. In order to do so, we need to fix a sampling interval and a geographical aggregation level. In our empirical analysis based on quasi-random variation (Section 3), we adopt a local labor market-year level specification for reasons that will be clarified later. However, for most of the descriptive analysis carried out in this Section, we also explore the heterogeneity stemming from other possible aggregation levels: month and quarter for the time aggregation,[6] municipality, province and region for the geographical aggregation. We do this to lend further support to our findings, and to guarantee that they are not simply a by-product of our own arbitrary choices.

2.1 The Data

SISCO data. The data we use is a selection – from January 2010 to December 2018 – from the Statistical Information System of Compulsory Communications (SISCO). The SISCO database contains all the employee and para-subordinate work relationships that have undergone an event (activation, transformation, extension, termination) since March 2008.[7] Hence, the resulting database covers the universe of labor market flows for all type of contracts and employers.[8] Overall, the dataset contains information on 119.1 million labor contracts, involving about 22 million workers throughout the sample period.[9]

[6] Gomes (2015) and Bertheau and Vejlin (2022) have recently shown the importance of this source of bias when measuring labor market transitions based on individual-level data.

[7] Since that date, each hiring, separation, contract renewal and contract transformation is collected for administrative purposes by the Italian Ministry of Labor through an online communication system named "comunicazione obbligatoria" (CO) to be filed by the employers at the time of the event.

[8] SISCO includes all public and private sector jobs including maids and caregivers hired by households and excludes only employment relationships in the armed forces and those involving senior figures such as presidents and CEOs of public and private companies.

[9] If we weight the number of individuals by the time spent in employment (i.e. assigning a weight of 1 to workers who are employed continuously throughout a period), the average number of workers for which we have information is about 9.1 million per year.

A job is defined as a contractual relationship identified by the employee, the employer and the activation date, and contains all the subsequent events (extensions in the case of fixed-term contracts, transformations to open-ended contracts, terminations).The information collected and made available to the researchers is very detailed at the level of worker (occupation, education level), job (length and type of contract) and employer (5-digit sector, municipality of work).[10] SISCO data are advantageous with respect to other administrative sources used to analyze the labor market – such as those collected by the Italian Social Security Administration (INPS) for social security contribution purposes – as they cover the universe of labor market flows and have additional detailed information at the worker and job level.[11] However, SISCO data do not collect any information on earnings or salary. Moreover, due to the particular structure of the data, it is not possible to observe workers who have not experienced any contractual event between January 1, 2010 and December 31, 2018. In other words, we do not have information on pre-existing stocks, i.e. these data cannot be used to assess employment stocks. We circumvent this issue by taking estimates of these stocks from external sources, namely from the Italian labor Force Survey (ILFS). This allows us to consistently construct flow rates.

ILFS data. The Italian labor Force Survey (ILFS) is a sample survey conducted since 2004 by the Italian National Statistical Institute (ISTAT) by interviewing each year more than 250,000 households resident in Italy (for a total of 600,000 individuals between 15 and 89 years of age), distributed in about 1,400 Italian municipalities and representative of the resident population.[12] It represents the primary source of statistical information on the Italian labor market, harmonized at the European level, and it is used for the official estimates of unemployment and the main aggregates of labor supply. For the purposes of this paper, ILFS data are used only to compute the aggregate stocks of payroll employment (as well as population and unemployment, for some additional checks), to be used as denominators for computing rates. The ILFS provides population, self-employment and employment stocks at the province-quarter level.[13] Starting from

[10]The worker's residence is only available for the last job recorded. Therefore, residence changes are not registered in the SISCO data. Since the SISCO data are collected continuously, the classification of the municipalities is not coherent in the whole period because of some mergers and abolition that took place between 2010 and 2018. We bring all the municipality codes to the classification in force on 1° of January 2019. The only geographical shifts we cannot adequately deal with are transfers of 'districts' from one municipality to another. For 0.20% of the contracts it was not possible to attribute the correct municipality code because of irrecoverable errors in the data.

[11]INPS data do not cover maids, caregivers and agricultural workers in the private sector or most of the public sector employment. Data on on-call and employment-agency-hired temporary workers are treated separately from other temporary workers.

[12]The survey is carried out during all weeks of the year using a uniform distribution of the sample over the weeks. The sampled households are interviewed four times over 15 months: each one is interviewed for two consecutive quarters and two more quarters after a two-quarter break.

[13]The summary statistics at the monthly level are constructed using quarter-level stocks at the de-

these, we impute the stocks at the municipality level by leveraging the information on municipalities coming from the 2011 Census and fixing the within-province shares over time. Finally, local labor market (LLM) aggregates are obtained by simply summing the corresponding stocks of the municipalities contained in each of them.[14]

2.2 Labor Market Dynamism

The forces behind labor market transitions can be grouped into two broad categories, commonly used in the analyses carried out by the existing literature (e.g. Davis and Haltiwanger (1992); Davis et al. (1998, 2006)). On the one hand, employers create new jobs and destroy old ones every period, thus affecting the distribution of jobs across space (*demand-side*). On the other hand, for a given distribution of jobs, workers switch jobs and change employment status because of *supply-side* events (e.g., relocation, labor force entry, migration, retirement, death, change in preferences). As the focus of this paper is on the impact of labor demand shocks, we analyze job flows exclusively.

Let $E_{r,t}$ be the employment level of location r at time t (where location can be municipality, local labor market, province, region, etc.). At any level of aggregation, the net change in employment between two points in time ($\Delta E_{r,t} = E_{r,t} - E_{r,t-1}$) satisfies the following accounting identity:

$$\Delta E_{r,t} \equiv \underbrace{JC_{r,t} - JD_{r,t}}_{\text{Job flows}} \equiv \underbrace{NJC_{r,t}}_{\text{Net Job Creation}} ,$$

where $JC_{r,t}$ denotes job creation and $JD_{r,t}$ denotes job destruction.[15] In turn, job creation is defined as the sum of net employment gains over all establishments that either expand or start-up within a given time interval. In a symmetric fashion, job destruction is defined as the sum of net employment losses over all establishments that either contract or shut down in the time interval:

nominator.

[14]Istat further publishes annual total employment (thus including self-employed) at the local labor market level estimated from the ILFS: we use it to compare with our imputed data and the results are robust. Moreover, we test the robustness of the results using employment stocks from the structural business registers (Istat ASIA) that are only available from 2012 onwards: the results are nearly unchanged.

[15]Throughout the paper, we refer to the increase in the number of active (i.e., not expired) labor market contracts as the change in payroll employment. In principle, this may potentially be imprecise, if workers hold multiple jobs. However, in our data about 94% of contracts do not overlap with any other active contract at the same time. Hence, we conclude that this does not represent a major issue for our measurement.

$$JC_{r,t} = \sum_{i \in \mathcal{G}_{r,t}} \Delta e^i_{r,t}, \qquad JD_{r,t} = -\sum_{i \in \mathcal{S}_{r,t}} \Delta e^i_{r,t},$$

where $\Delta e^i_{r,t}$ denotes the employment change at establishment i belonging to location r, $\mathcal{G}$ denotes the set of growing establishments ($\mathcal{G}_{r,t} = \{i : \Delta e^i_{r,t} > 0\}$) and $\mathcal{S}$ denotes the set of shrinking establishments ($\mathcal{S}_{r,t} = \{i : \Delta e^i_{r,t} < 0\}$). We define an establishment as the combination of a firm id and the municipality of the workplace, i.e., establishments of the same firm in a given municipality are pooled together.[16]

In order to obtain rates, we divide the absolute flows by the current periods' corresponding stocks of payroll employment $E_{r,t}$ as estimated from ILFS data. Eventually, we define $JCR_{r,t}$ and $JDR_{r,t}$ respectively as the job creation and job destruction rate. Last, we define the excess job turnover rate $EJTR$ as the ratio between the job turnover rate JTR – that is the sum of the job creation and job destruction rates – and the absolute value of the net job creation rate:

$$EJTR_{r,t} = \frac{JCR_{r,t} + JDR_{r,t}}{|NJCR|_{r,t}}.$$

This synthetic measure captures how large the differences between gross and net flows are. Note that its minimum value is 1, and that it is large when gross flows are mostly offsetting (that is, when they roughly cancel one another, resulting in small net flow rates). At the aggregate level, excess turnover rates capture both cross-region and cross-firm reallocation, whereas at the local level these indexes capture uniquely the job reallocation occurring across firms.

Aggregate flows. We first examine labor market flow rates at the national level, obtained by summing up events across locations and dividing the total by the aggregate stocks. Figure 1 (panel (a)) plots the average of yearly flows over the period 2010-2018, revealing that gross flows are generally much larger than net flows, i.e. excess turnover is high.[17] Each year, job creation corresponds to 11% of total jobs, whereas destruction amounts to 9%, confirming results in Citino et al. (2023), who analyze job flows for Italy over the period 1984-2021.[18] Turning to the evolution of these flows over time, we notice

[16]The data do not allow to directly identify establishments. In practice, we claim that our proxy for establishments (firm id-municipality pair) is very precise, as we know from restricted-access ISTAT data, not available for research purposes, that only about 2% of firms have multiple establishments within the same municipality in the sample period.

[17]When we split gross flows by contract type, we find that temporary jobs play a crucial role: despite representing only about 14% of the total stock of payroll employment on average during the period 2010-2018, they account on average for 39% of job creation and for 50% of job destruction. Notice that these statistics are computed using the sum of the contract-specific job flows (that does not necessarily correspond to the overall job flows).

[18]These figures are also quite close to the estimates provided for several other countries: see Pinkston

that the job creation and job destruction rates tend to negatively co-move (Figure 1, panel (b). In practice, gross job flow rates seem to be affected by aggregate shocks, following the business cycle as expected, that is job creation (destruction) is high (low) in expansionary phases and low (high) during recessions.[19] This is also confirmed by the correlation between these variables and the net employment growth rate: job creation has a correlation coefficient of 0.60, while the job destruction rate of -0.85 (see Table 1).

Location-specific flows. We now turn to the analysis of location-specific flows. Figure 2 plots the geographical distribution of average job flows at the local labor market level (LLMs). It is immediately apparent that these flows are highly correlated across space. In particular, we find that Southern LLMs are characterized by a remarkably high level of gross flows, apparent for both job creation and job destruction. However, many of these flows are almost exactly offsetting each other, so that net job creation is concentrated in the Northern LLMs, with the exception of some other specific locations. When we investigate these patterns distinguishing jobs by contract type (temporary vs. open-ended), we find that the larger degree of labor market dynamism (job creation and destruction) in Southern areas was mainly due to the dynamics of open-ended contracts, perhaps surprisingly (see Figure C.1). This was likely due to a number of policy interventions that targeted those regions with subsidies that incentivized the creation of open-ended positions during our sample period (Camussi et al., 2022). Instead, net job creation was primarily driven by temporary contracts, that expanded especially in the North.

Table 2 shows summary statistics of job flows at LLM level at different time (month, quarter, year) aggregation levels. Overall, it confirms the patterns already uncovered at the aggregate level, namely that gross flows are much larger than net flows, implying high levels of excess turnover. In particular, depending on the time aggregation level, average excess turnover rates range between 10.6 and 36.2. For instance, this implies that, on average, if the employment stock of a given LLM expands or shrinks by 1%, the cumulative flow of jobs being created and destroyed within the year in that location will be equal to 36.2%. This highlights the large differences between gross and net flows. It is important to notice that excess turnover at the location level can be only brought about by job reallocation across firms. These features of our data echo results by Davis et al. (2006), who study flows at the establishment level in the US, finding high excess turnover.[20]

and Spletzer (2004) for the US, Hijzen et al. (2010) for the UK, Boeri and Cramer (1992) for Germany, Stiglbauer et al. (2003) for Austria, and Persson (2000) for Sweden.

[19] Our sample period covers only the 2011-2013 crisis.

[20] Summary statistics for different geographical aggregation level – municipality, province and region – are reported in Appendix D. From Table D.1 we notice that the distributions of both gross and net labor

To get further insights on the relationship between gross and net job flows, in Figure 3 we plot yearly (panel (a)) and monthly (panel(b)) average gross job flow rates against the employment growth rate at the LLM level (see Figure C.2 for the whole scatter).[21] The shape of the gross-to-net flows relationship is very relevant for our exercise because it reveals potential asymmetries across different flows. The graph shows that job creation and destruction change in different directions vis-à-vis employment growth changes. Moreover, the average gross rates lie far above the 45-degree line, reflecting the high excess turnover.[22] That is, local labor markets where employment is expanding (shrinking) still experience, on average, a substantial amount of job destruction (creation). Overall, these pieces of evidence confirm the previous results on aggregate flows. From Figure 3, we also notice the presence of pronounced non-linearities in gross flows, namely that the job creation (destruction) rate is roughly constant for LLMs where employment is shrinking (expanding). For the purpose of our main exercise, evidence of pronounced non-linearities calls for separate analyses of the effects of specific job flows. This is because a given change in net rates cannot be unambiguously traced back to a given change in gross flows.[23]

The above exercises deal with both time and space variation. A different, though related, question is to ask which gross flows drive the variation over time in net flows at the local level. In order to shed light on this, we employ a simple statistical decomposition, as proposed by Monras (2018). By regressing gross flow rates on the corresponding net flow rates, one can measure the extent to which each flow contributes to aggregate fluctuations in the net rates. For instance, to decompose employment growth dynamics, we run the following regressions:

$$JCR_{r,t} = \beta_1 NJCR_{r,t} + \alpha_r + \gamma_t + \epsilon_{r,t} \tag{1}$$

$$JDR_{r,t} = \beta_2 NJCR_{r,t} + \alpha_r + \gamma_t + \epsilon_{r,t} \tag{2}$$

flows are systematically more dispersed the finer the geographical level (one can see this by comparing vertically the standard deviations of flows, for a given time-frequency). The interpretation of this fact is that relatively larger shocks, i.e. involving a relatively higher share of the local employment stock, are more likely to happen in areas identified at a more disaggregated level.

[21] Qualitative results are essentially unchanged at other levels of aggregation.

[22] The 45-degree line represents the minimum necessary level of job creation (job destruction) for LLMs where employment is expanding (shrinking).

[23] More in general, the relationship between gross and net flows also offers useful insights on the nature of aggregate fluctuations. Indeed, aggregate rates are the result of the combination between these average gross rates and the underlying employment growth rate distribution. In particular, strong non-linearities in the gross flow rates imply that even small changes in the underlying employment growth rate distribution may bring about large movements in aggregate rates. Moreover, when we investigate the extent to which the employment growth rate distribution is subject to swings over time in Figure C.3, we find that these movements are actually very large. Therefore, this implies that shifts in the employment growth rate distribution over time represent a primary source of fluctuations in labor market flow rates, in line with Davis et al. (2006).

Given the definition of the variable ($NJCR = JCR - JDR$), in this setup the condition $\beta_1 - \beta_2 = 1$ must hold.[24] It is important to notice that this exercise decomposes within-location variation in employment growth rates. Hence, we can directly interpret the estimated coefficients as the share of variance of net rates accounted for by the specific gross flow. Table 3 shows the results of this decomposition for the different levels of time aggregations. At the yearly frequency, the estimated value of β_1 is 0.62, implying that job creation accounts for more than half of the fluctuations. Overall, the share of variance accounted for job creation is 34 and 71%, if one extends the analysis to the other possible combinations of sampling interval and geographical aggregation level (see Appendix D for more results at different geographical aggregations; Table D.2).[25]

Summing up, two important lessons can be drawn from this descriptive evidence. First, gross flows starkly differ from net flows, both in terms of levels and dynamics. Second, it is crucial to account for both job creation and job destruction, as they are both important drivers of employment growth. Consistently with this, our subsequent analysis in Section 3 will focus separately on specific gross job flows, allowing for potentially asymmetric effects.

2.3 Internal Migration

To measure internal migration flows, we leverage the SISCO individual-level data exploiting the information of the workplace location, which we use as a proxy for residence.[26] Compared to using the more standard residence measures, this has a number of implications, which we discuss at length in Appendix B. Overall, we claim that SISCO data are actually better suited to measure internal migration with respect to traditional data sources based on administrative data (e.g., changes of residence from ISTAT) or surveys (e.g., ILFS). Indeed, SISCO data are extremely granular and do not suffer from (i) misreporting, known to be potentially quite large in other sources (Rubolino, 2020), (ii) under-counting (residence-based data are likely not to record short-distance transfers),

[24]To see this, notice that $\hat{\beta}_1 = \frac{cov(JCR,NJCR)}{var(NJCR)}$, and $\hat{\beta}_2 = \frac{cov(JDR,NJCR)}{var(NJCR)}$.

[25]Differences across time aggregation levels can be understood referring to Figure 3. To a first approximation, gross flows are important determinants of net flows if and only if they systematically vary with the latter, i.e. for instance job creation is increasing in employment growth rates (not necessarily true by construction). Moreover, for a given shape of the gross-to-net-flows relationship, the distribution of employment growth rates also matters for the decomposition results. This is because, depending on the actual realizations of shocks, more or less weight is given to parts of the support where job creation (destruction) is more (less) correlated with the employment growth rate. In our data, such distribution at the yearly frequency has much more mass in the positive region than the one at the monthly frequency (see Figure C.4), explaining the different decomposition results.

[26]This choice is mainly due to the fact that in our data the information on the individuals' residence is not updated over time. Identifying the residence through the workplace is a strategy that was adopted, among others, also by Bartolucci et al. (2018). For more details, see A.2.

which we find to be a very severe problem in ILFS data, or (iii) attrition, that has been documented for labor force surveys (Martí and Ródenas, 2007). The main drawback of SISCO data is that they do not record movements of non-employed people within their unemployment or inactivity spells (i.e., until they find a new job in a new location). In practice, we find that such limitation is likely to be very small, possibly because most of the internal migration also entails a job change. Indeed, in Appendix B we show that our measures of internal migration are very highly correlated with administrative-based residence changes from the ISTAT, which is reassuring of our proxy being valid.

To construct our migration measures we first need to transform the contract-level dataset into a worker-level panel. This involves assigning to each worker-period combination the prevalent job, for all those cases with multiple contracts within a given time interval. Details on how we pick the prevalent job for each period can be found in Appendix A.1. In the baseline version of our dataset, we focus only on *direct* transitions, that is we do not consider transitions that involve non-employment spells. We do this to avoid having to impute the exact timing of the transitions, as well as to avoid the possibility of spurious transitions, given that we do not observe residence changes of non-employed individuals.[27]

With the worker-level panel dataset, it is straightforward to compute aggregate migration flows through individual transitions. We define a dummy $m^j_{s\rightarrow r,t}$ that takes value 1 if worker j has made a transition from location s (i.e., any location different from r) to location r at time t.

Therefore, location-specific inflows $IM_{r,t}$, outflows $OM_{r,t}$ and net inflows $NIM_{r,t}$ are simply defined as:

$$IM_{r,t} = \sum_{s\neq r}\sum_{j} m^j_{s\rightarrow r,t}, \qquad OM_{r,t} = \sum_{s\neq r}\sum_{j} m^j_{r\rightarrow s,t}, \qquad NIM_{r,t} = IM_{r,t} - OM_{r,t}.$$

To better interpret magnitudes, we divide these flows by the previous period's payroll employment stocks (derived from ILFS data), thus obtaining inflow, outflow and net inflow rates: $IMR_{r,t}$, $OMR_{r,t}$ and $NIMR_{r,t}$. Last, we define the excess migration turnover

[27]Notice that, at the yearly frequency, this is only excluding workers who completely leave employment for at least one full calendar year. However, we also compile another version of our dataset in which we keep this type of transitions, assuming that the worker's location corresponds to her last workplace location until the new job is found. That is, we assign the location switch at the end of the non-employment spell. In this alternative dataset, we include all cases in which the non-employment spell covers exactly one yearly observation (i.e. we retrieve all histories of the type E-N-E), which represent about 51% of all cases with non-employment yearly observations. Notice that this implies that the non-employment spell can practically last for up to almost three full calendar years. For the purposes of our main empirical exercise, in a robustness check we show that including also indirect transitions does not substantially affect our results (Table D.4).

rate $EMTR$ as the ratio between the migration turnover rate MTR – that is the sum of the inflow and outflow rates – and the absolute value of the net inflow rate:

$$EMTR_{r,t} = \frac{IMR_{r,t} + OMR_{r,t}}{|NIMR|_{r,t}}.$$

In the context of migration, excess turnover is a particularly relevant statistics, since it embeds information on the nature of shocks that possibly cause migration. For instance, if migration were driven almost only by aggregate (i.e. equal for all workers) shocks, excess turnover should be minimal. Instead, if idiosyncratic shocks (i.e. heterogeneous across workers) were prevalent for migration choices, then excess turnover would be large. In the first case, most of the migration choices would be nearly identical across individuals, whereas in the second case migration decisions would be heterogeneous, resulting in largely offsetting flows.

Aggregate flows. Before delving into location-specific flows, we first study aggregate migration flows, which we obtain by simply summing up all events and dividing them by the corresponding aggregate stock. Figure 4 shows trends of yearly and monthly internal migration in Italy for all the geographical levels (municipality, LLM, province, region). In our sample period gross migration rates at the yearly frequency were about 7.2% at the municipality level, 4.7% at the local labor market level, 3.4% at the province level and 1.7% at the region level. Nonetheless, the overall dynamics are quite robust across aggregation levels. We observe a substantial drop in internal mobility during the recession (2011-13) and subsequent recovery, especially apparent in the last two years. These dynamics are more clearly detected in high-frequency data (panel (b) of Figure 4), whereas yearly data tend to smooth out these changes over time. Importantly, virtually identical patterns are found also using other traditional data sources on internal mobility (Figure B.1, panel (a)), which is reassuring that the cyclicality is not simply a by-product of our definition of residence linked to the workplace.

Location-specific flows. Figure 5 shows the distribution of relocation flows across space, plotting the average migration rates at the LLM level. We see that gross migration flows are larger in the Southern provinces, while net flows are higher in the North, which is a net receiver of internal migration flows in our sample period. Once again, very similar patterns are detected using administrative data on residence changes (Figure C.5), namely a disconnection between gross and net flows. These results are suggestive of an important link between internal migration and labor market flows, given that similar geographical patterns were uncovered for job flows.

When comparing gross and net flows, we again find a very large degree of excess turnover (see Table 4) and pronounced non-linearities in the gross-to-net flows relationship (see

Figure 6, with the corresponding scatterplot in Figure C.6). At the local labor market level, the average excess turnover rate ranges between 16.4 and 71.5, depending on the time interval.[28] These large numbers imply that internal migration flows in Italy systematically go in opposite directions, reflecting a large degree of heterogeneity in workers' choices. Importantly for our analysis, this calls for a separate assessment of gross vs. net flows.

In order to shed light on the relationship between net and gross migration flows over time, we now perform the same decomposition exercise carried out in the previous section for labor market flows. In particular, we run the following regressions:

$$IMR_{r,t} = \beta_1 NIMR_{r,t} + \alpha_r + \gamma_t + \epsilon_{r,t}, \tag{3}$$

$$OMR_{r,t} = \beta_2 NIMR_{r,t} + \alpha_r + \gamma_t + \epsilon_{r,t}, \tag{4}$$

where the estimated β's represent the share of variance of the net inflow rate accounted for by fluctuations in the specific gross flow rate. Table 5 reports the results of this decomposition.[29] The split between inflow and outflow rates is very balanced: overall, inflow rates account for between 46 and 50% of the total variance.

Last, we investigate the geographical reach of the observed internal migration transitions. Figure C.7 shows the density of distance (measured in kilometers) involved in the transitions.[30] It is immediately apparent that the lower the geographical aggregation level, the lower the distance involved. This effect is mainly mechanical, as progressively broader definitions of the location tend to exclude shorter moves. At any rate, differences are very large: for instance, the median move at the municipality level involves a distance of just 24.9 km, whereas it corresponds to 51.8 km, 119.2 km and 300.7 km at the local labor market, province and region level, respectively (Table D.7). Given that the focus of our study is on geographical relocation, as opposed to commuting, we decide to adopt LLMs as the baseline for our analysis, the equivalent to US commuting zones. Otherwise, there would be important concerns that our measures of internal migration actually capture changes in commuting patterns.[31]

[28] See Table D.5 in Appendix D for summary statistics at the other frequencies and geographical levels of aggregation.

[29] See Table D.6 for the results of the same exercise at the different geographical levels of aggregation.

[30] See Appendix A.3 for details on the distance statistics.

[31] With SISCO data, we can study commuting patterns for a cross-section of workers (as already mentioned, this is because the residence variable is only available for the last job). Conditional on commuting, we find that the median distance between residence and workplace municipality is 19.4 km. This implies that a large part of the distribution of workplace municipality changes may indeed capture commuting. This lends support to our choice of using the workplace local labor market as a reliable proxy of the residence one.

Overall, in a symmetric fashion as for job flows, this Section has shown that it is key to distinguish gross and net flows, and that both in-migration and out-migration rates are important determinants of net variations. Consistently with this, our empirical analysis in the next Section will separately study the behavior of in- and out-migration rates.

3 Causal Evidence

Following up on the descriptive evidence of Section 2, we now analyze whether labor market flows correlate with internal migration flows and whether the former drives the latter. We are particularly interested in analyzing the contemporaneous effects of both job creation and job destruction, as we saw that the two gross flows are spatially correlated. We first show simple associations by means of OLS regressions, and then provide causal evidence by instrumenting job creation and job destruction with sudden and plausibly exogenous mass hire and mass layoff events.

3.1 OLS Regressions

Using the same LLM-level yearly data presented in Section 2, we relate gross and net internal migration flows with gross job flows.[32] The empirical model we base our analysis on is the following:

$$OMR_{r,t} = \beta_1 JCR_{r,t} + \beta_2 JDR_{r,t} + \alpha_r + \gamma_{p(r),t} + \varepsilon_{r,t} \quad (5)$$

$$IMR_{r,t} = \beta_1 JCR_{r,t} + \beta_2 JDR_{r,t} + \alpha_r + \gamma_{p(r),t} + \varepsilon_{r,t} \quad (6)$$

$$NIMR_{r,t} = \beta_1 JCR_{r,t} + \beta_2 JDR_{r,t} + \alpha_r + \gamma_{p(r),t} + \varepsilon_{r,t} \quad (7)$$

where $OMR_{r,t}$, $IMR_{r,t}$ and $NIMR_{r,t}$ are, respectively, the gross out-, gross in- and net in-migration flows as a percentage of the employment of the LLM r in the previous year, and $JCR_{r,t}$ and $JDR_{r,t}$ are the gross job flows as a percentage of local employment in the current year.[33] We further account for LLM and province-by-year fixed effects – $p(r)$ denotes the province to which LLM r belongs – to capture both fixed differences in LLMs' characteristics and local area time-varying shocks. Finally, the regressions are weighted

[32] We base our analysis on yearly data, as our instrumental variables, mass hire and layoff events, can be credibly defined only at the yearly level (see Section 3.2 for more details).

[33] Unlike migration flows, which are measured with respect to the previous period's stock of employment, job flows are the cumulative sum within a period. Therefore, it is conceptually more correct to use the current period's stocks for the latter flows (consistent with Davis et al. (1998, 2006)). We verified that having employment at the denominator does not affect our results: our estimates are also robust to using the total population as the relevant stock, instead of employment (not reported, available upon request).

using the stock of payroll employment in 2010 and the errors are clustered at the province level.[34]

The results, presented in Table 6, indicate that labor market dynamism is correlated with migration flows. While the signs are as expected, the estimated associations are rather small in magnitude suggesting that jobs are mainly filled in by local workers. A 1 percentage point increase in the JCR is associated with an increase in gross in-migration of 0.15 percentage points, while a similar increase in the JDR is associated to a slightly smaller drop in gross out-migration (0.11). JCR is also negatively correlated with outflows (-0.06) and JDR with inflows (-0.03), though the cross-effects are much smaller than the main ones.

These associations are likely partly due to the fact that JCR and JDR are spatially correlated, as shown in Figures 2 and 3. This may cause issues in the interpretation of these coefficients. More in general, the OLS results cannot ensure that migration follows, in a causal sense, changes in labor demand. It could well be that the effects are partly due to reverse causality as changes in labor supply due to movements of workers across areas determine a growth or a reduction of jobs in a given location. Moreover, as highlighted above, the concurrence of job creation and job destruction flows does not allow to separately identify the drivers of gross migration flows. For all these reasons, we turn to an instrumental variable identification strategy.

3.2 IV Regressions

Empirical Strategy. Borrowing the idea of leveraging variation in mass layoffs in large firms from Gathmann et al. (2020), we further augment the specification by also including mass hire events. Such a strategy allows us to contemporaneously identify the effects of job creation and job destruction on migration flows. We isolate large mass layoff and mass hire events in the SISCO data by focusing on establishment-level net terminations and hires of more than 500 workers in a given year (but we also explore the robustness of the results using thresholds of 250 and 750 workers).[35] The idea is that large mass layoff/exit and hire/entry events are able to affect the labor demand of the entire area due to their direct effect, but most importantly because of spillovers at the local level (e.g., through local value chains or shifts in local goods and services demand). To exclude confounding factors generated by mergers and acquisitions, sales of business units or

[34] Results are robust to using the levels on the current period taken from the ILFS data. Moreover, results are essentially unchanged also when we do use not weights altogether (the regression tables are available upon request).

[35] As already mentioned, we define an establishment as the combination of a firm and a municipality of work, i.e., establishments of the same firm in a given municipality are pooled together.

temporary contracts with employment agencies, we exclude layoff (hire) events for which we observe most of the same workers being hired in (laid off from) another firm in the same municipality during the next (previous) year.[36] To prove that these events are both relevant – i.e., they matter for the local labor demand – and plausibly exogenous – to satisfy the exclusion restriction the events must not follow pre-existing trends – we provide event study and local projections-based evidence.

Mass events. First, let us note that the Italian labor market is characterized by various policies and institutions that foster employment protection and increase the costs of mass layoffs. Various schemes, such as short-time work (*Cassa integrazione guadagni*), allow to preserve employment relations during downturns and tend to be used to protect labor even when a firm crisis is permanent rather than transitory. Such policies reduce the ex-ante likelihood of observing mass layoffs. Nonetheless, we find that both mass layoff and hire events are rather common and spread across the country (Figure C.8). Table 7 reports the main characteristics of the events we analyze.[37] We observe mass hires and layoffs involving more than 500 workers occurred in 67 LLMs over the sample period and mainly concentrated in the private services sector; the average size of the events is about 970 workers. The mass hire events involve between 0.05 percent and about 12 percent of the yearly local labor market employment, while the mass layoff ones affect between 0.04 and 11 percent of the local employment. In Table D.9 we report the summary statistics of mass events by geographical macro area (North-East, North-West, Center, South and Islands): we detect a concentration of the events (45% on average) in the North-west of the country, consistent with the unbalanced distribution of employment. However, all the macro areas are hit by shocks that are comparable in absolute and relative size.[38]

We estimate establishment-level event studies according to the following specifications:

$$\Delta e_{i,t} = \sum_{k=1}^{3} \beta_k MH_{i,t-k} + \sum_{k=0}^{3} \beta_k MH_{i,t+k} + \alpha_i + \gamma_t + \varepsilon_{i,t} \quad (8)$$

$$\Delta e_{i,t} = \sum_{k=1}^{3} \beta_k ML_{i,t-k} + \sum_{k=0}^{3} \beta_k ML_{i,t+k} + \alpha_i + \gamma_t + \varepsilon_{i,t} \quad (9)$$

[36] More specifically, we exclude events for which we observe at least 70 (for 250-unit events), 50 (for 500) and 30% (for 750) of the workforce being employed in (or laid off from) another firm in the same municipality the next (previous) year. The results are robust to the inclusion of these events (not reported, but available upon request).

[37] The Table D.8 reports the summary statistics for the other thresholds (250 and 750); Figures C.9-C.10 report the corresponding geographical distributions.

[38] The Italian South experiences, on average, bigger shocks than the other areas in terms of relative employment, due to an outlier mass layoff of more than 8,000 workers dismissed following the takeover of a large Italian steel producer in the Taranto local labor market in 2018.

where α_i and γ_t are establishment and year fixed effects and $\Delta e_{i,t}$ represents the net activations in each establishment i and year t. The standard errors are clustered at the establishment level. We define $MH_{i,t}$ and $ML_{i,t}$ as dummy variables that take value one if establishment i is affected by a mass hire or a mass layoff event at time t, respectively (i.e. $MH_{i,t} = \mathbb{1}\{\Delta e_{i,t} \geq 500\}$, $ML_{i,t} = \mathbb{1}\{\Delta e_{i,t} \leq -500\}$ in the baseline, while we use 250 and 750 as the relevant threshold in the robustness checks). The treated units are all firms in the data where a mass event occurs (i.e., we do not impose any minimum or maximum firm size): in the main specification, we do not include untreated units, allowing the not-yet treated and already-treated firms to act as controls units.[39]

The regression results of the event studies are reported in Figure 7, where the left-hand panel shows the results for mass hire events, and the right-hand panel for mass layoff events (the robustness checks for the 250 and 750 thresholds are reported in Figure C.11). Both types of events show a similar pattern. First, and most notably, the pre-trends are flat indicating that mass hires and layoffs do not follow a pre-existing dynamic. This test reassures us about the plausible exogeneity of the instruments used for the identification strategy and confirms that such events occur despite the existence of labor institutions aimed at reducing, or spreading over time, the extent of workers' layoffs. Second, mass hires imply, on average, an increase in employment of just above the relative thresholds (500 units in the main specification) in the event year, which only partially offsets future hires. In the case of mass layoffs, the average decline in the establishment workforce is larger than the relative threshold in each specification and it keeps declining though at lower levels in the subsequent years.

While mass layoffs have been widely studied in the literature, we are the first to our knowledge to use mass hires as an instrument for job creation. There are mainly two categories of mass hire events in our data: i) the opening or expansion of establishments, with the consequent creation of mainly permanent jobs, concentrated in the manufacturing and transport sectors; ii) the hiring en masse of temporary staff for specific projects and short-term needs of expansion of the production capacity. This second type of event mainly concerns business services (marketing, business consulting, but also cleaning and software development). Representative examples in our data are increases in the workforce in 2015 at a plant in the province of Potenza (+1837) of a well-known car company and at a regional public transport company in the province of Cagliari (+520). On the other hand, examples of massive fixed-term hires are the recruitment by marketing and business support companies linked to the Expo Milano 2015 event, and the temporary

[39] Following a recent growing literature that highlights the potential pitfalls of having only treated units in difference-in-difference regressions (see de Chaisemartin and D'Haultfoeuille (2022) for a recent survey), in a robustness check we also included untreated units in the control group: the results, available upon request, are robust to such specification of the event studies.

hiring of more than 750 people in Turin in 2017 for a project launched by a well-known sporting club.

Construction and validation of the IV. We define our aggregate exogenous shifter as the number of employees involved in mass hire and layoff events over the LLM employment, i.e. we consider the intensive margin of the events, by pooling all the events that occurred in the same LLM in the same period (as in Gathmann et al., 2020).[40] Therefore, the IV variables are defined as:

$$MH^{IV}_{r,t} = \sum_{i \in I(r)} \frac{\Delta e_{i,t} \cdot MH_{i,t}}{E_{r,t}} \tag{10}$$

$$ML^{IV}_{r,t} = - \sum_{i \in I(r)} \frac{\Delta e_{i,t} \cdot ML_{i,t}}{E_{r,t}} \tag{11}$$

where the sums are taken over the set of establishments located in LLM r, denoted $I(r)$.

The estimation results in Table 8 are extremely reassuring: the mass hire events are positively correlated with local job creation, while the mass layoff events are positively and strongly correlated with job destruction. The Kleibergen-Paap statistics (57.13 in the main specification) suggests that a weak first stage is highly unlikely.[41] Importantly, the cross-effects are limited indicating that mass hire and layoff events are able to separately identify JC and JD, respectively.[42] To provide corroborating evidence that the instrument is likely to be exogenous at the local labor market level, we further test the absence of pre-trends in the correlation between our instruments and the JC and JD rates. The local projection estimates (Jordà, 2005), reported graphically in Figure 8, confirm that both instruments have a one-time impact on the endogenous variables and are not affected by anticipation effects or confounding trends.[43] We discuss additional potential threats to identification stemming from the correlation of these events over time and across space in Section 5.

[40] The results are qualitatively similar if we include a dummy variable for the LLM-year of the events instead of the intensive margin (the 2SLS are available upon request).

[41] The strength of the first stage cannot be formally tested because the literature has not yet converged on a single procedure. The Stock-Yogo critical values for size distortion are below the Kleibergen-Paap statistics (7.03 for a 10 per cent size distortion) but are inapplicable because they rely on homoschedastic errors.

[42] See Appendices C and D for robustness on the first stage and ancillary analyses at different event thresholds.

[43] Similar to distributed-lag regressions, the local projections allow to estimate the impact of a treatment on an outcome over time (for more details see Jordà (2005) and Jordà et al. (2020)). The specification used here is the same as that of the first stage reported in Table 8, though the outcome variable is lagged or forwarded accordingly (i.e., $y_{r,t+h} = \beta \Delta Empl^{MassEv}_{i(r),t} + \alpha_r + \gamma_{p(r)t} + \varepsilon_{r,t+h}$ for $h = -3, .., 0, 1, .., 3$, where $y_{r,t+h}$ represents either JCR or JDR in LLM r located in province p). The results are robust to the inclusion of lags in the explanatory variables. Figures C.12 and C.13 show the same picture for the other two thresholds.

Main effects. Having shown the plausibility of mass hire and layoff events as independent determinants of local job creation and destruction, we now turn to the 2SLS estimation. Table 9 partly confirms the OLS results, but provides further interesting evidence. First, the magnitude of the job creation effect on in-migration is about 55 percent larger than the OLS estimates, possibly reflecting a local effect, while that of job destruction is about half as large as before, indicative of an upward bias in the OLS. More specifically, a 1 percentage point increase in the job creation rate leads to a 0.23 percentage points increase in the in-migration rate; the same change in the job destruction rate causes an increase in the out-migration rate of just .06 percentage points.[44] This shows that JC has a greater power in generating migration flows than JD does. Importantly, we separately identify the effects of each labor market flow on gross migration flows, revealing a large degree of asymmetry in their effects. It is important to remark that the effect of JD on out-migration, despite being small, is nonetheless statistically significant, something rarely observed in the existing literature on the US and Germany (Notowidigdo, 2020; Monras, 2018). Finally, we also uncover an effect of JCR on outflows, i.e., the cross-effect, that has the expected sign and a very similar magnitude to the one estimated with the OLS. On the contrary, the effect of JDR on inflows is not statistically different from zero. These results highlight the importance of accounting for both margins of labor market dynamics when estimating adjustments to demand shocks.

Dynamic effects. The main results speak only to the contemporaneous response of migration flows to local labor demand variations. The short panel available to us does not allow to fully test for dynamic effects. In Table 10, however, we experiment by including one lag of the independent variables (properly instrumented). The results, interestingly, point to a delayed and larger effect of JD on both out-migration and in-migration (of opposite sign); the effect of JC on in-migration is instead confirmed to be contemporaneous. However, the bulk of the asymmetry in the effect of JC shocks on in-migration relative to the one of JD shocks on out-migration survives.

Effects by distance of migration. The richness of the SISCO data allows us to further characterize the flows into and out of an area in response to job creation and job destruction. In particular, we focus on the distance to see how local the effects of labor demand are: this margin is relevant from a policy perspective, as it informs about the extent of geographical mobility in response to different labor demand shocks. We first look at two case studies to exemplify our empirical strategy. Figure C.14, panel (a), shows the percentage point change in migration rate from each local labor market to

[44]See Tables D.10 and D.11 for the corresponding tables for the different thresholds, and Tables D.12 and D.13 for the corresponding tables using different geographical aggregation levels (province and municipality).

that of Milan after a mass hire event in the city of Milan in 2012. The strongest effect is concentrated in the nearby areas (Varese and Brianza, north of Milan, and Lodi and Cremona, south-east of Milan), while also other nearby local labor markets experience smaller impacts. More distant labor markets, such as those in the region of Liguria (south of Milan), experience only a minor rise in migration outflows. Interestingly, also the local labor markets of Livorno and Grosseto, in the Central region of Tuscany, experience a rise in migration directed to Milan. In panel (b), we show the same estimates, but for an opposite-sign event, i.e., a mass layoff occurred in Palermo, Sicily, in 2013. Interestingly, the outflows of workers from Palermo to other LLMs are much smaller and less dispersed across space: people moved mainly to the LLMs of Agrigento and Caltanissetta, south of Palermo.

We then show more systematically the geographical extent of migration flows in response to labor demand shocks to confirm that the examples are not driven by idiosyncratic factors (e.g., regional differences). We replicate the analysis of Equations (5)-(7), estimated by 2SLS, binning the migration flows by distance. The results, reported in Table 11, confirm the descriptive patterns presented in the previous exercise. The out-migration rate responds only to a change in JDR and is a rather local phenomenon (panel (a), less than 100 km). On the contrary, the increase in IMR in response to JCR has instead a much larger geographical reach, though with a decaying intensity.

4 Inspecting the Asymmetry

One of the key results presented above was that the effect of JC (i.e. positive shocks) on in-migration is much larger than the one of JD (i.e. negative shocks) on out-migration. We believe that this is a very important finding, with clear implications on how different variations in labor demand are absorbed through migration flows and on how we should think of the reaction of migration choices to labor market shocks. In this Section, we try to shed some light on the difference in the magnitude of the responses.

First, we consider the possibility that the different event types are affecting different segments of the labor market. In that case, composition effects in terms of the population involved may be responsible for the differential effects that we retrieve. Regarding this, it is useful to recall that the sectoral distribution of these events is very similar, suggesting the absence of systematic differences (Figures C.15-C.17). Even more compellingly, the populations involved in mass hire and mass layoff events have overall quite similar observables, with the only exception of age (Table 7). That is, the gender, education and nationality composition across the two types of events are remarkably in line: the share of women is 58% for mass hires and 54% for mass layoffs, the corresponding figures for the share of foreigners are 10% and 9%, and the share of graduates affected is virtually identical at about 13%. The only significant difference is the average age, about six years lower among workers affected by mass hire events (35.6) than those affected by mass layoffs (41.5). However, a sizable part of this difference is simply due to the fact that contract terminations tend to affect older people more frequently than younger workers. Indeed, we verify that these events have only a minor effect on the average age of separations (hires). To understand what part of the asymmetry in our estimated coefficients can be attributed to the age composition of these mass events, we run again our IV estimation including as control the average age of local gross hires and terminations (Table D.14). Our estimates hold robust, with only a slight decrease in the magnitude of the JC effect on in-migration and a similar increase in the coefficient of JD on out-migration. Overall, the difference in the two coefficients is reduced by less than 20 percent. We conclude that composition effects may at most explain only a small fraction of the asymmetry.

Therefore, we dig deeper into the nature of this asymmetry. First, it is useful to note that, by construction, in-migration flows reflect decisions of households of *all other* locations, implying a much larger originating stock than out-migration, which is instead bounded by the local population. From this observation, we write down a simple decomposition equation of the in-migration rate that allows us to distinguish the extent of the population at risk of in-migrating from the actual decision of migrating towards a given local labor market. That is:

$$IMR_{r,t} = \frac{\sum\limits_{s\neq r}\sum\limits_{j} m^j_{s\to r,t}}{E_{r,t-1}} = \underbrace{\frac{\sum\limits_{s\neq r}\sum\limits_{s'\neq s}\sum\limits_{j} m^j_{s\to s',t}}{E_{r,t-1}}}_{Migrants\,from\,s\neq r} \underbrace{\frac{\sum\limits_{s\neq r}\sum\limits_{j} m^j_{s\to r,t}}{\sum\limits_{s\neq r}\sum\limits_{s'\neq s}\sum\limits_{j} m^j_{s\to s',t}}}_{Share\,picking\,r} \tag{12}$$

$$= \underbrace{\frac{\sum\limits_{s\neq r} E_{s,t-1}}{E_{r,t-1}}}_{\equiv ER} \underbrace{\frac{\sum\limits_{s\neq r}\sum\limits_{s'\neq s}\sum\limits_{j} m^j_{s\to s',t}}{\sum\limits_{s\neq r} E_{s,t-1}}}_{=OMR_{s\neq r}} \underbrace{\frac{\sum\limits_{s\neq r}\sum\limits_{j} m^j_{s\to r,t}}{\sum\limits_{s\neq r}\sum\limits_{s'\neq s}\sum\limits_{j} m^j_{s\to s',t}}}_{\equiv RAR}. \tag{13}$$

Equation (12) makes it clear that the in-migration rate of local labor market r is equal to the product of two terms. The first one represents *potential* in-migrants (i.e., workers relocating from all other locations), while the second one is the decision of actually migrating into r, which we can interpret as the probability that local labor market r represents the best choice for relocating households. Loosely speaking, the first term has to do with the binary decision of whether to relocate or not, whereas the second term reflects the ranking of different alternatives (we, therefore, name it *relative attractiveness* *ratio*, RAR). In fact, the first term can be decomposed further into a component that represents the relative size effect (that we term ER – *employment ratio* – i.e. how large the stock of employment in all other locations is relative to the one of local labor market r) and a component that corresponds to the overall out-migration rate of a macro-region made of all locations minus r (Equation (13)). Note that, by construction, it is not possible to derive any decomposition of this kind for the out-migration rate.

From Equation (13), we derive three counterfactual series of the IMR for each local labor market generated by letting only one component vary over time and fixing the others at their average. Regressing the actual series on these counterfactual ones allows us to gauge the quantitative role of these components in generating movements of the IMR over time. Table D.15 reveals that all components are responsible for part of the overall dynamics, but with marked differences. In particular, the RAR stands out as the most important component, with a coefficient of the counterfactual series of about 0.98, very close to unity. Even more importantly, the share of variance accounted for only by movements in RAR is about 97%, substantially more than the one explained by changes in the ER or in the OMR of the other locations (about 49% in both cases). Having established that the relative attractiveness ratio is a key source of variation in the in-migration rate, we now study whether this component can also explain the stronger reaction of the IMR to job creation shocks than that of the OMR to job destruction.

To do so, we repeat the IV regressions of Section 3.2 by using as a LHS variable the three components of the in-migration rate (ER, $OMR_{s \neq r}$, RAR) after taking logs.[45] Table 12 reveals that virtually the whole positive reaction of IMR to JCR shocks can in fact be traced back to changes in the relative attractiveness ratio.[46] This means that positive shocks do *not* cause more workers to decide to relocate, but rather that they cause relocating households to change their desired destination. We believe that this is a crucial finding that enhances our understanding of the migration reaction to labor demand shocks. First, we document that the extensive margin (the decision to in-migrate or not) is almost unresponsive to shocks, whereas the ranking of destinations in a revealed preference sense is highly sensitive to local economic conditions. Moreover, these findings imply the existence of negative externalities, as positive shocks in a local labor market relatively worsen the RAR for other competing markets. Last, we claim that the strong reaction of the RAR largely explains the asymmetry between the effect of positive shocks on in-migration and the one of negative shocks on out-migration. In fact, through the lens of our separate regressions, we show that positive shocks also do not cause more

[45] Taking logs is needed to make the decomposition into a sum. Furthermore, this also helps at making the scale of the variables comparable, being otherwise very different.

[46] The results are confirmed for different IV thresholds: see Table D.16.

relocation, but rather they act on a substantially different margin, one that is not at play for out-migration.

5 Additional Threats to Identification

To deliver a clean identification and avoid bias induced by the over time correlation of mass events, the literature imposes restrictions on the events' definition (Gathmann et al., 2020). Moreover, a recent contribution by Borusyak et al. (2022) shows that empirical studies often deliver biased estimates of the migration response due to omitted shocks to relevant alternative locations that are correlated with that to the location of interest (even when shocks are uncorrelated with local unobservables).

To ensure that our IV, which leverages the over time and across space variation in the intensity of local mass events, allows for unbiased identification of the effects of JC and JD on migration flows, we conduct a battery of tests on mass events' spatial and serial correlations. Figure C.18 plots the distribution of the events across space (horizontal axis) and over time (vertical axis).[47] Regarding the possibility of correlations over time, a visual inspection of the figure reveals that, even though some LLMs have repeated events – clearly, larger locations mechanically have more chances to be affected by such events – no systematic patterns emerge. To test more formally for such correlations, in Table D.17 we report the coefficient estimates of regressions of our instrumental variables against their own lags as well as against the lags of the opposite-sign events, confirming the pattern: the intensity of these mass events are not systematically *positively* correlated with past realizations nor they increase the size of the events of the opposite type. If anything, a higher intensity of mass hires two years prior reduces the intensity of the current event; similarly, the intensity of the previous year's mass layoff reduces the current year's mass layoff intensity. Note that while these negative correlations indicate that the events do not occur randomly in time, they indicate that we are not confounding the responses to preceding (or following) hires or layoffs nor that the responses to one type of events is actually due to that of another type.

Turning to the correlations across space, Figure C.8 shows that these events are scattered across the whole country, without any clear spatial pattern.[48] A more formal test is provided in Tables D.18 and D.19, where we regress our instrumental variables on the average intensity of the mass events – i.e. the average labor demand shock, as captured by our instruments – occurred at various distances. We show that there is some degree

[47]See Figures C.19 and C.20 for the corresponding figures at the other thresholds.

[48]This can also be seen from Figure C.18, as LLMs' codes contiguity implies geographical contiguity; therefore, the Figure suggests that the events are not clustered in a subset of localities.

of crowding-out at short distances for the same type of events, while distant events are not correlated with one another. Thus, to guarantee that our IV still capture the local labor demand effect only, in a robustness check we include as controls the JC and JD of contiguous locations (within 100 km), also instrumented by their mass events (Table D.20): the results hold robust. We conclude that, in our setting, the spatial correlation of the instruments is not an issue for the identification of the causal nexus between local labor demand shocks and the migration response.

6 Concluding remarks

Exploiting high-quality administrative data on the universe of labor market flows, this paper estimates the causal impact of both positive and negative labor demand shocks on gross and net internal migration flows. Our empirical strategy is based on plausibly exogenous shifts of labor demand stemming from mass hire or layoff events at the establishment level. The 2SLS estimates reveal that both job creation and job destruction have important (opposite) effects on net in-migration, with the former being almost four times as large as the latter. These differences are due to the greater effect of job creation on in-migration (along with a muted response of out-migration), as opposed to the smaller – though not negligible – impact of job destruction on the out-migration rate. Moreover, the former effect takes place within the same year of the shock, whereas the reaction of out-migration is more delayed. Finally, we also document that job creation shocks induce larger in-migration responses even from relatively distant locations, whereas job destruction causes locally concentrated out-migration.

We dig deeper into the large reaction of in-migration to positive shocks, documenting that it is not mainly driven by composition effects nor brought about by an increase in the number of relocating workers, but rather by a reshuffling among their preferred alternatives. We see this as a crucial finding, both for correctly modeling migration choices and for better understanding the different reactiveness of in- vs. out-migration to labor market variations.

Overall, our results remark the importance of accounting for gross job and internal migration flows when designing labor market and social policies. Our regression analysis implies that the consequences of positive shifts of labor demand are more largely shared across space through internal migration; the incidence of negative labor demand is instead mainly, though not completely, local. Such asymmetry might be a source of inequality of job opportunities across areas in the short-run. Therefore, policy makers may want to pose greater attention on the realization of negative events and act accordingly to avoid the insurgence of cross-regional disparities. Future research will uncover relevant underlying determinants of geographical mobility that will better inform policy decisions. The availability of rich administrative data, in particular, will allow to investigate dimensions of heterogeneity such as workers' education level, demographic characteristics and the geographical distribution of occupations and job opportunities.

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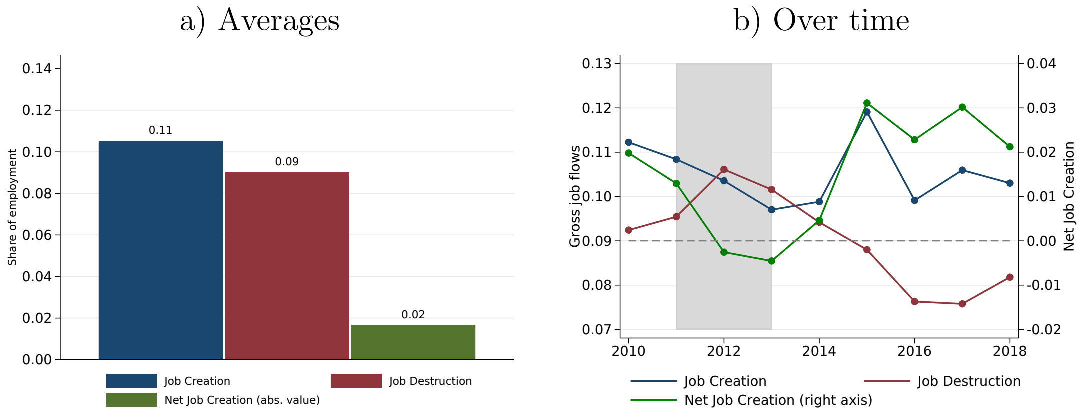
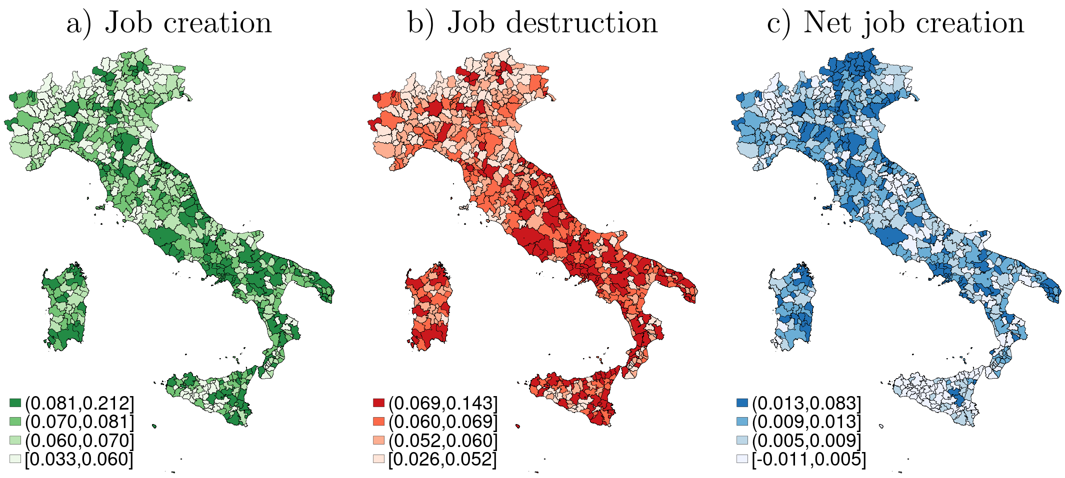
Figures

Figure 1: Job flows in Italy



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the average levels (panel (a)) and the time series (panel (b)) of yearly job flow rates for Italy. Job flow rates are the sum across establishments of net job activations at the establishment-level, divided by the stock of payroll employment in the current period taken from the ILFS data. The shaded area represents the 2011-2013 recession.

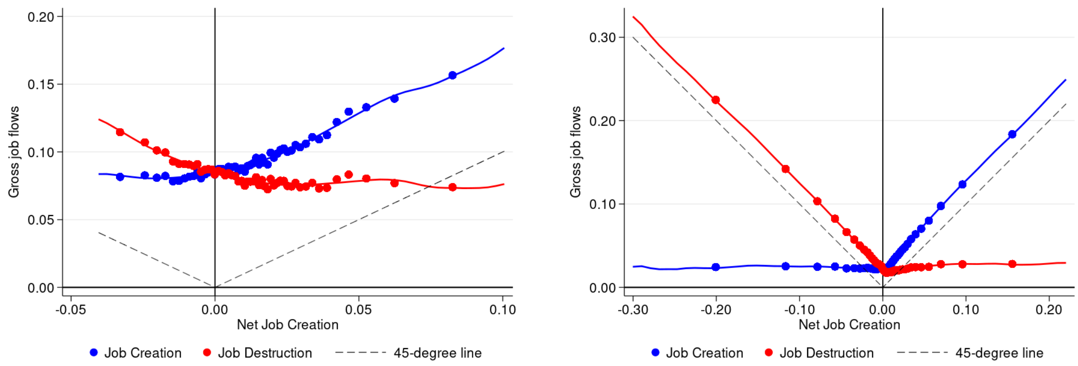
Figure 2: Average job flow rates across local labor markets



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the geographical distribution of average job flow rates. Job flow rates are the sum across establishments of net activations at the establishment-level, divided by the stock of payroll employment in the current period taken from the ILFS data.

Figure 3: Average gross vs. net job flow rates

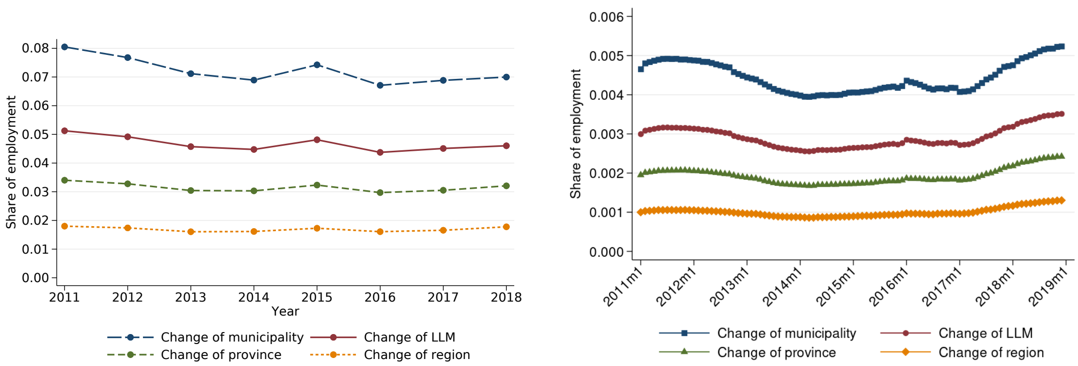
a) Yearly frequency b) Monthly frequency



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the average gross job flow rates against the corresponding net flows at local labor market level, at yearly (panel (a)) and monthly (panel (b)) frequencies. Solid lines are the prediction of second-degree local polynomial regressions. Scatter points represent averages of two percentiles of the underlying distribution. Dashed lines represent the 45-degree lines. Gross and net flows are divided by the stock of payroll employment in the current period taken from the ILFS data.

Figure 4: Time series of internal migration

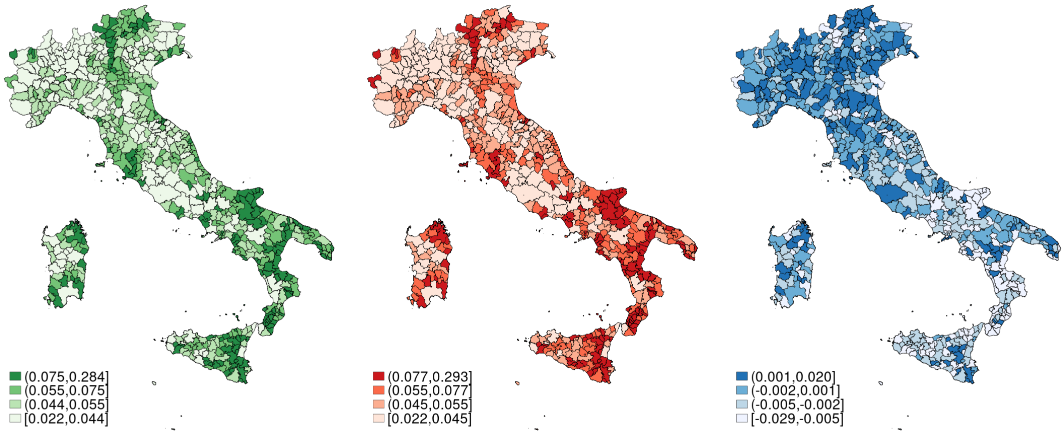
a) Yearly frequency b) Monthly frequency



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the time trends of internal migration rates for different geographical levels (municipality, LLM, province, region) at yearly (panel (a)) and monthly (panel (b)) frequencies. Monthly series are smoothed using a twelve-periods window. Migration rates are computed by dividing the number of observed transitions in the SISCO microdata by the corresponding stocks of payroll employment in the previous period taken from the ILFS data.

Figure 5: Average internal migration rates across local labor markets

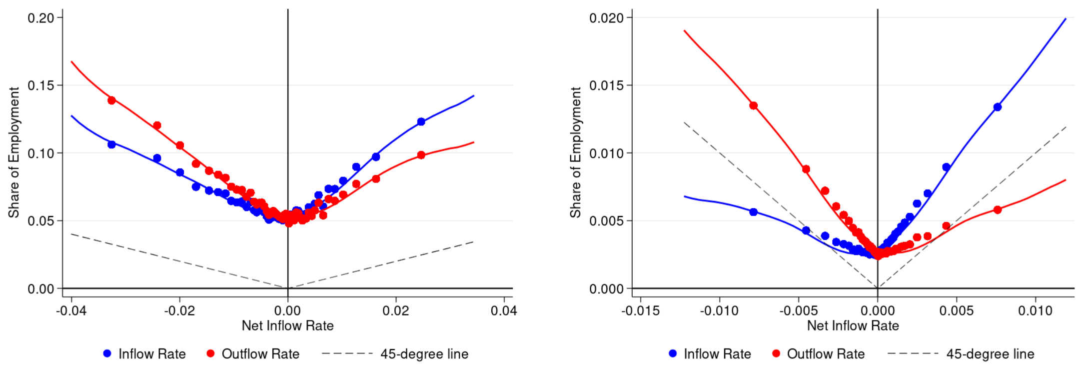
a) Inflows rate b) Outflows rate c) Net inflows rate



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the geographical distribution of average internal migration rates. Migration rates are computed by dividing the number of observed transitions in the SISCO microdata by the corresponding stocks of payroll employment in the previous period taken from the ILFS data.

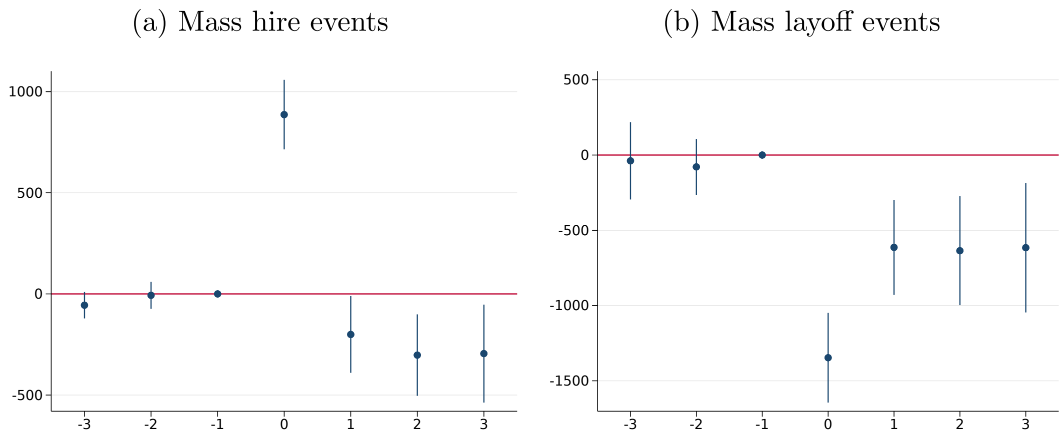
Figure 6: Gross vs. net internal migration flows

a) Yearly frequency b) Monthly frequency



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows average gross migration flow rates against the corresponding net flows at local labor market level, at yearly (panel (a)) and monthly (panel (b)) frequencies. Solid lines are the prediction of second-degree local polynomial regressions. Scatter points represent averages of two percentiles of the underlying distribution. Dashed lines represent the 45-degree lines. Gross and net flows are divided by the stock of payroll employment in the previous period taken from the ILFS data.

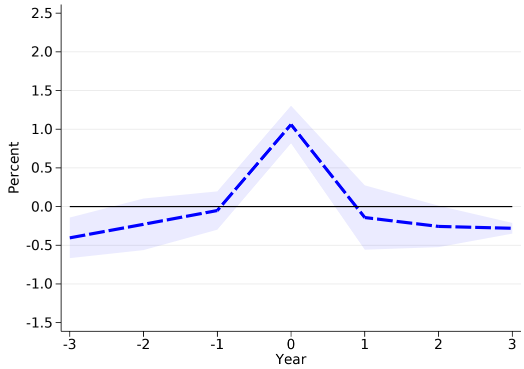
Figure 7: Establishment-level mass hires and layoffs in Italy, event studies



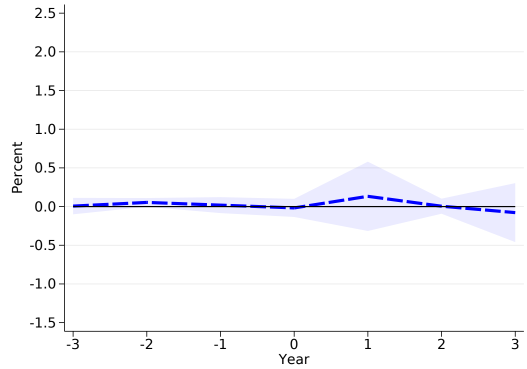
Source: SISCO data 2010-2018. *Note*: The figure shows the results of the event studies for establishment-level mass hires and layoffs (equations (8) and (9)) involving more than 500 workers. We isolate large mass layoff and mass hire events in the SISCO data by focusing on establishment-level terminations and hires above the threshold in a given year. The 95 percent confidence intervals (bars) are clustered at the establishment level.

Figure 8: Mass events intensive margin on JCR and JDR, local projection estimates. Events 500+

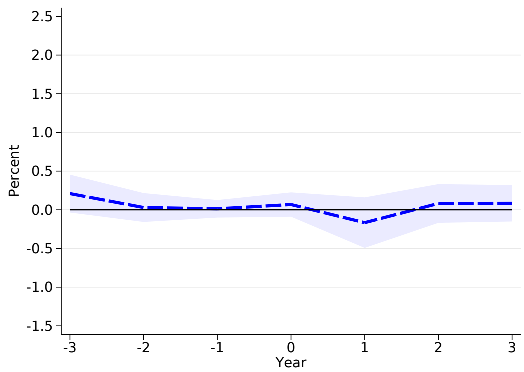
(a) Effect of mass hire on JCR



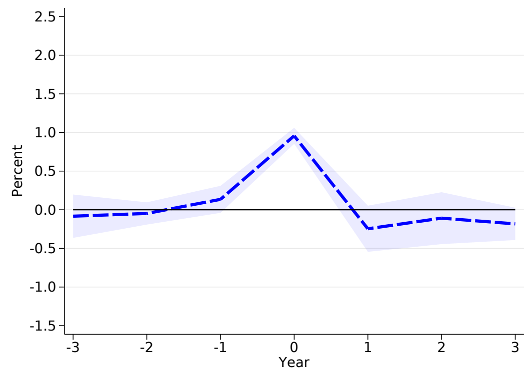
(b) Effect of mass hire on JDR



(c) Effect of mass layoff on JCR



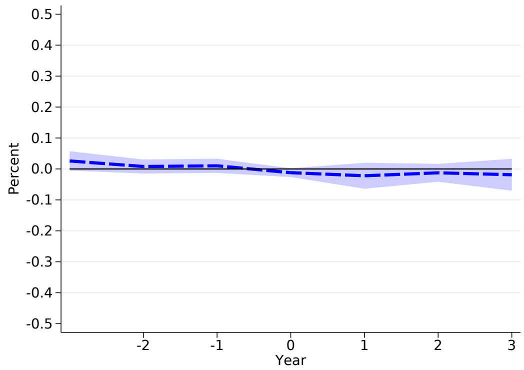
(d) Effect of mass layoff on JDR



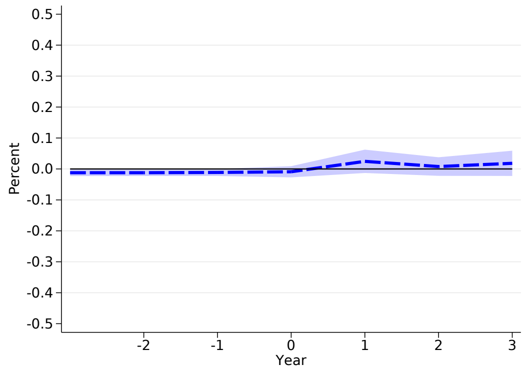
Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the local projection estimates of the yearly variation in employment following a mass event at local labor market level of more than 500 net activations or terminations on the local job creation and the job destruction rates. The intensive margin is obtained by dividing the employment change in the local labor market by the stock of employment in 2010 taken from ILFS data. The 95 percent confidence intervals (shaded areas) are estimated by clustering pointwise standard errors at the provincial level.

Figure 9: Mass events intensive margin on various ratios, local projection estimates. Events 500+

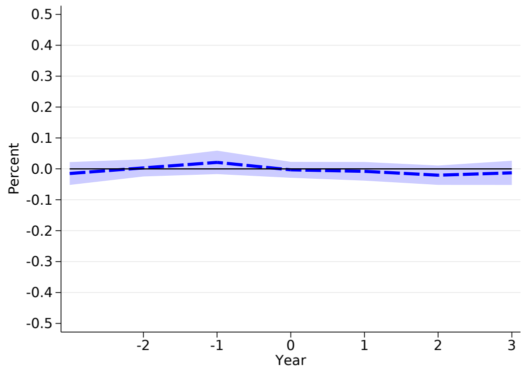
(a) Effect of mass hire on Employment/Population ratio



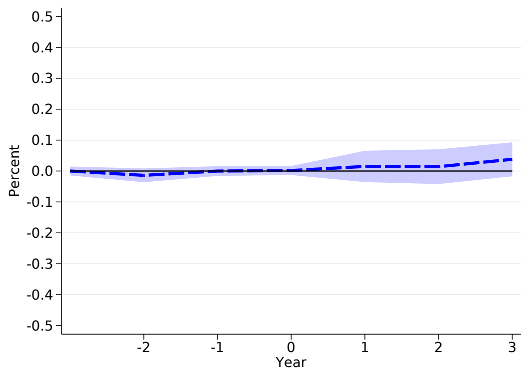
(b) Effect of mass layoff on Employment/Population ratio



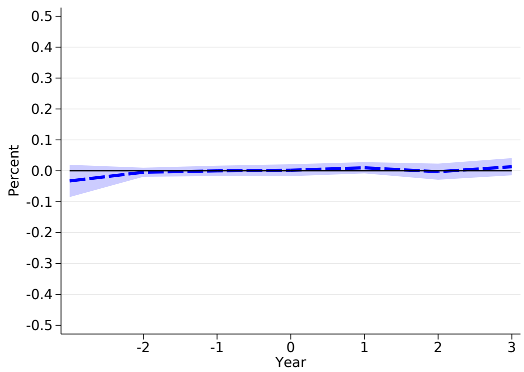
(c) Effect of mass hire on the Activity Rate



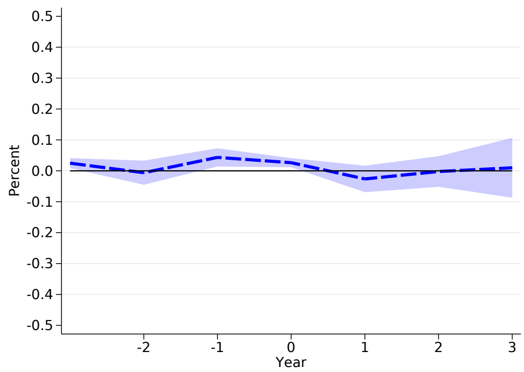
(d) Effect of mass layoff on the Activity Rate



(e) Effect of mass hire on the Unemployment Rate



(f) Effect of mass layoff on the Unemployment Rate



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the local projection estimates of the yearly variation in the employment-to-population ratio ((a)-(b)), the activity rate ((c)-(d)), and the unemployment rate ((e)-(f)) following a mass event at local labor market level of more than 500 net activations or terminations on the local job creation and the job destruction rates. The intensive margin is obtained by dividing the employment change in the local labor market by the stock of employment in 2010 taken from ILFS data. The 95 percent confidence intervals (shaded areas) are estimated by clustering pointwise standard errors at the provincial level.

Tables

Table 1: Correlation matrix

	JCR	JDR	NJCR
JCR	1		
JDR	-0.084	1	
NJCR	0.603	-0.846**	1

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows the correlation matrix of yearly aggregate job flow rates for Italy. Job flow rates are the sum across establishments of net activations at the establishment-level, divided by the stock of payroll employment in the current period taken from the ILFS data. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table 2: Summary statistics, job flow rates

	Job flows			
Frequency	JCR	JDR	|NJCR|	$\frac{\text{JTR}}{\lvert\text{NJCR}\rvert}$
Monthly	0.041	0.040	0.037	10.6
	(0.052)	(0.062)	(0.073)	(52.8)
Quarterly	0.087	0.083	0.079	13.0
	(0.099)	(0.098)	(0.121)	(84.2)
Yearly	0.097	0.083	0.021	36.2
	(0.033)	(0.026)	(0.022)	(253.5)

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows summary statistics (average and standard deviation) of job flow rates at local labor market level at monthly, quarterly, and yearly frequency. Job flow rates are the sum across establishments of net activations at the establishment-level, divided by the stock of payroll employment in the current period taken from the ILFS data.

Table 3: Decomposition, Labor market dynamism

	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	JCR	JDR	JCR	JDR	JCR	JDR
JNCR	0.445	-0.555	0.528	-0.472	0.616	-0.384
	(0.020)	(0.020)	(0.014)	(0.014)	(0.018)	(0.018)
N	58,560	58,560	19,520	19,520	4,880	4,880
R2	0.648	0.778	0.826	0.827	0.697	0.640

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows the results of linear regressions of gross against net labor market flows at local labor market level for different time aggregation levels. Estimated coefficients can be interpreted as the share of total variance of net flows accounted for by the variation in the specific gross flow. All regressions include time and location fixed effects. Standard errors in parenthesis are clustered at the location level, and all the coefficients are significant at 99% level.

Table 4: Summary statistics, Internal migration

	Migration flows			
Frequency	IMR	OMR	|NIMR|	$\frac{\text{MTR}}{\lvert\text{NIMR}\rvert}$
Monthly	0.004	0.004	0.002	16.4
	(0.005)	(0.005)	(0.004)	(46.8)
Quarterly	0.016	0.016	0.007	29.8
	(0.017)	(0.017)	(0.017)	(85.9)
Yearly	0.066	0.068	0.008	71.5
	(0.039)	(0.040)	(0.010)	(199.0)

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows summary statistics (average and standard deviation) of internal migration rates at local labor market level at monthly, quarterly, and yearly frequency. Migration rates are computed by dividing the number of observed transitions in the SISCO microdata by the corresponding stocks of payroll employment in the previous period taken from the ILFS data.

Table 5: Decomposition, Internal migration

	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	IMR	OMR	IMR	OMR	IMR	OMR
NIMR	0.462	-0.538	0.502	-0.498	0.473	-0.527
	(0.068)	(0.068)	(0.020)	(0.020)	(0.023)	(0.023)
N	58,560	58,560	19,520	19,520	4,880	4,880
R2	0.446	0.518	0.681	0.675	0.429	0.462

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows the results of linear regressions of gross against net internal migration flows at local labor market level for different time aggregation levels. Estimated coefficients can be interpreted as the share of total variance of net flows accounted for by variation in the specific gross flow. All regressions include time and location fixed effects. Standard errors in parenthesis are clustered at the location level, and all the coefficients are significant at 99% level.

Table 6: Internal migration flows and labor market dynamism, OLS

	(1)	(2)	(3)
	OMR	IMR	NIMR
JCR	-0.056***	0.151***	0.208***
	(0.017)	(0.024)	(0.019)
JDR	0.108***	-0.028**	-0.136***
	(0.020)	(0.013)	(0.019)
N	4,880	4,880	4,880
R^2	0.973	0.974	0.440

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the OLS estimates of the effect of job creation and job destruction rates on internal migration flow rates (out-migration, in-migration, net in-migration) from SISCO data as described in Section 3.1. The specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table 7: Mass events summary statistics

	Mass hire events	Mass layoff events
Number of events	130	110
Number of LLMs hit by events	69	67
Min (Avg) Max size of events	501 (965) 4,861	501 (973) 8,414
% of LLM employment	0.05 (1.35) 11.97	0.04 (1.04) 10.57
Number of events by industry		
Manufacturing	5	8
Construction	0	0
Private services	115	74
Public services	7	18
Other sector/not specified	3	10
Characteristics of workers involved		
Share of women	0.58	0.54
Average age	35.6	41.5
Share of foreigners	0.10	0.09
Share of graduates	0.13	0.13

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the summary statistics for mass layoff and hiring events at local labor market (LLM) level involving more than 500 workers calculated from SISCO data as described in Section 3.2. Public services include privately-provided education and health services.

Table 8: Internal migration flows and labor dynamism, first-stage (intensity of mass events IV)

	(1) JCR	(2) JDR
Employment in mass hire	1.079^{***}	0.009
	(0.112)	(0.065)
Employment in mass layoff	0.103^{**}	0.965^{***}
	(0.048)	(0.043)
N	4880	4880

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the first stage estimates of mass layoff and hiring events on job creation and job destruction rates from SISCO data as described in Section 3.2. We selected events that involve more than 500 net activations or terminations. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table 9: Internal migration and labor dynamism, 2SLS (intensity of mass events IV)

	(1) OMR	(2) IMR	(3) NIMR
JCR	-0.057**	0.233***	0.290***
	(0.025)	(0.037)	(0.046)
JDR	0.061*	0.022	-0.039
	(0.037)	(0.052)	(0.074)
N	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass hiring and layoff events, on migration flow rates (out-migration, in-migration, net in-migration) from SISCO data as described in Section 3.2. We selected events that involve more than 500 net activations or terminations. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table 10: Internal migration and labor dynamism, 2SLS with lagged regressors (intensity of mass events IV)

Threshold IV	250 workers			500 workers			750 workers		
	(1) OMR	(2) IMR	(3) NIMR	(4) OMR	(5) IMR	(6) NIMR	(7) OMR	(8) IMR	(9) NIMR
JCR	-0.060***	0.229***	0.290***	-0.060**	0.234***	0.294***	-0.071***	0.246***	0.317***
	(0.021)	(0.031)	(0.030)	(0.025)	(0.034)	(0.043)	(0.025)	(0.035)	(0.043)
L.JCR	-0.008	0.007	0.015	0.023	-0.003	-0.026	0.010	-0.010	-0.020
	(0.028)	(0.032)	(0.052)	(0.031)	(0.039)	(0.063)	(0.025)	(0.030)	(0.046)
JDR	0.049	-0.010	-0.059	0.054	0.030	-0.024	0.103***	-0.018	-0.121***
	(0.035)	(0.029)	(0.052)	(0.035)	(0.059)	(0.083)	(0.018)	(0.014)	(0.017)
L.JDR	0.129***	-0.132***	-0.261***	0.126***	-0.117	-0.244**	0.182	-0.188	-0.370
	(0.043)	(0.044)	(0.062)	(0.048)	(0.082)	(0.098)	(0.112)	(0.192)	(0.294)
N	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates and their lags, instrumented by mass hiring and layoff events, on migration flow rates (out-migration, in-migration, net in-migration) from SISCO data as described in Section 3.2. We selected events that involve more than 250 (specifications (1)-(3)), more than 500 (specifications (4)-(6)), or more than 750 (specifications (7)-(9)) net activations or terminations. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table 11: Internal migration and labor dynamism by distance bin, 2SLS

	(1)	(2)	(3)	(4)	(5)
km	$[0, 50)$	$[50, 100)$	$[100, 200)$	$[200, 400)$	≥ 400
			Panel (a). OMR		
JCR	-0.004	-0.015**	-0.014*	-0.003	-0.023
	(0.009)	(0.006)	(0.008)	(0.003)	(0.016)
JDR	0.007	0.030***	0.010*	0.008*	0.004
	(0.032)	(0.008)	(0.005)	(0.005)	(0.004)
			Panel (b). IMR		
JCR	0.047	0.038	0.063***	0.038***	0.047***
	(0.030)	(0.036)	(0.015)	(0.013)	(0.012)
JDR	-0.005	-0.003	0.014	0.014	0.001
	(0.014)	(0.009)	(0.017)	(0.022)	(0.004)
			Panel (c). NIMR		
JCR	0.051*	0.052*	0.076***	0.041***	0.070***
	(0.027)	(0.032)	(0.009)	(0.011)	(0.025)
JDR	-0.012	-0.033**	0.003	0.006	-0.003
	(0.030)	(0.015)	(0.018)	(0.023)	(0.006)
N	4,872	4,880	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events involving more than 500 workers, on migration flow rates from SISCO data as described in Section 3.2. The specifications (1)-(5) differentiate migration flows into five distance bins (km $\in [0, 50)$, km $\in [50, 100)$, km $\in [100, 200)$, km $\in [200, 400)$, km ≥ 400). Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

Table 12: In-migration rate components and labor dynamism, IV 2SLS

	(1)	(2)	(3)
	ER	$OMR_{s \neq r}$	RAR
JCR	-0.069*	0.001	2.872***
	(0.040)	(0.002)	(0.291)
JDR	0.043**	-0.004	-0.203
	(0.018)	(0.003)	(0.557)
N	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events involving more than 500 workers, on the three components of yearly in-migration flow rates from SISCO data as described in Section 4, namely the employment ratio, the out-migration rate of other provinces, and the relative attractiveness ratio. The three ratios are taken in logarithms to allow comparability as they are scaled differently. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

A Data Construction

A.1 Prevalent Job Definition in the SISCO Data

The standard procedure in the economic literature for selecting the prevalent job in a period is to keep the contract with the highest wage and/or duration. Since the SISCO database does not record wages, we rely on the duration as measured in days. However, selecting as prevalent in each period (year, quarter or month) the contract with the longest spell *within* the period may introduce spurious mobility in our sample. Indeed, when more than one contract covers more than one period, the overlapping contracts may have the same duration and be located in different places; if we randomly choose one contract per period, the duration within the period being equal, we may select different workplaces in different times, without the worker having actually changed the main place of work.

To solve this problem and avoid this bias, we select the prevalent contract in each period looking at the *overall* duration of each contract: we delete the contracts whose entire spell is strictly contained in another contract (that started earlier and finished later); in case of partial overlapping, we keep for the overlapping periods only the contract with the longest overall duration; in case of perfect overlapping and exact same duration, we give priority to full-time jobs, open-ended contracts, and jobs that started earlier, following this ordering of criteria. Finally, in the residual cases in which it is still not possible to choose a prevalent contract (jobs started the same day, with the same characteristics and duration), we proceed with a random selection; again, the selection covers the entire overlapping period to avoid the bias in mobility mentioned above.

A.2 Mobility Definition in the SISCO Data

We record an internal mobility flow from location A to location B in period t whenever a worker has a prevalent contract in location A in period $t-1$ and a prevalent contract in location B in period t. An outflow for location A and an inflow for location B are registered in t. Using this procedure, in every period the sum of the inflows equals the sum of the outflows. In our robustness checks, we use an extended version of the data set in which the missing observations (non-employment spells) in the career are filled assuming that the worker is looking for a job in the location of the last employment relationship: therefore, in the case of a job flow from unemployment in period t, the outflow in t is attributed to the last location of work even if it is distant in time. Since we assume that the worker remains at the place of his last job until a new contract is activated, we restrict the analysis to cases where the unemployment period is only one year in order to avoid introducing spurious mobility.

A.3 Details on Distance Statistics

ISTAT releases origin-destination matrices of distances in meters and travel times in minutes between all Italian municipalities (using the centroids in 2013), computed using a commercial road graph. For the islands, it provides the internal distances and those between the main ports of connection with the peninsula. We, therefore, complement information about internal distances with those between internal municipalities and the nearest port. From the end of 2013 and 1 January 2019, 687 transformations of municipalities took place, of which: 156 changes of province due to the creation and then suppression of new provinces in Sardinia; 1 change of region of the municipality of Sappada from Veneto to Friuli-Venezia-Giulia; 260 new institutions from mergers of pre-existing municipalities; 270 consequent terminations of merged municipalities. We adjust the distances taking into account these transformations, and use symmetric distances for simplicity. For local labor markets and provinces, we use the distance between the capital municipality. For the municipalities of Monte Isola and Campione d'Italia, for which ISTAT does not provide the distances from the rest of the Italian municipalities, we use the data of the near municipalities of Sulzano and Alta Valle Intelvi, respectively.

B Measuring Internal Migration through Workplace-based Data: A Comparison with other Traditional Data Sources

Measuring internal migration through SISCO microdata entails several benefits with respect to existing datasets (ILFS microdata or aggregate administrative data on residence transfers from ISTAT). First, the information on geographical location is very detailed (i.e., the municipality of work) and so is the frequency of movements (up to the daily level). Therefore, the data allow to construct aggregate gross (and net) migration flows accounting for many individual and job characteristics. More traditional data sources such as the Italian LFS data and administrative data on residence transfers fall short in several dimensions. The former only ask retrospective questions on the residence the year before at provincial level. Such a rather coarse measure might fail to capture intra-annual movements across provinces as well as all within-province movements (including those across LLMs). Moreover, the data are survey-based and there is evidence that attrition due to internal mobility might induce composition bias (Martí and Ródenas, 2007). On the other hand, changes of residence data register all changes of official residence within a year summing up individual movements (the unit of observation is the change, and not the individual). Furthermore, the data are available only at annual cell level (defined by year, municipality and demographic characteristics[49]). Most importantly, these data might be biased due to misreporting for tax purposes (Rubolino, 2020). With respect to the existing dataset, SISCO data contain far richer information, in terms of both timing and geography, and record the universe of movements that also entail a job change. However, they do not record the movements of non-employed persons (within their periods of unemployment or inactivity), nor do they record information on changes of residence that do not involve changes in the workplace. In practice, the drawbacks of the SISCO data are likely to be very small, if the bulk of internal migration is indeed job-related.

All of these differences notwithstanding, we check whether major differences arise between migration patterns detected in the SISCO data and the administrative data on changes of residence. Panel (a) of Figure B.1 shows that the overall extent of migration is remarkably similar between SISCO and residence changes data in terms of levels. However, some differences arise in the specific dynamics of the two series, as transfer of residence data report an abnormal drop in 2011, a peak in 2012 and a drop again in 2015. With regard to the 2011-12 drop and peak, this is due to a well-known change in the method of collecting residence data to correct misreporting prior to 2011, which itself led to record transfers in 2012 even though they occurred in earlier years (ISTAT, 2016). The drop in 2015 appears instead as an anomaly, as the labor market was particularly healthy in that year.

Moreover, Figure B.1, panel (b), shows that the distribution of distance of the migration moves is almost identical between SISCO and residence-based change data, with some minor differences in the lower part of the distribution (residence changes are underrepresented within shorter distance bins). Finally, we also test whether SISCO and residence-based bilateral flows across local labor markets are correlated, finding a large elasticity of about 0.6-0.7 (Table B.1). We conclude that the two administrative measures of internal mobility line up well in terms of overall magnitude and across space, though they exhibit some differences in the dynamics over time because of the problems with the residence data highlighted above.

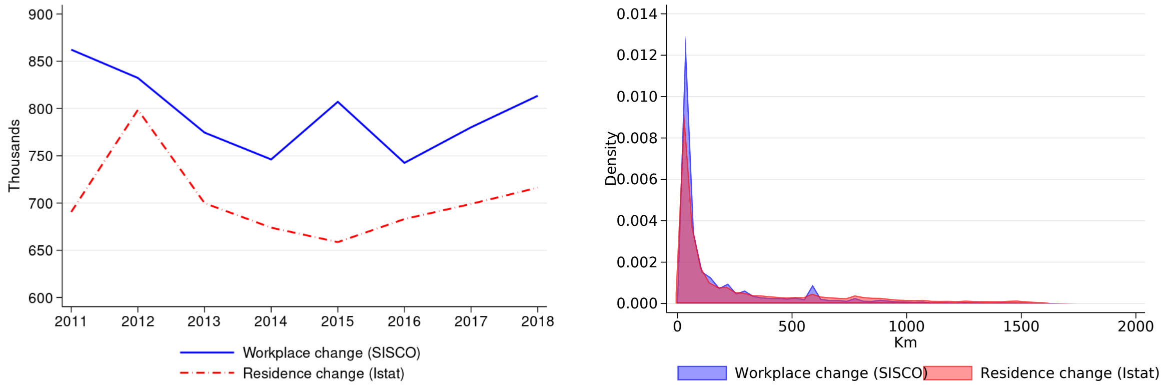
We further test whether the main 2SLS results based on SISCO data (Table 9) hold if using changes of residence data (Table D.3). While some of the effects do (e.g., that of JDR on OMR), most do not. We believe that the difference between our baseline results and the robustness check lies in the inability of residence data to correctly capture the dynamics of internal migration across years, as pointed out above. Such a source of mismeasurement causes the estimates to be biased towards zero. On the contrary, we

[49]Some demographic characteristics are incomplete, especially for foreigners.

already observed that the geographical correlation between the two source is remarkably high.

Figure B.1: Comparison between workplace-based and residence-based migration

a) Number of yearly transitions b) Distribution of distance



Source: SISCO and residence changes (ISTAT) data, 2010-2018. *Note*: The figure shows a comparison between workplace-based (SISCO) and residence-based (ISTAT) internal migration at local labor market level. Panel (a) plots the time series of total yearly location switches. Panel (b) plots the distribution of distance between the origin and destination local labor market, pooling data from all the years.

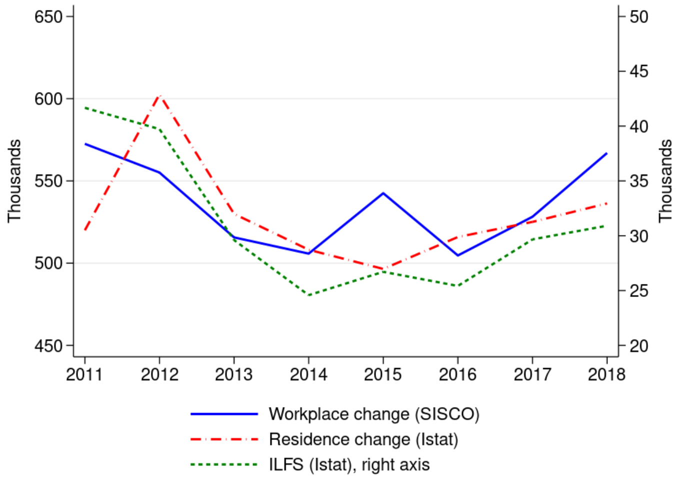
The ILFS data, as already mentioned, cannot be compared for the measurement of migration flows across local labor markets, as it only provides information on the province of residence. When we compare overall flows at the province level, we find that ILFS data systematically record only a minor share – less than 10% – of all annual moves across provinces (Figure B.2), consistently with Martí and Ródenas (2007). In this sense, the ILFS seems to underestimate geographical mobility in a significant way, but at the same time it tracks the dynamics of SISCO data remarkably well. That is, survey-based statistics underestimate actual movements, but are in line with SISCO in terms of the dynamics over time. Overall, the evidence provided herein is very reassuring regarding the use of a workplace-based measure of migration from SISCO data.

Table B.1: Workplace-based vs. residence-based migration flows

	(1) Log flows	(2) Log flows	(3) Log flows
Log flows (workplace-based)	0.714***	0.677***	0.677***
	(0.001)	(0.006)	(0.006)
Log population of origin			-0.112
			(0.239)
Log population of destination			-0.559
			(0.308)
N	346,058	346,058	346,058
Origin FE	NO	YES	YES
Destination FE	NO	YES	YES
R^2	0.581	0.660	0.660

Source: SISCO and residence changes (ISTAT) data, 2010-2018. *Note*: The table shows the results of log-log regressions between residence-based (ISTAT source) and workplace-based (SISCO source) yearly migration bilateral flows across local labor markets. Standard errors reported in parentheses are clustered at the origin and destination local labor market level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

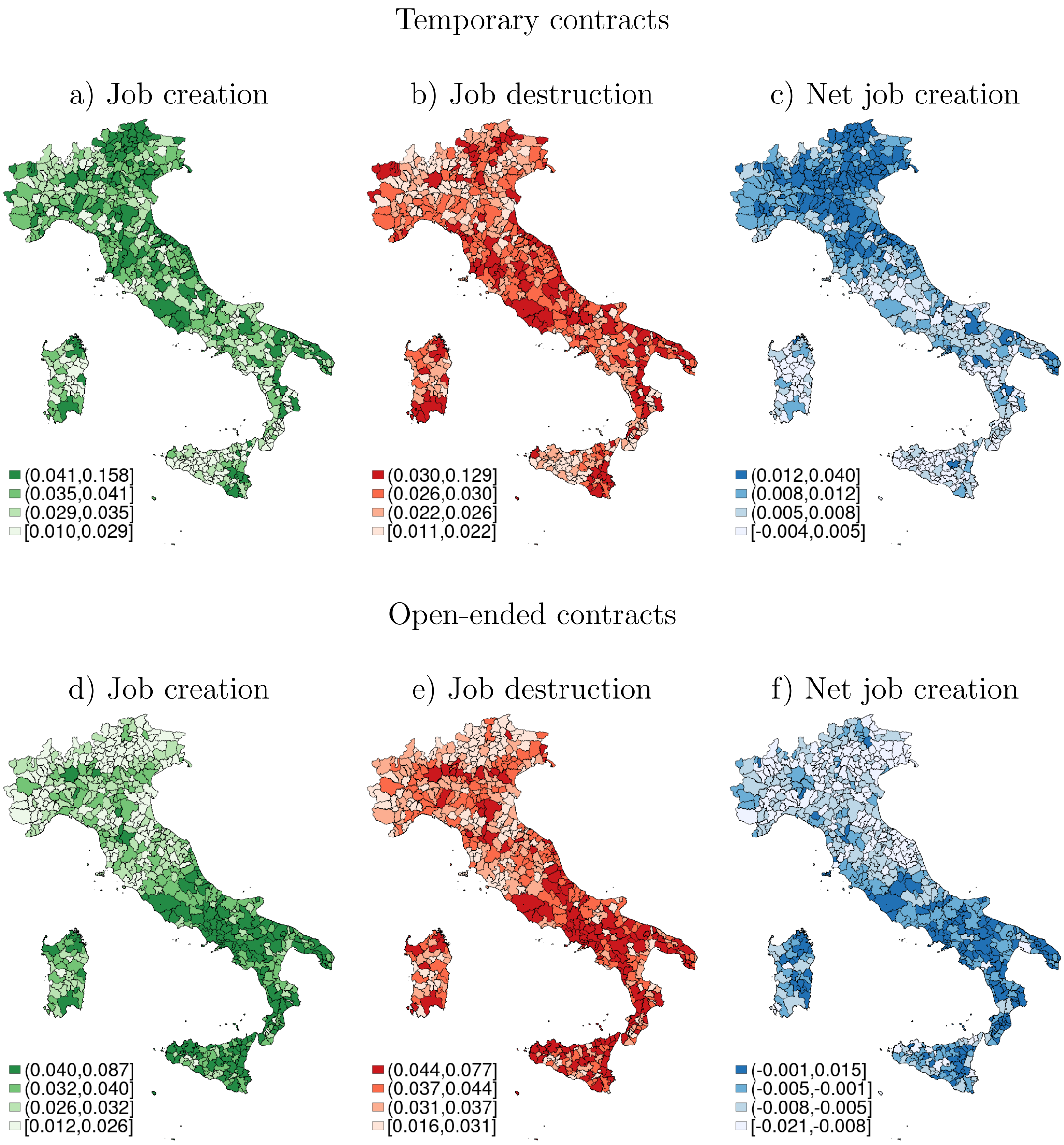
Figure B.2: Comparison between workplace-based and residence-based migration



Source: SISCO, ILFS and residence changes (ISTAT) data, 2010-2018. *Note*: The figure shows the time series of total yearly changes of province of work (SISCO) and of residence (ISTAT and ILFS).

C Additional Figures

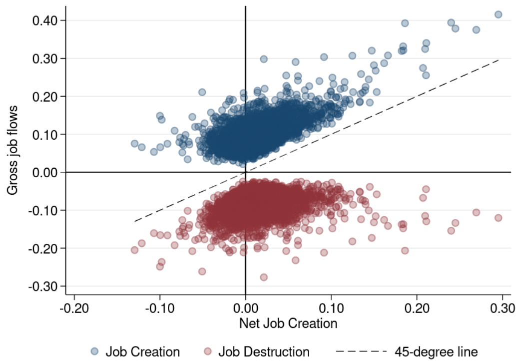
Figure C.1: Average job flow rates across local labor markets, by contract type



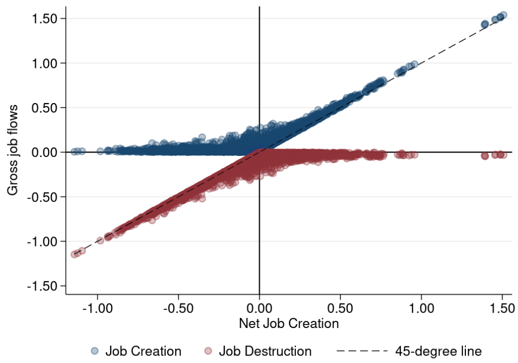
Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the geographical distribution of average job flow rates. Job flow rates are the sum across establishments of net flows at the establishment-level, divided by the stock of payroll employment in the current period taken from the ILFS data.

Figure C.2: Gross vs. net job flow rates

a) Yearly frequency

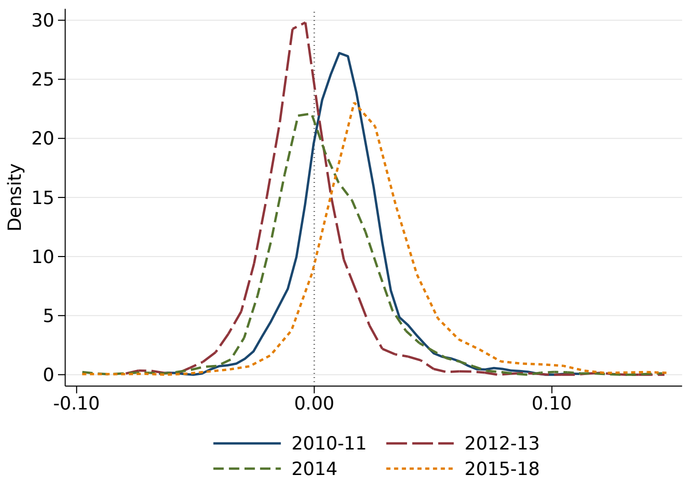


b) Monthly frequency



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows province-level gross job flow rates against the corresponding net flows, at yearly (panel (a)) and monthly (panel (b)) frequency. The flows are divided by the stock of payroll employment in the current period taken from the ILFS data. Dashed lines represent the 45-degree lines.

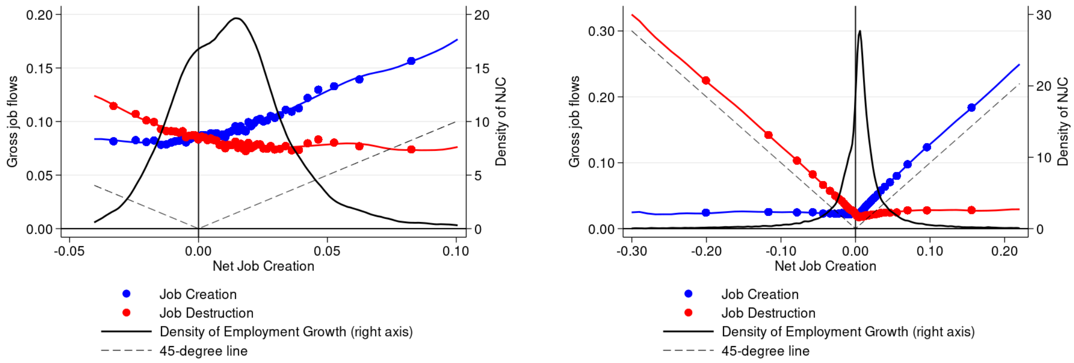
Figure C.3: The employment growth rate distribution over time



Source: SISCO data 2010-2018. *Note*: The figure shows the employment growth rate distribution at the LLM-year aggregation level, for different years.

Figure C.4: Average gross vs. net job flow rates, with density

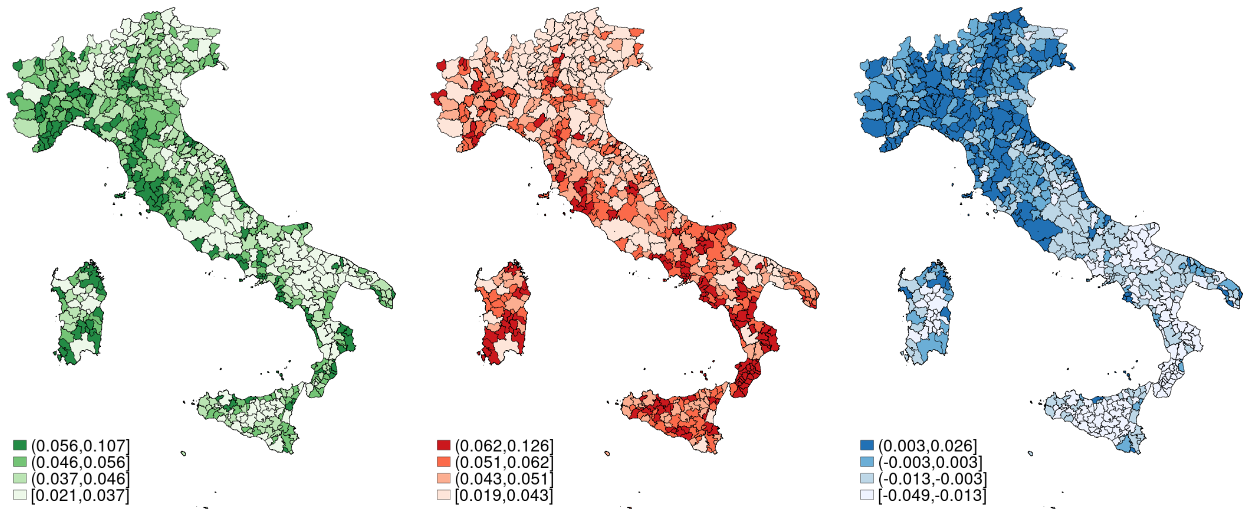
a) Yearly frequency b) Monthly frequency



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows gross job flow rates against the corresponding net flows at local labor market level. The flows are divided by the stock of payroll employment in the current period taken from the ILFS data. Solid red and blue lines are the prediction of second-degree local polynomial regressions. Scatter points represent averages of two percentiles of the underlying distribution. The black solid line represents the kernel density of the employment growth rate distribution. Dashed lines represent the 45-degree lines.

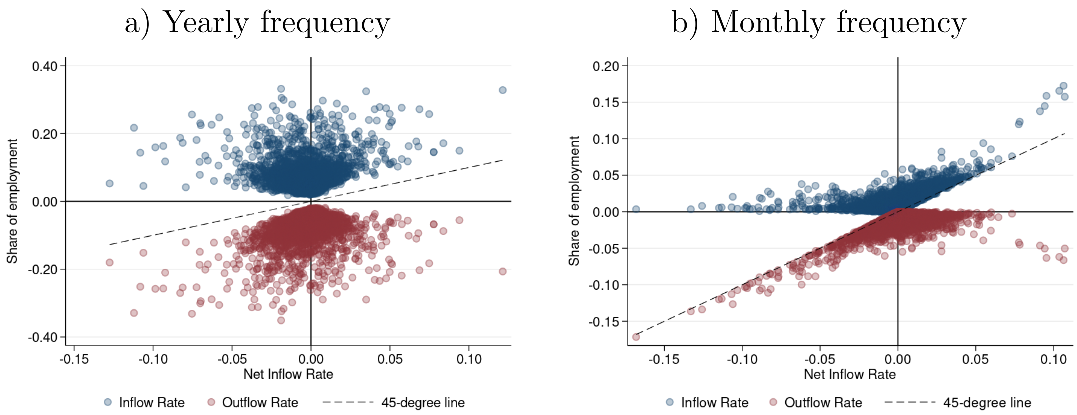
Figure C.5: Average internal migration rates across provinces using residence-based data

a) Inflow rate b) Outflow rate c) Net inflow rate



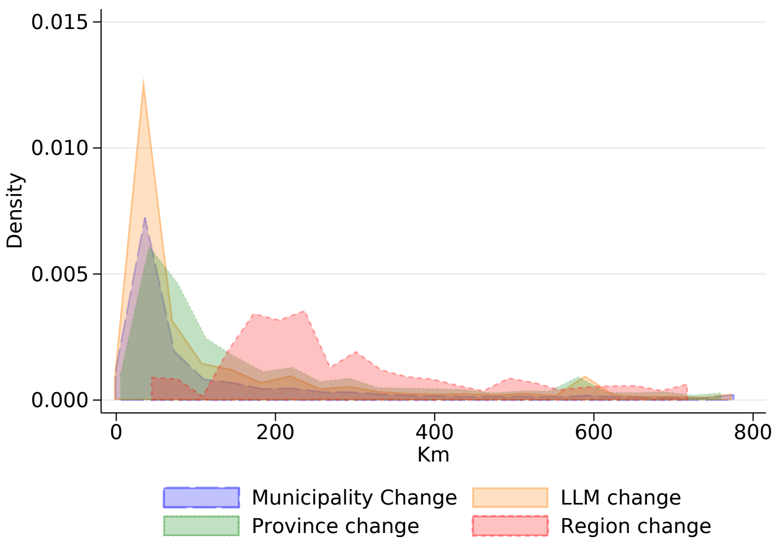
Source: Istat data on residence changes and ILFS data 2010-2018. *Note*: The figure shows the geographical distribution of average internal migration rates across provinces, computed using administrative data on residence changes (Istat). The migration flows are divided by the stock of payroll employment in the previous period taken from the ILFS data.

Figure C.6: Gross vs. net internal migration flow rates



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows gross internal migration flow rates against the corresponding net flows at local labor market level, at yearly (panel (a)) and monthly (panel (b)) frequency. The flows are divided by the stock of payroll employment in the previous period taken from the ILFS data. Dashed lines represent the 45-degree lines.

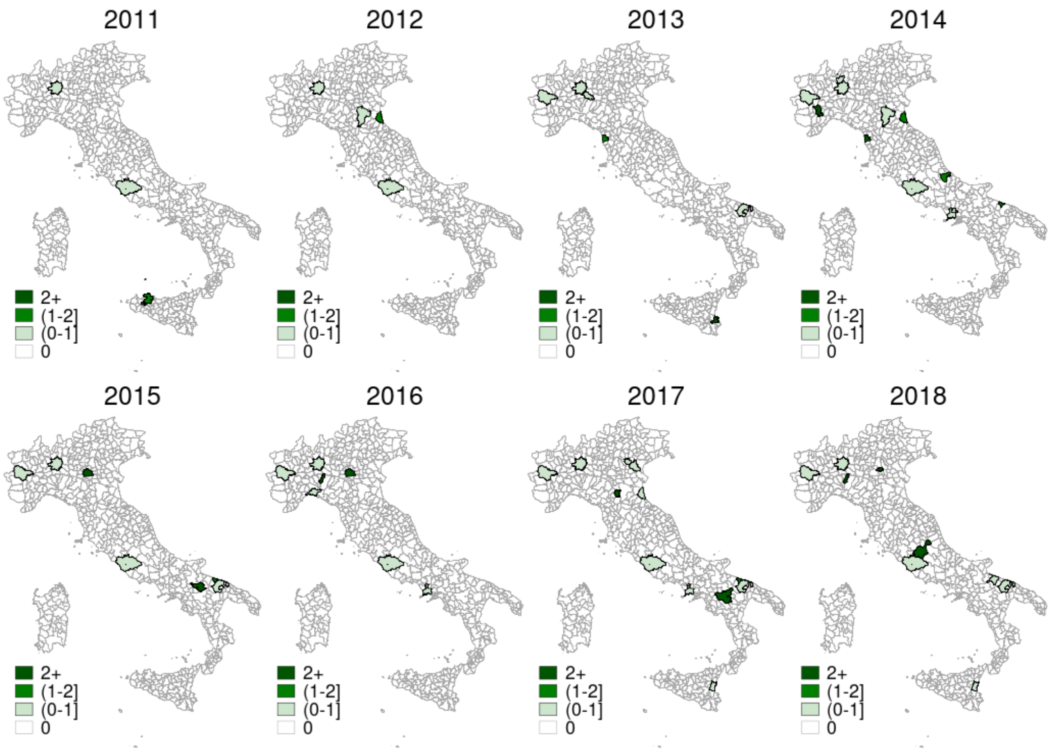
Figure C.7: Distribution of distance of internal migration



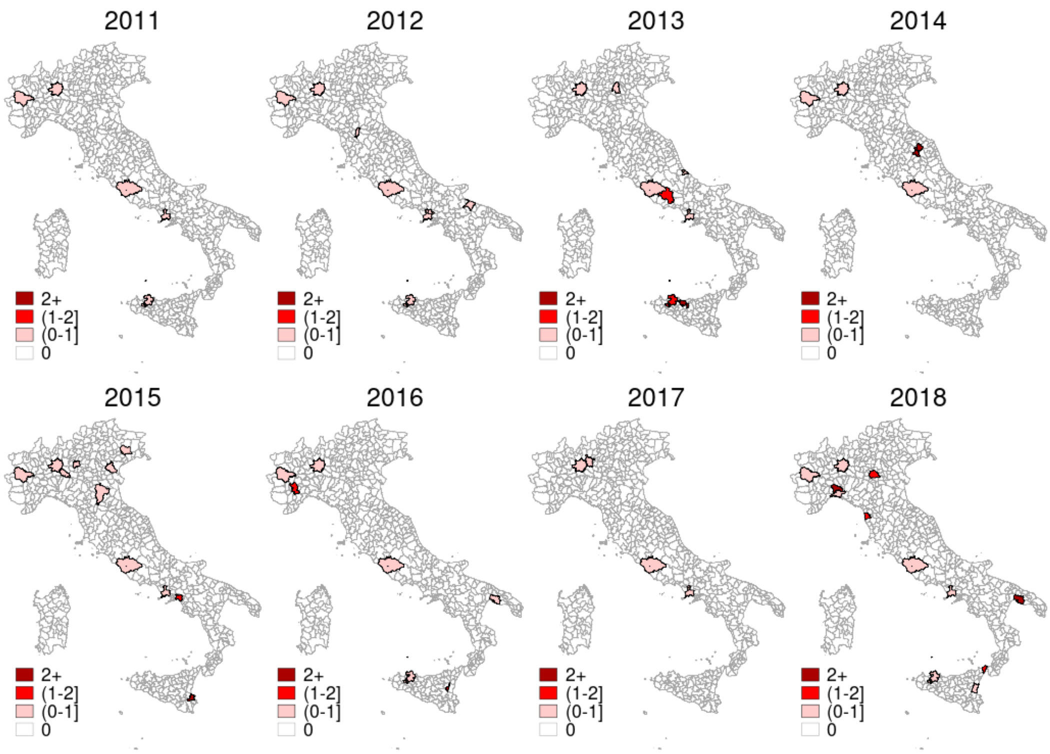
Source: SISCO data 2010-2018. *Note*: The figure shows the distribution of distance in km between origin and destination location of internal mobility individual transitions for different geographical aggregation levels (municipality, LLM, province, region). The plot is trimmed at 800 km for readability, but the distance arrives at slightly more than 1,800 km for regional moves.

Figure C.8: Geographical distribution of mass hires and layoffs in Italy. Events 500+

a) Mass hire events



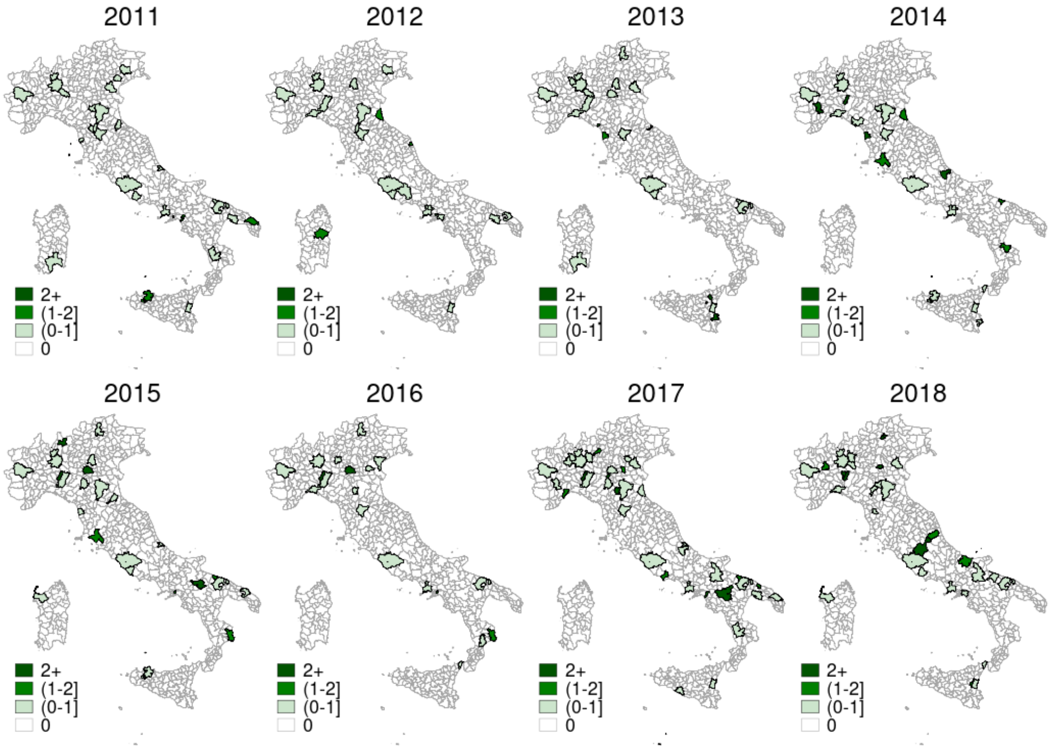
b) Mass layoff events



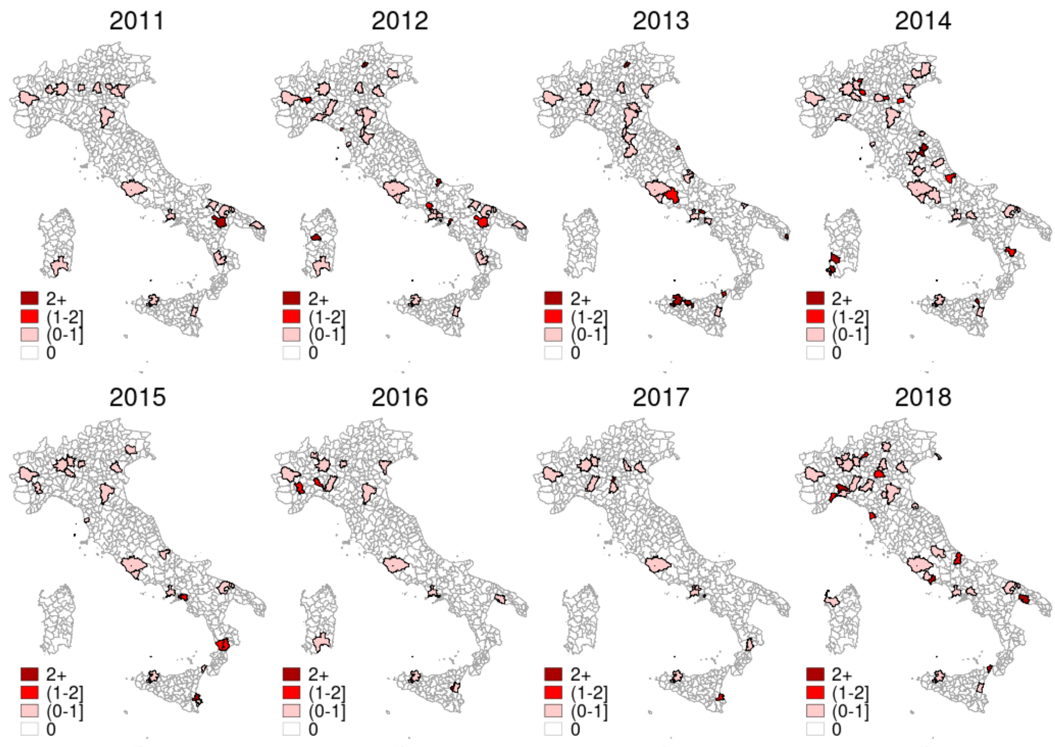
Source: SISCO and ILFS data 2011-2018. *Note*: The figure shows the maps of mass hires and layoffs as a percentage of local employment for events involving more than 500 net activations or terminations. Local employment is taken from the ILFS data. The unit of analysis is the pseudo-establishment.

Figure C.9: Geographical distribution of mass hires and layoffs in Italy. Events 250+

a) Mass hire events



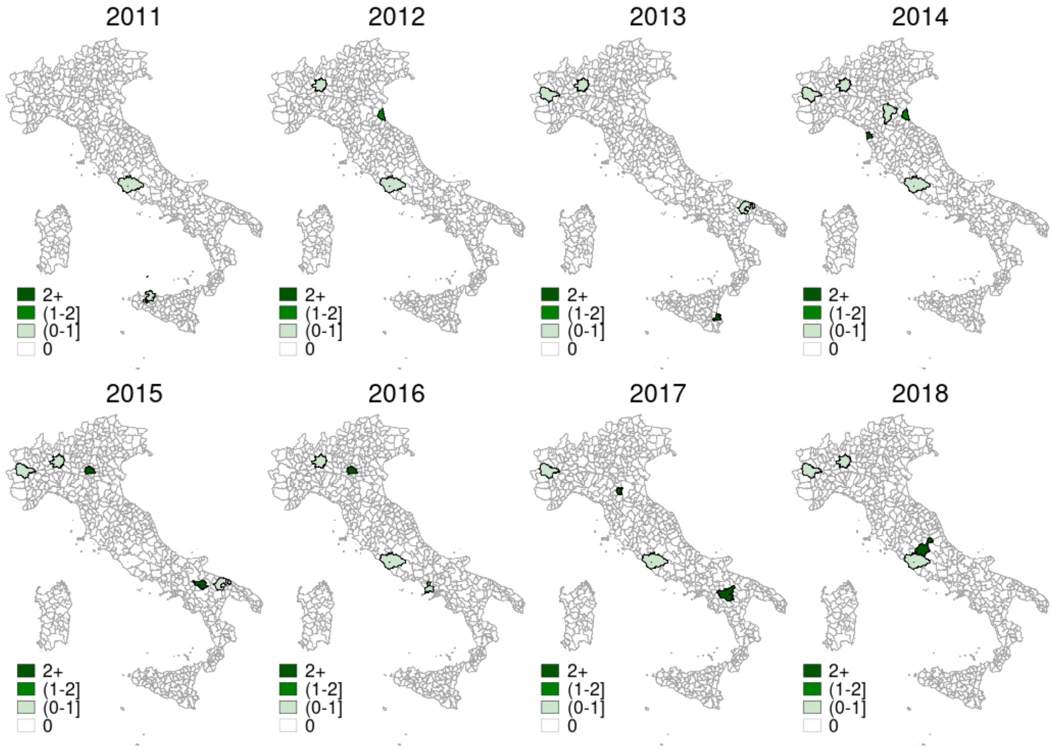
b) Mass layoff events



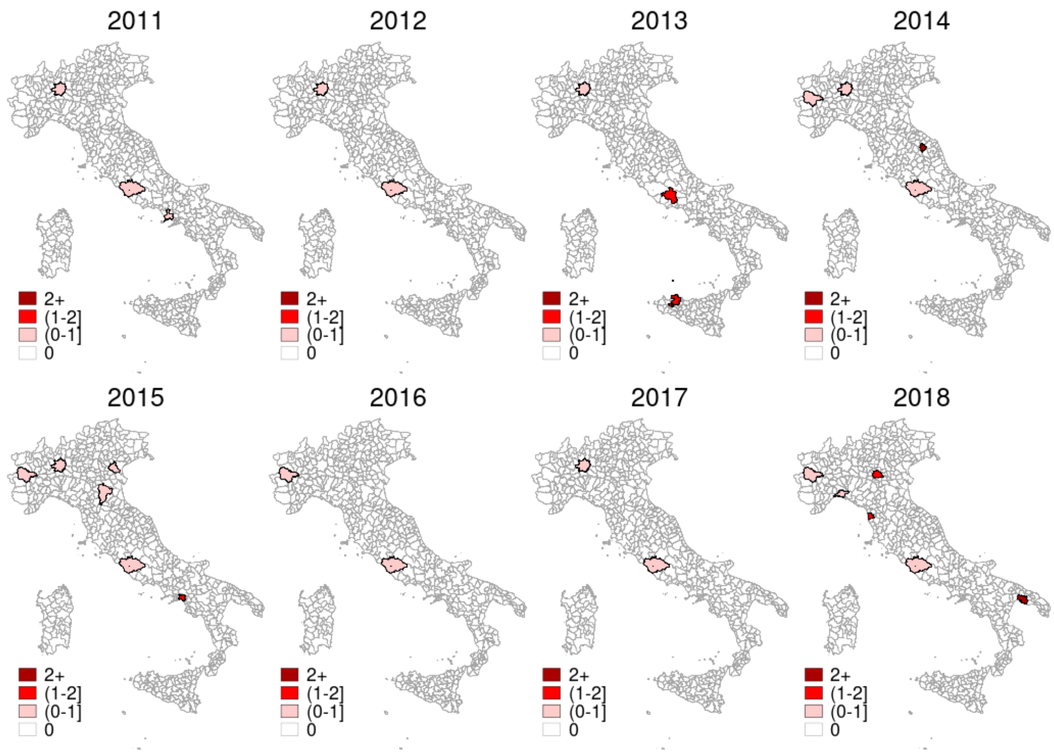
Source: SISCO and ILFS data 2011-2018. *Note*: The figure shows the maps of mass hires and layoffs as a percentage of local employment, only for events that involve more than 250 net activations or terminations. Local employment is taken from the ILFS data. The unit of analysis is the pseudo-establishment.

Figure C.10: Geographical distribution of mass hires and layoffs in Italy. Events 750+

a) Mass hire events



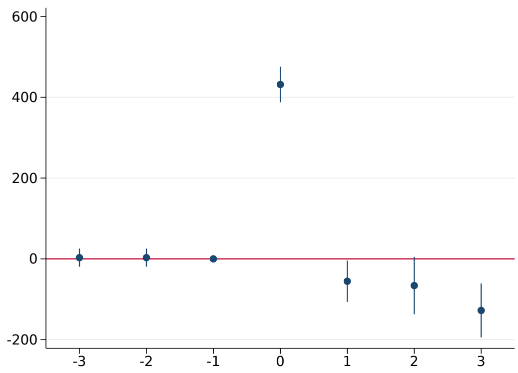
b) Mass layoff events



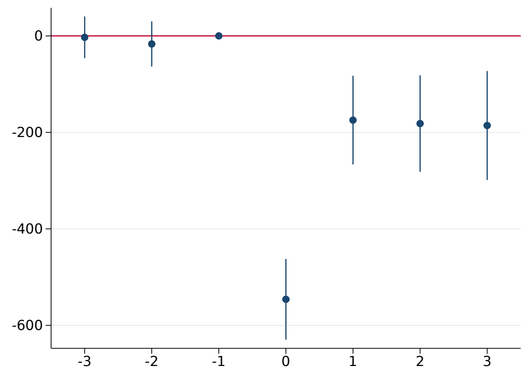
Source: SISCO and ILFS data 2011-2018. *Note*: The figure shows the maps of mass hires and layoffs as a percentage of local employment, only for events that involve more than 750 net activations or terminations. Local employment is taken from the ILFS data. The unit of analysis is the pseudo-establishment.

Figure C.11: Establishment-level mass hires and layoffs in Italy, event studies – thresholds 250 and 750

Events involving more than 250 workers

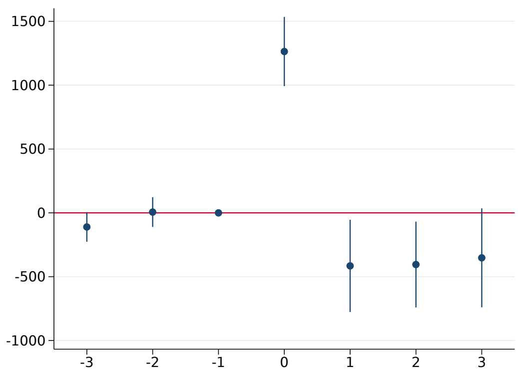


(a) Mass hire events

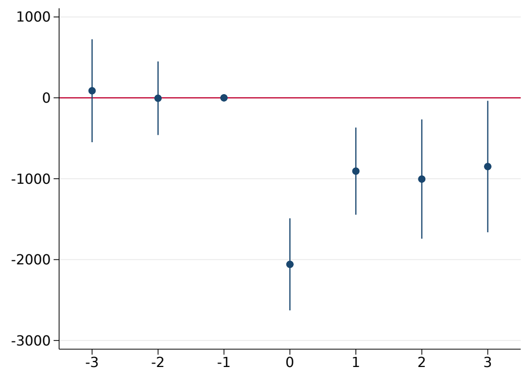


(b) Mass layoff events

Events involving more than 750 workers



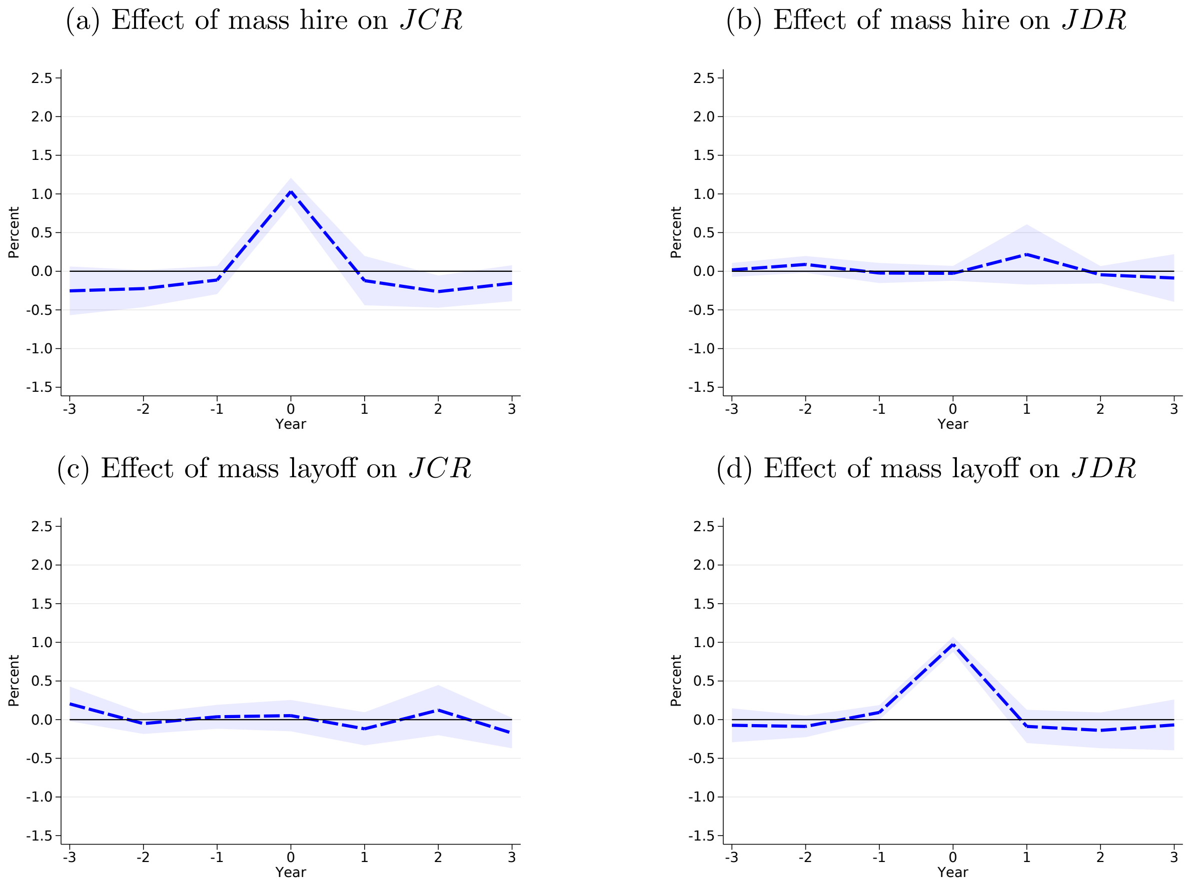
(c) Mass hire events



(d) Mass layoff events

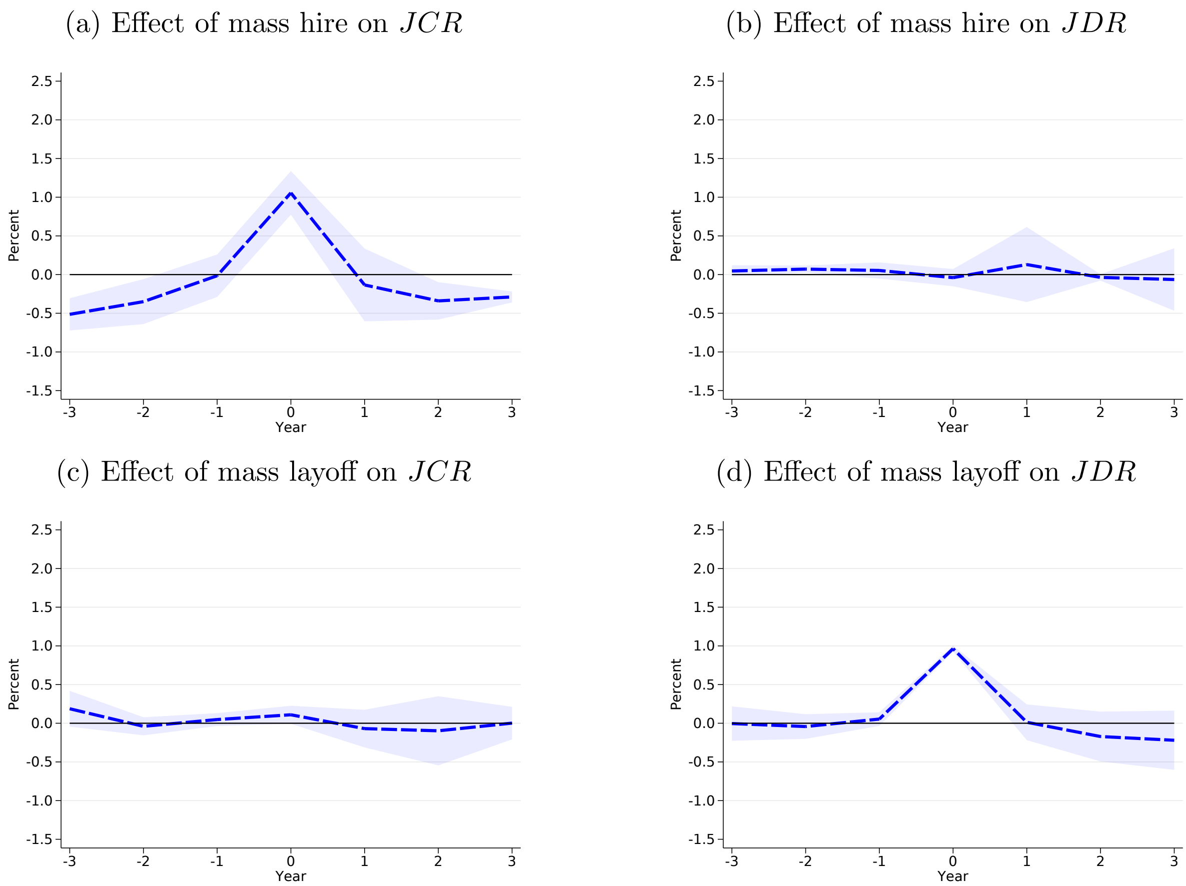
Source: SISCO data 2010-2018. *Note*: The figure shows the results of the event studies for establishment-level mass hires and layoffs (equations (8) and (9)), at thresholds 250 and 750. We isolate large mass layoff and mass hire events in the SISCO data by focusing on establishment-level terminations and hires above the specified threshold in a given year. The 95 percent confidence intervals (bars) are clustered at the establishment level.

Figure C.12: Mass events intensive margin on JCR and JDR, local projection estimates. Events 250+



Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the local projection estimates of the yearly variation in employment following a mass event at local labor market level of more than 250 net activations or terminations on the local job creation and the job destruction rates. The intensive margin is obtained by dividing the employment change in the local labor market by the stock of employment in 2010 taken from ILFS data. The 95 percent confidence intervals (shaded areas) are estimated by clustering pointwise standard errors at the provincial level.

Figure C.13: Mass events intensive margin on JCR and JDR, local projection estimates. Events 750+

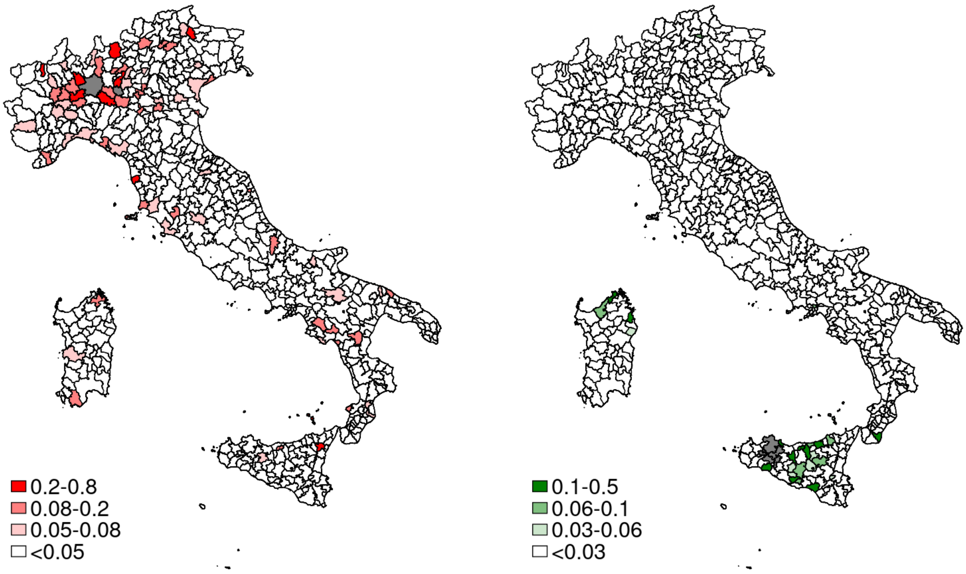


Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the local projection estimates of the yearly variation in employment following a mass event at local labor market level of more than 750 net activations or terminations on the local job creation and the job destruction rates. The intensive margin is obtained by dividing the employment change in the local labor market by the stock of employment in 2010 taken from ILFS data. The 95 percent confidence intervals (shaded areas) are estimated by clustering pointwise standard errors at the provincial level.

Figure C.14: The geographical impact of local mass events

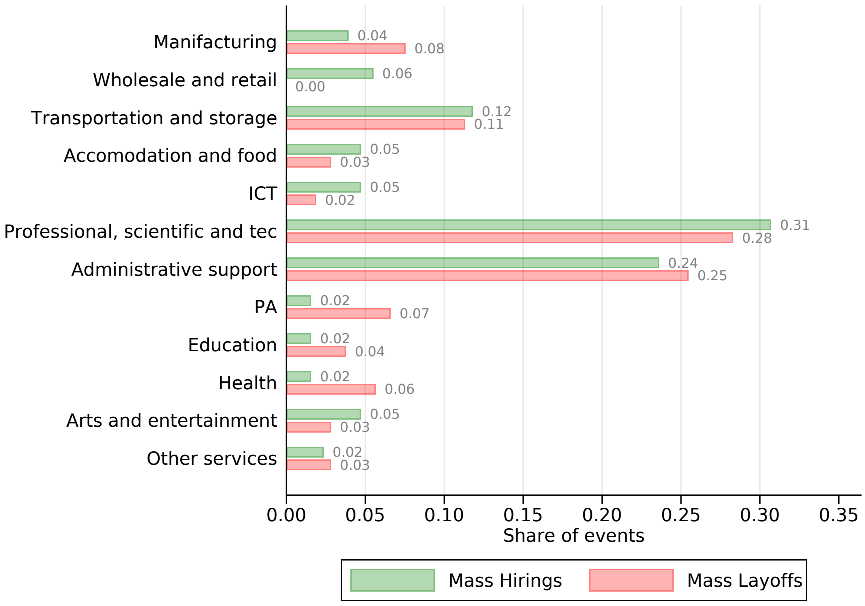
(a) In-migration rate in the LLM of Milan after a mass hire event in 2012

(b) Out-migration rate out of the LLM of Palermo after a mass layoff event in 2013



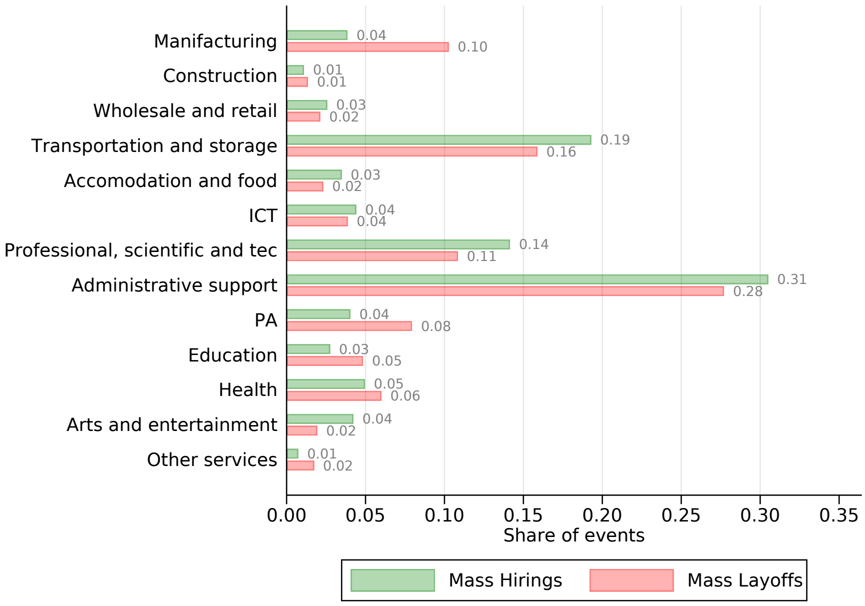
Source: SISCO and ILFS data 2010-2018. *Note*: The figure shows the geographical distribution of the effects of two large mass events in the SISCO data. Panel (a) shows the percentage point change in in-migration rate in the local labor market of Milan from each Italian LLM following a mass hire event that occurred there in 2012. Panel (b) shows the percentage point change in the out-migration rate from the LLM of Palermo to each Italian LLM following a mass layoff event that happened there in 2013. All underlying regressions include time and origin-destination fixed effects.

Figure C.15: Mass events by sector – 500 threshold



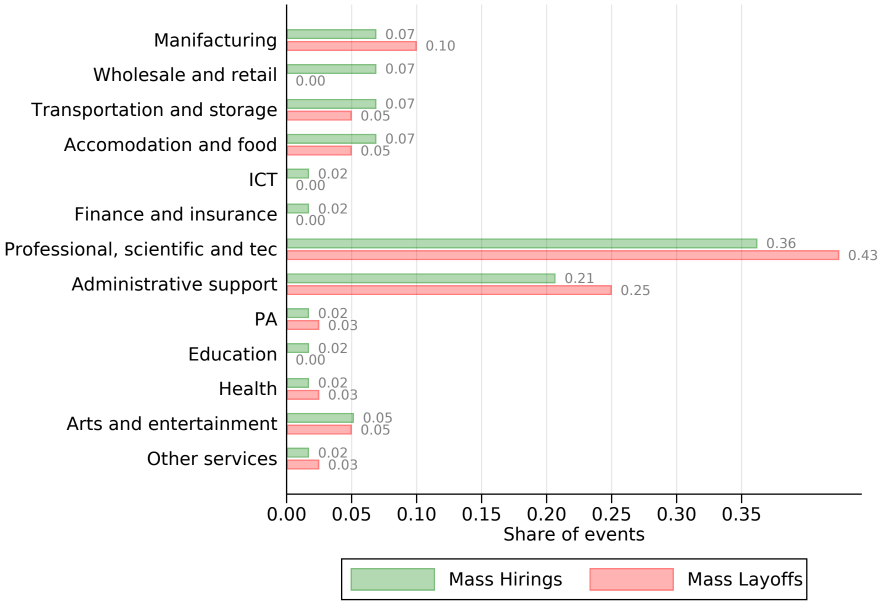
Source: SISCO data 2010-2018. *Note*: The figure shows the distribution by sector of activity (ATECO letters) of the mass events involving more than 500 net activations or terminations defined at the pseudo-establishment level.

Figure C.16: Mass events by sector – threshold 250



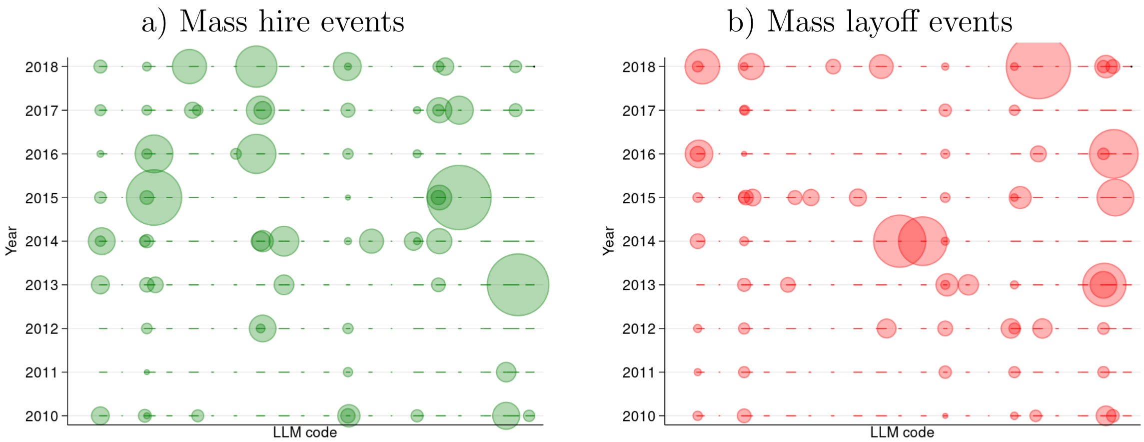
Source: SISCO data 2010-2018. *Note*: The figure shows the distribution by sector of activity (ATECO letters) of the mass events involving more than 250 net activations or terminations defined at the pseudo-establishment level.

Figure C.17: Mass events by sector – threshold 750



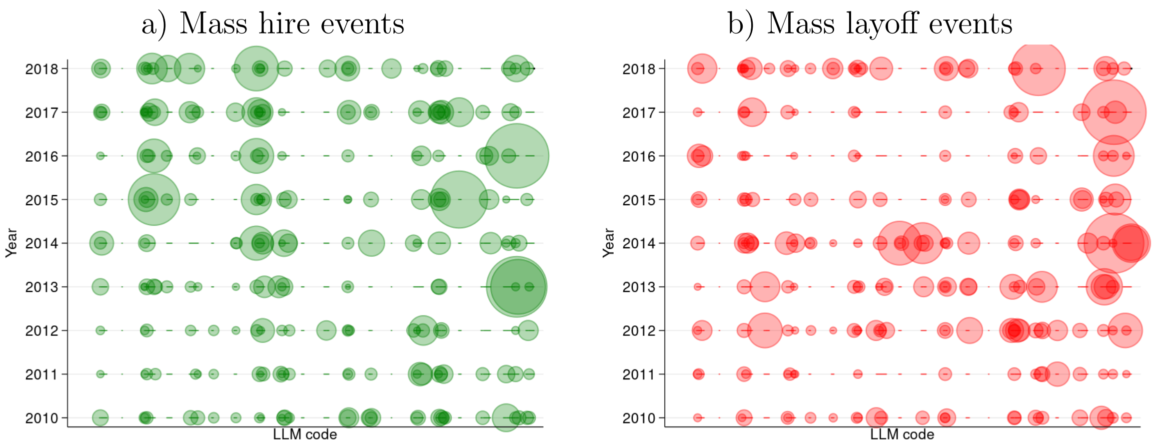
Source: SISCO data 2010-2018. *Note*: The figure shows the distribution by sector of activity (ATECO letters) of the mass events involving more than 750 net activations or terminations defined at the pseudo-establishment level.

Figure C.18: Mass events over time and across local labor markets – threshold 500



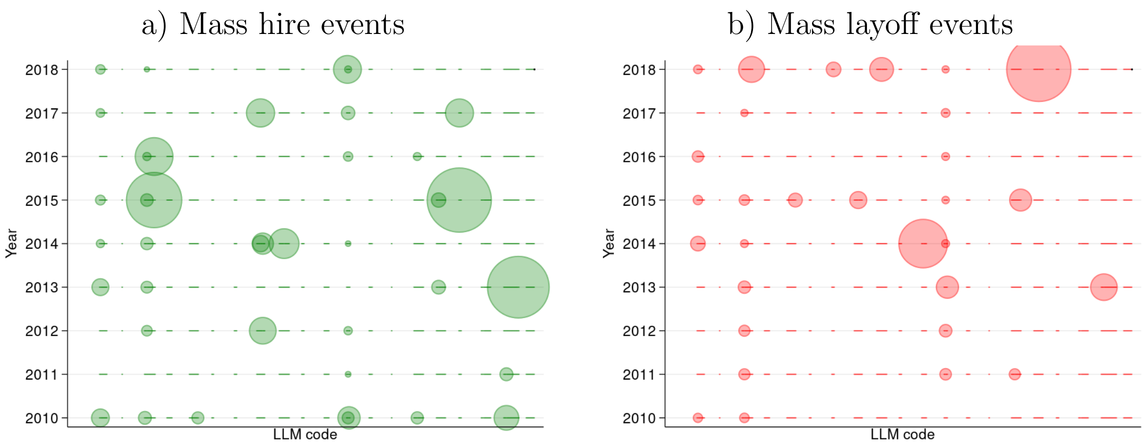
Source: SISCO and ILFS data 2010-2018. *Note*: The figure plots mass hiring (panel (a)) and layoff (panel (b)) events calculated from SISCO data as described in Section 3.2 as a percentage of local labor market employment for events involving more than 500 net activations or terminations. Each point in the x-axis corresponds to a local labor market, and each point on the y-axis to a year. The size of the bubbles represents the intensity of the mass event with respect to local employment.

Figure C.19: Mass events over time and across local labor markets – threshold 250



Source: SISCO and ILFS data 2010-2018. *Note*: The figure plots mass hiring (panel (a)) and layoff (panel (b)) events calculated from SISCO data as described in Section 3.2 as a percentage of local labor market employment for events involving more than 250 net activations or terminations. Each point in the x-axis corresponds to a local labor market, and each point on the y-axis to a year. The size of the bubbles represents the intensity of the mass event with respect to local employment.

Figure C.20: Mass events over time and across local labor markets – threshold 750



Source: SISCO and ILFS data 2010-2018. *Note*: The figure plots mass hiring (panel (a)) and layoff (panel (b)) events calculated from SISCO data as described in Section 3.2 as a percentage of local labor market employment for events involving more than 750 net activations or terminations. Each point in the x-axis corresponds to a local labor market, and each point on the y-axis to a year. The size of the bubbles represents the intensity of the mass event with respect to local employment.

D Additional Tables

Table D.1: Summary statistics, job flow rates

Location	Frequency	Job flows			
		JCR	JDR	|NJCR|	$\frac{\text{JTR}}{\lvert\text{NJCR}\rvert}$
Municipality	Monthly	0.029	0.028	0.031	5.2
		(0.063)	(0.073)	(0.089)	(15.0)
	Quarterly	0.062	0.059	0.061	7.1
		(0.107)	(0.108)	(0.136)	(28.9)
	Yearly	0.079	0.069	0.033	13.9
		(0.065)	(0.056)	(0.047)	(47.0)
Province	Monthly	0.032	0.031	0.019	17.0
		(0.020)	(0.029)	(0.027)	(151.2)
	Quarterly	0.069	0.065	0.041	16.1
		(0.039)	(0.045)	(0.044)	(83.7)
	Yearly	0.102	0.089	0.018	38.7
		(0.022)	(0.020)	(0.013)	(138.8)
Region	Monthly	0.033	0.031	0.018	15.8
		(0.017)	(0.025)	(0.024)	(103.0)
	Quarterly	0.070	0.066	0.035	21.7
		(0.029)	(0.036)	(0.032)	(162.3)
	Yearly	0.105	0.091	0.018	40.2
		(0.015)	(0.015)	(0.012)	(157.7)

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows summary statistics (average and standard deviation) of job flow rates for different combinations of geographical (municipality, province, region) and time (monthly, quarterly, yearly) aggregation levels. Job flow rates are the sum across establishments of net activations at the establishment-level, divided by the stock of payroll employment in the current period taken from the ILFS data.

Table D.2: Decomposition, labor market dynamism at different geographical levels

Panel (a). Municipality level

	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	JCR	JDR	JCR	JDR	JCR	JDR
JNCR	0.433	-0.567	0.502	-0.498	0.529	-0.471
	(0.014)	(0.014)	(0.009)	(0.009)	(0.013)	(0.013)
N	760,800	760,800	253,600	253,600	63,400	63,400
R^2	0.572	0.713	0.752	0.769	0.535	0.485

Panel (b). Province level

	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	JCR	JDR	JCR	JDR	JCR	JDR
JNCR	0.347	-0.653	0.464	-0.536	0.632	-0.368
	(0.016)	(0.016)	(0.018)	(0.018)	(0.039)	(0.039)
N	10,272	10,272	3,424	3,424	856	856
R^2	0.717	0.906	0.845	0.903	0.760	0.790

Panel (c). Region level

	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	JCR	JDR	JCR	JDR	JCR	JDR
JNCR	0.373	-0.627	0.475	-0.525	0.713	-0.287
	(0.060)	(0.060)	(0.056)	(0.056)	(0.044)	(0.044)
N	1,920	1,920	640	640	160	160
R^2	0.771	0.921	0.868	0.929	0.911	0.917

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows the results of linear regressions of gross against net labor market flows, for different geographical and time aggregation levels. Estimated coefficients can be interpreted as the share of total variance of net flows accounted for by the variation in the specific gross flow. All regressions include time and location fixed effects. Standard errors in parenthesis are clustered at the location level, and all the coefficients are significant at 99% level.

Table D.3: Internal migration and labor dynamism, IV 2SLS using data on residence changes (ISTAT)

Threshold IV	250 workers			500 workers			750 workers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OMR	IMR	NIMR	OMR	IMR	NIMR	OMR	IMR	NIMR
JCR	0.013	0.012	-0.001	-0.002	0.008	0.010	-0.001	0.021	0.021
	(0.014)	(0.019)	(0.029)	(0.018)	(0.021)	(0.035)	(0.018)	(0.024)	(0.041)
JDR	0.018	-0.017	-0.035	0.024*	-0.022	-0.046*	0.016	-0.022	-0.038
	(0.015)	(0.017)	(0.027)	(0.013)	(0.020)	(0.026)	(0.011)	(0.024)	(0.025)
N	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880

Source: Residence changes (ISTAT) and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events, on yearly migration flow rates from residence changes administrative data (ISTAT). Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

Table D.4: Internal migration and labor dynamism, 'full' dataset 2SLS

Threshold IV	250 workers			500 workers			750 workers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OMR	IMR	NIMR	OMR	IMR	NIMR	OMR	IMR	NIMR
JCR	-0.069***	0.334***	0.404***	-0.074**	0.338***	0.412***	-0.079**	0.331***	0.409***
	(0.027)	(0.047)	(0.058)	(0.032)	(0.065)	(0.080)	(0.037)	(0.071)	(0.091)
JDR	0.053*	-0.016	-0.069	0.048	0.010	-0.037	0.082***	-0.051	-0.133***
	(0.031)	(0.041)	(0.056)	(0.031)	(0.072)	(0.088)	(0.022)	(0.031)	(0.034)
N	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events, on yearly migration flow rates between local labor markets from SISCO data as described in Section 3.2. The 'full' dataset is built assuming that the worker's location corresponds to her last workplace location until a new job is found. We allow for a maximum of one year out of employment before relocation. We selected events that involve more than 250 (specifications (1)-(3)), more than 500 (specifications (4)-(6)), or more than 750 (specifications (7)-(9)) net activations or terminations. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

Table D.5: Summary statistics, internal migration

Location	Frequency	Internal migration flows			
		IMR	OMR	|NIMR|	$\frac{\text{MTR}}{\lvert\text{NIMR}\rvert}$
Municipality	Monthly	0.004	0.004	0.004	5.2
		(0.008)	(0.010)	(0.010)	(11.9)
	Quarterly	0.016	0.017	0.010	9.9
		(0.026)	(0.026)	(0.026)	(29.2)
	Yearly	0.074	0.076	0.022	22.1
		(0.076)	(0.079)	(0.042)	(68.1)
Province	Monthly	0.002	0.002	0.001	31.6
		(0.001)	(0.002)	(0.001)	(73.9)
	Quarterly	0.008	0.008	0.002	50.5
		(0.004)	(0.004)	(0.003)	(163.1)
	Yearly	0.033	0.034	0.003	107.6
		(0.011)	(0.011)	(0.003)	(481.4)
Region	Monthly	0.001	0.001	0.000	40.3
		(0.001)	(0.001)	(0.001)	(115.1)
	Quarterly	0.005	0.005	0.002	54.9
		(0.004)	(0.004)	(0.003)	(256.6)
	Yearly	0.020	0.021	0.002	412.8
		(0.008)	(0.008)	(0.002)	(4324.8)

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows summary statistics (average and standard deviation) of internal migration rates for different combinations of geographical (municipality, province, region) and time (monthly, quarterly, yearly) aggregation levels. Migration rates are computed by dividing the number of observed transitions in the SISCO microdata by the corresponding stocks of payroll employment in the previous period taken from the ILFS data.

Table D.6: Decomposition, Internal migration at different geographical levels

	Panel (a). Municipality level					
	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	IMR	OMR	IMR	OMR	IMR	OMR
NIMR	0.384	-0.616	0.503	-0.497	0.487	-0.513
	(0.082)	(0.082)	(0.016)	(0.016)	(0.017)	(0.017)
N	760,800	760,800	253,600	253,600	63,400	63,400
R^2	0.351	0.576	0.581	0.575	0.484	0.507

	Panel (b). Province level					
	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	IMR	OMR	IMR	OMR	IMR	OMR
NIMR	0.288	-0.712	0.483	-0.517	0.434	-0.566
	(0.074)	(0.074)	(0.011)	(0.011)	(0.083)	(0.083)
N	10,272	10,272	3,424	3,424	856	856
R^2	0.505	0.743	0.710	0.741	0.428	0.460

	Panel (c). Region level					
	Monthly data		Quarterly data		Yearly data	
	(1)	(2)	(3)	(4)	(5)	(6)
	IMR	OMR	IMR	OMR	IMR	OMR
NIMR	0.216	-0.784	0.524	-0.476	0.429	-0.571
	(0.036)	(0.036)	(0.027)	(0.027)	(0.072)	(0.072)
N	1,920	1,920	640	640	160	160
R^2	0.532	0.862	0.823	0.791	0.627	0.651

Source: SISCO and ILFS data 2010-2018. *Note*: The table shows the results of linear regressions of gross against net internal migration flows, for different geographical and time aggregation levels. Estimated coefficients can be interpreted as the share of total variance of net flows accounted for by variation in the specific gross flow. All regressions include time and location fixed effects. Standard errors in parenthesis are clustered at the location level, and all the coefficients are significant at 99% level.

Table D.7: Summary statistics, Distance of internal migration moves (km)

Statistics	Municipality	LLM	Province	Region
Mean	119.0	180.8	271.6	439.3
Min	0.8	1.6	14.8	59.7
Max	1,809.6	1,804.3	1,756.6	1,598.7
P1	2.3	4.8	15.8	59.7
P5	4.4	12.3	27.3	59.7
P10	6.4	16.4	36.6	160.1
P25	11.9	28.5	57.2	193.5
P50	24.9	51.8	119.2	300.7
P75	75.8	185.7	364.3	619.4
P90	372.1	585.9	755.8	929.0
P95	666.9	833.8	989.2	1164.5
P99	1,248.5	1,365.5	1,447.7	1,439.7
N	10,679,804	6,785,001	4,291,503	2,303,722

Source: SISCO data 2010-2018. *Note*: The table shows summary statistics of the distribution of distance (km) of internal migration transitions at the yearly frequency identified from the SISCO microdata, for different geographical levels (municipality, province, region).

Table D.8: Mass events summary statistics – thresholds 250 and 750

	Mass hire events	Mass layoff events
Panel (a). Events with at least 250 workers involved		
Number of events	548	520
Number of LLMs hit by events	241	228
Min (Avg) Max size of events	251 (482) 4,861	251 (463) 8,414
% of LLM employment	0.07 (1.07) 15.31	0.08 (1.02) 15.17
Number of events by industry		
Manufacturing	22	45
Construction	6	6
Private services	439	327
Public services	66	95
Other sector/not specified	15	47
Characteristics of workers involved		
Share of women	0.49	0.48
Average age	35.6	42.0
Share of foreigners	0.19	0.14
Share of graduates	0.16	0.15
Panel (b). Events with at least 750 workers involved		
Number of events	31	26
Number of LLMs hit by events	39	30
Min (Avg) Max size of events	1,023 (1,911) 4,861	1,013 (2,009) 8,414
% of LLM employment	0.05 (1.55) 11.97	0.10 (1.00) 10.57
Number of events by industry		
Manufacturing	2	3
Construction	0	0
Private services	28	17
Public services	1	2
Other sector/not specified	0	4
Characteristics of workers involved		
Share of women	0.62	0.64
Average age	35.4	40.7
Share of foreigners	0.06	0.07
Share of graduates	0.14	0.09

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the summary statistics for mass layoff and hiring events at local labor market level involving more than 250 (panel (a)) and 750 (panel (b)) workers calculated from SISCO data as described in Section 3.2. Public services include privately-provided education and health services.

Table D.9: Mass events summary statistics by macro area

	Mass hire events					Mass layoff events				
	North-East	North-West	Center	South	Islands	North-East	North-West	Center	South	Islands
Panel (a). Events with at least 250 workers involved										
Events	70	228	123	84	40	56	185	132	96	47
LLMs hit	54	55	41	63	28	49	48	39	57	35
Min (Avg) Max size	251(406)2,055	251(521)4,861	252(488)2,713	251(415)1,837	251(485)3,169	251(370)2,057	251(486)3,460	252(470)2,487	251(456)8,414	252(454)3,111
% of LLM's empl.	0.1(1.0)7.3	0.1(0.8)9.7	0.1(0.7)2.5	0.1(1.1)12.0	0.1(2.1)15.3	0.1(0.5)4.3	0.1(0.7)3.0	0.1(1.0)6.9	0.1(1.1)10.6	0.1(2.1)15.2
By industry										
Manifacturing	6	9	2	2	0	4	16	10	11	4
Construction	0	2	0	1	3	2	1	1	0 2	
Private services	55	200	5	53	21	40	134	97	40	13
Public services	9	16	0	22	11	8	20	16	34	16
.	0	1	0	6	5	2	14	8	11	12
Panel (b). Events with at least 500 workers involved										
Events	13	60	28	17	9	4	44	30	16	12
LLMs hit	12	23	12	16	6	4	23	14	14	12
Min (Avg) Max size	513(809)2,055	501(1,030)4,861	509(1,020)2,713	527(750)1,837	520(1,025)3,169	555(1,073)2,057	508(987)3,460	501(946)2,487	516(1,133)8,414	522(791)3,111
% of LLM's empl.	0.2(1.8)4.8	0.0(1.9)8.9	0.1(0.8)2.5	0.1(1.6)12.0	0.3(2.5)11.0	0.4(0.6)0.7	0.0(0.5)3.0	0.0(1.3)6.9	0.1(1.2)10.6	0.3(1.7)6.0
By industry										
Manifacturing	1	1	2	1	0	0	2	3	2	1
Construction	0	0	0	0	0	0	0	0	0	0
Private services	12	59	24	12	6	3	35	23	5	5
Public services	0	0	1	4	1	0	3	3	7	4
.	0	0	1	0	2	1	4	1	2	2
Panel (c). Events with at least 750 workers involved										
Events	5	28	15	7	3	2	21	13	3	1
LLMs hit	5	15	10	6	3	2	14	10	3	1
Min (Avg) Max size	785(1,147)2,055	766(1,532)4,861	762(1,387)2,713	757(992)1,837	829(1,909)3,169	945(1,501)2,057	753(1,411)3,460	810(1,417)2,487	875(3,517)8,414	3,111
% of LLM's empl.	0.4(1.3)2.2	0.1(1.2)8.9	0.1(0.8)2.5	0.2(2.6)12.0	0.4(4.4)11.0	0.4(0.6)0.7	0.1(0.4)1.7	0.1(1.0)6.0	0.3(4.0)10.6	0.017
By industry										
Manifacturing	1	1	1	1	0	0	1	2	1	0
Construction	0	0	0	0	0	0	0	0	0	0
Private services	4	27	14	4	2	1	17	9	1	0
Public services	0	0	0	2	1	0	0	1	1	0
.	0	0	0	0	0	1	3	1	0	1

Source: SISCO data 2010-2018. *Note*: The table reports the summary statistics (average and standard deviation) for mass layoff and hiring events with thresholds set at 250 (panel (a)), 500 (panel (b)) and 750 (panel (c)) units calculated from SISCO data as described in Section 3.2 by geographic macro area. Public services include privately-provided education and health services.

Table D.10: Internal migration flows and labor dynamism, first-stage (intensity of mass events IV, 250 and 750 thresholds)

Threshold IV	250 workers		750 workers	
	(1)	(2)	(5)	(6)
	JCR	JDR	JCR	JDR
Employment in mass hire	1.047***	0.021	1.079***	-0.020
	(0.084)	(0.047)	(0.131)	(0.063)
Employment in mass layoff	0.147***	0.973***	0.132***	0.959***
	(0.042)	(0.045)	(0.025)	(0.018)
N	4,880	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the first stage estimates of mass layoff and hiring events on job creation and job destruction rates from SISCO data as described in Section 3.2. We selected events that involve more than 250 (specifications (1)-(3)), and more than 750 (specifications (4)-(6)) net activations or terminations. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table D.11: Internal migration and labor dynamism, 2SLS (intensity of mass events IV, 250 and 750 thresholds)

Threshold IV	250 workers			750 workers		
	(1)	(2)	(3)	(4)	(5)	(6)
	OMR	IMR	NIMR	OMR	IMR	NIMR
JCR	-0.062**	0.231***	0.293***	-0.061**	0.236***	0.297***
	(0.024)	(0.031)	(0.036)	(0.029)	(0.039)	(0.052)
JDR	0.050	-0.011	-0.061	0.105***	-0.020	-0.125***
	(0.038)	(0.026)	(0.053)	(0.019)	(0.016)	(0.024)
N	4,880	4,880	4,880	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass hiring and layoff events, on migration flow rates (out-migration, in-migration, net in-migration) from SISCO data as described in Section 3.2. We selected events that involve more than 250 (specifications (1)-(3)), and more than 750 (specifications (4)-(6)) net activations or terminations. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table D.12: Internal migration flows and labor dynamism, first-stage at municipality and province level (intensity of mass events IV)

	Municipality		Province	
	(1)	(2)	(5)	(6)
	JCR	JDR	JCR	JDR
Employment in mass hire	0.999***	-0.002	1.019***	-0.002
	(0.035)	(0.057)	(0.136)	(0.104)
Employment in mass layoff	0.108	0.963***	0.149***	1.074***
	(0.115)	(0.065)	(0.044)	(0.054)
N	63,216	63,216	856	856

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the first stage estimates of mass layoff and hiring events involving more than 500 workers on job creation and job destruction rates from SISCO data as described in Section 3.2 at municipality ((1)-(3)) and province ((4)-(6)) level. The specifications in (1)-(3) ((4)-(6)) include municipality (province) and province-year (region-year) fixed effects, and the observations are weighted using the stock of payroll employment in the location in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province (region) level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table D.13: Internal migration and labor dynamism, IV 2SLS at municipality and province level

	Municipality			Province		
	(1)	(2)	(3)	(4)	(5)	(6)
	OMR	IMR	NIMR	OMR	IMR	NIMR
JCR	-0.007	0.243***	0.251***	-0.039	0.228***	0.268***
	(0.009)	(0.047)	(0.042)	(0.028)	(0.052)	(0.038)
JDR	0.057*	0.042	-0.015	0.013	-0.029	-0.041***
	(0.034)	(0.065)	(0.081)	(0.018)	(0.030)	(0.015)
N	63,216	63,216	63,216	856	856	856

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events involving more than 500 workers, on yearly migration flow rates at municipality ((1)-(3)) and province ((4)-(6)) level. The specifications in (1)-(3) ((4)-(6)) include municipality (province) and province-year (region-year) fixed effects, and the observations are weighted using the stock of payroll employment in the location in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province (region) level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table D.14: Internal migration and labor dynamism, IV 2SLS, controlling for average age

	(1) OMR	(2) IMR	(3) NIMR
JCR	-0.080***	0.219***	0.299***
	(0.024)	(0.036)	(0.050)
JDR	0.078**	0.030	-0.048
	(0.036)	(0.058)	(0.081)
$\text{Age}_{Hirings}$	-0.000	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
$\text{Age}_{Terminations}$	-0.00***	-0.006***	-0.002***
	(0.001)	(0.001)	(0.001)
N	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events involving more than 500 workers, on yearly migration flow rates between local labor markets from SISCO data as described in Section 3.2. Each specification includes local labor market and province-year fixed effects, the average age of hired workers and the average age of workers experiencing a job termination. The observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**}p < .05,^{***}p < .01$.

Table D.15: Relevance of the in-migration rate components

	(1) IMR	(2) IMR	(3) IMR
IMR keeping $OMR_{s\neq r}$ and RAR constant	0.438		
	(0.305)		
IMR keeping ER and RAR constant		0.434	
		(0.263)	
IMR keeping ER and $OMR_{s\neq r}$ constant			0.982***
			(0.011)
N	4,880	4,880	4,880
Within-R^2	0.489	0.491	0.971

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the correlation between yearly in-migration rates at local labor market level and three counterfactual in-migration rate variables constructed by moving one of its three components at a time and keeping the others constant at the average of the period 2011-2018. The three components, namely the employment ratio, the out-migration rate of the other local labor markets, and the relative attractiveness ratio, are computed using SISCO data as described in Section 4. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

Table D.16: In-migration rate components and labor dynamism, IV 2SLS

Threshold IV	250 workers			750 workers		
	(1)	(2)	(3)	(4)	(5)	(6)
	ER	$OMR_{s\neq r}$	RAR	ER	$OMR_{s\neq r}$	RAR
JCR	-0.035	0.001	3.000***	-0.037	-0.001	2.789***
	(0.023)	(0.002)	(0.351)	(0.031)	(0.003)	(0.295)
JDR	0.021	-0.005	-0.299	0.044*	-0.005**	-0.565*
	(0.021)	(0.003)	(0.391)	(0.023)	(0.002)	(0.338)
N	4,880	4,880	4,880	4,880	4,880	4,880

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events involving more than 250 (specifications (1)-(2)) and 750 (specifications (4)-(6)) workers, on the three components of yearly in-migration flow rates from SISCO data as described in Section 4, namely the employment ratio, the out-migration rate of other provinces, and the relative attractiveness ratio. The three ratios are taken in logarithms to allow comparability as they are scaled differently. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

Table D.17: Auto- and cross-correlation of mass events – threshold 500

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MH_t	MH_t	ML_t	ML_t	MH_t	MH_t	ML_t	ML_t
MH_{t-1}	-0.006	-0.052					-0.016	-0.020
	(0.098)	(0.119)					(0.014)	(0.023)
MH_{t-2}		-0.207***						0.107
		(0.065)						(0.069)
ML_{t-1}			-0.159***	-0.201***	-0.071	-0.085		
			(0.020)	(0.006)	(0.046)	(0.066)		
ML_{t-2}				-0.099		-0.072		
				(0.130)		(0.066)		
N	4,880	4,270	4,880	4,270	4,880	4,270	4,880	4,270
R^2	0.513	0.543	0.633	0.638	0.514	0.524	0.630	0.638

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the auto and cross-correlation over time of mass hiring ((1)-(2) and (5)-(6)) and layoff ((3)-(4) and (7)-(8)) events involving more than 500 workers. The mass events are defined at local labor market level as a fraction of local employment taken from ILFS data. Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

Table D.18: Spatial correlation of mass events – threshold 500

	(1) MH	(2) ML	(3) MH	(4) ML	(5) MH	(6) ML	(7) MH	(8) ML	(9) MH	(10) ML
$MH_{<50km}$	-1.020***									
	(0.264)									
$ML_{<50km}$		-1.151								
		(0.977)								
$MH_{[50,100)km}$			-0.647*							
			(0.384)							
$ML_{[50,100)km}$				-0.622*						
				(0.371)						
$MH_{[100,200)km}$					-0.214					
					(0.365)					
$ML_{[100,200)km}$						-0.068				
						(0.089)				
$MH_{[200,400)km}$							0.032			
							(0.149)			
$ML_{[200,400)km}$								1.494		
								(1.217)		
MH_{400+km}									-0.006	
									(1.708)	
ML_{400+km}										-3.695
										(3.840)
N	4,872	4,872	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880
R^2	0.578	0.662	0.519	0.636	0.513	0.630	0.513	0.631	0.513	0.630

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the correlation across space of mass hiring ((1), (3), (5), (7), (9)) and layoff ((2), (4), (6), (8), (10)) events involving more than 500 workers. The mass events are defined at local labor market level as a fraction of local employment taken from ILFS data. The events in the other locations on the RHS are average events within a certain range of distance (km). Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01.^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table D.19: Spatial cross correlation of mass events – threshold 500

	(1) MH	(2) ML	(3) MH	(4) ML	(5) MH	(6) ML	(7) MH	(8) ML	(9) MH	(10) ML
$ML_{<50km}$	0.052									
	(0.082)									
$MH_{<50km}$		0.031								
		(0.019)								
$ML_{[50,100)km}$			0.065							
			(0.115)							
$MH_{[50,100)km}$				0.027						
				(0.081)						
$ML_{[100,200)km}$					0.018					
					(0.231)					
$MH_{[100,200)km}$						-0.232				
						(0.219)				
$ML_{[200,400)km}$							-0.524			
							(0.772)			
$MH_{[200,400)km}$								0.699		
								(0.781)		
ML_{400+km}									3.047	
									(3.680)	
MH_{400+km}										-3.148
										(3.622)
N	4,872	4,872	4,880	4,880	4,880	4,880	4,880	4,880	4,880	4,880
R^2	0.513	0.630	0.513	0.630	0.513	0.630	0.513	0.630	0.513	0.630

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the correlation across space of mass hiring ((1), (3), (5), (7), (9)) and layoff ((2), (4), (6), (8), (10)) events involving more than 500 workers. The mass events are defined at local labor market level as a fraction of local employment taken from ILFS data. The events in the other locations on the RHS are average events within a certain range of distance (km). Each specification includes local labor market and province-year fixed effects, and the observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01.^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table D.20: Internal migration and labor dynamism, IV 2SLS, spatial controls

	(1) OMR	(2) IMR	(3) NIMR
JCR	-0.034	0.245***	0.279***
	(0.034)	(0.046)	(0.048)
JDR	0.082**	0.020	-0.061
	(0.040)	(0.051)	(0.077)
$\text{JCR}_{<100km}$	0.513	0.239	-0.274
	(0.439)	(0.325)	(0.332)
$\text{JDR}_{<100km}$	0.288	-0.081	-0.369
	(0.284)	(0.319)	(0.499)
N	4,872	4,872	4,872

Source: SISCO and ILFS data 2010-2018. *Note*: The table reports the 2SLS estimates of job creation and job destruction rates, instrumented by mass layoff and hiring events involving more than 500 workers, on yearly migration flow rates between local labor markets from SISCO data as described in Section 3.2. Each specification includes local labor market and province-year fixed effects, and the average job creation and destruction rates of the neighboring LLMs in a range of 100 km instrumented using mass hirings and layoffs. The observations are weighted using the stock of payroll employment in 2010 taken from the ILFS data. The standard errors in parentheses are clustered at the province level. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

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