Jobs at risk, regional growth, and labor market flows*

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Abstract

This paper studies how regional growth trends shape the dynamics of regional labor markets. New data on manufacturing worker flows for US cities 1957-1981 show that growing cities see higher job creation than shrinking cities, but also more voluntary quits and fewer forced layoffs. Growing and shrinking cities also behave differently in recessions: Recessions manifest as periods of depressed hiring and quits in growing cities, whereas they manifest as layoff spikes in shrinking cities. A model with on-the-job search explains this cross-sectional differences in flows with differences in growth trends alone. Its key feature is that jobs can become *at risk*: they have lower match surplus and are more likely to terminate in recessions. In growing cities, better prospects from on-the-job search lead workers to quit jobs *at risk* earlier, which reduces layoffs and misallocation.

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1 Introduction

Theories of labor market dynamics highlight a central role for the reallocation of workers across firms in the allocative efficiency of an economy. For example, a decline in the rates of reallocation is often seen as conducive to misallocation: Workers are stuck with low-productivity firms or in jobs that do not fit them, and may take longer to find new jobs when they lose their old ones. Data on labor market flows show that workers and firms are indeed frequently separated, and that new worker-firm relationships are created at similarly high rates. In addition, the gross labor market flows, including new hires, voluntary quits, and forced layoffs systematically co-vary with indicators of the business cycle.

This paper studies how long-run growth trends, such as growth in productivity or employment, affect the rates of reallocation and shape the dynamics of regional labor markets. We use new data on manufacturing worker flows for US cities 1957-1981 to document new stylized facts. We classify cities based on their mean employment growth in manufacturing. Growing cities see more new hires than shrinking cities, but also more quits and fewer layoffs. Growing and shrinking cities also differ in the way they experience business cycles: Growing cities exhibit drops in hires and quits during recessions, while shrinking cities exhibit large layoff spikes during some recessions, but not all.

We interpret these results through a model with on-the-job search. Its key feature is that jobs can become *at risk*: jobs that are more likely to terminate during a recession. In growing cities, there are many available vacancies per searcher and so workers in jobs at risk seek new employment and quit instead of waiting to be laid off, thus reducing layoffs and misallocation. In the quantitative implementation of the model we show that differences in trend growth alone explain a considerable share of the cross-sectional variation in gross reallocation flows, and also capture key differences in cyclical fluctuations.

The empirical part of the paper uses newly digitized archival records from the Bureau of Labor Statistics' Labor Turnover Survey (LTS). We construct a data set of monthly manufacturing worker flows for more than 130 Standard Metropolitan Statistical Areas (SMSAs) during 1957-1981. SMSAs are delineated to capture large central cities as well as the surrounding towns and suburbs where many of the central city workers reside, and therefore are a suitable unit of observation for a local labor market. While not technically identical, we use the term "city" to refer to these SMSAs.

The data reveal a remarkable regional variation in the mean employment growth rate in manufacturing during the sample period. Some cities in the so called "rust belt" experienced a long-run mean decline in manufacturing employment of almost 5% per year, while some cities in the so called "sun belt" experienced long-run employment growth of more the 2.5% per year. These differences are reflected in the mean quit and layoff rates. We calculate that cities that

grow at 2.5% per year have a mean quit rate of 33% per year and a mean layoff rate of 20% per year, while cities that shrink at 2.5% per year have a mean quit rate of only 19% per year and a mean layoff rate of 28% per year. In addition, the volatility of the quit and hiring rates in growing cities is almost double and the volatility of the layoff rate one half what it is in shrinking cities.

The theoretical part of the paper develops a "small open city" model with growth, to account for the new stylized facts. The model consists of two blocks: a population dynamics block and a search and matching block. The population dynamics block determines the flow of migrant workers into the city. Cities that offer higher expected wages attract more workers. Productivity follows a city specific growth trend, but a congestion externality in production guarantees that expected wages in steady state grow at the same rate in all cities.

The search and matching block features costly on-the-job search. When workers become unsatisfied with their jobs, they have to exert effort to seek new employment. In cities that have more available vacancies, it is easier to find a new job, which leads unsatisfied workers to search harder and quit more quickly. A key feature of the model is that jobs can become "at risk": they receive a match-specific shock that reduces the match quality by making job destruction more likely, especially during recessions. Workers in jobs at risk search for safety and quit their jobs when they meet a new employer.

Growing cities have tighter labor markets. When the jobs of workers in these cities become at risk, they exert more effort and quit their jobs quickly, before being laid off. This both raises the quit rate and reduces the layoff rate relative to shrinking cities, which explains the cross section of labor market flows.

The model also provides an explanation for the different impact of recessions on growing and shrinking cities. We think of recessions as a shock to aggregate productivity that simultaneously destroys many of the jobs at risk. Shrinking cities that have a larger share of jobs at risk see larger spikes in layoffs and a higher peak unemployment rate. In growing cities, firms reduce the number of vacancies per searcher and workers reduce their on-the-job search effort, which leads to a decline in the hiring and quit rates.

2 Related literature

The last three decades have seen the emergence of a large literature on gross flows in both jobs and workers. Job flows are measured using micro data on firms, recording job creation by new or expanding establishments as well as job destruction by shrinking establishments.[1] Worker flows are often measured using worker or household surveys, recording new hires as well as

[1]See the seminal work of Davis and Haltiwanger (1992) on the US Census of Manufacturing, the detailed treatment in Davis, Haltiwanger, and Schuh (1998), as well as Davis and Haltiwanger (2014) for a recent overview.

separations, which in turn consist of forced layoffs and voluntary quits.[2] Two key stylized facts are that gross flows are much larger than net flows, and worker flows are larger than job flows.[3]

Our theme that long-run trends drive worker flows by city is related to findings on job reallocation by industry or firm. Foote (1998) notes that job creation and destruction are larger in growing than in shrinking sectors.[4] Davis, Faberman, and Haltiwanger (2012) study the relationship between worker and job flows in the cross section of firms. They show in particular, that job reallocation (creation plus destruction) rates are higher in retail and services than in manufacturing and higher at growing firms. Only recently has the literature considered variations in labor market flows by region. Davis and Haltiwanger (2014) show that job reallocation moves with the employment rate across states. For the period since 1998, they show a similar result for worker reallocation rates (hiring plus separation).[5]

Our empirical work contributes to the literature by providing evidence on worker flows – including a distinction between quits and layoffs – by metropolitan area over a long period of time, from the late 1950s to the early 1980s. The sample size allows us to measure growth trends for individual cities, which is critical for exploring our basic idea. The LTS is the precursor of the Job Opening and Labor Turnover Survey (JOLTS), which much of the recent research on worker flows relies on. JOLTS provides monthly series on hiring, quits, and layoffs for broad sectors at the national level or at the Census-region level, but without distinction between sectors. A unique feature of the LTS is that it provides labor market flows for a cross section of cities within a single industry. The regional variation in worker flows that we document are therefore not driven by differences in industry composition.

Facts on job and worker flows have informed a large literature on quantitative search models. The basic building block is the framework introduced by Peter Diamond, Dale Mortensen, and Christopher Pissarides. The so called "DMP model" relates fluctuations in fundamental shocks, such as productivity, to movements in unemployment, hiring, and separations. A key question is then how to understand the volatility of employment over the business cycle. A limitation of the basic DMP approach is that it cannot distinguish between job and worker flows. This has motivated the introduction of on-the-job search (Burdett and Mortensen, 1998;

[2]Early work matches workers across monthly labor surveys and then calculate mean transition rates between different labor market states. For example, Abowd and Zellner (1985), Blanchard, Diamond, Hall, and Murphy (1990). An alternative approach uses duration data from the cross section of workers. For example Shimer (2005, 2012).

[3]See, for example, Anderson and Meyer (1994) or Hamermesh, Hassink, and Ours (1996).

[4]Foote (1998) also finds that growing sectors have a higher volatility of job creation than job destruction. He proposes an (S,s) employment adjustment model that qualitatively captures this relationship, but then concludes that such a model is not sufficient to explain the level of volatility in manufacturing job creation and destruction in the data.

[5]Other studies have looked at the determinants of cross-city migration and the employment rate. Amior and Manning (2018) document persistent differences in employment-to-population ratios across US metropolitan areas that increase with the net in-migration rate. Yagan (ming) uses differences across local labor markets' experience in the Great Recession to explain the long-run decline in the employment rate.

Barlevy, 2002; Postel-Vinay and Robin, 2002) as well as replacement hiring (Kiyotaki and Lagos, 2007; Burgess and Turon, 2010).

Most of the existing research studies labor reallocation at the national level, assuming one common labor market for the entire US (or other countries). The properties of this model labor market are then dictated by patterns in the aggregate data: the job finding rate is highly procyclical, whereas the separation rate is fairly acyclical.[6] In the DMP framework, this calls for a mechanism that drives labor market flows without shocks to the separation rate. As a result, the literature has explored shocks that decrease the gross hiring rate in recessions, in particular productivity shocks.

Shimer (2005) has shown that a standard DMP model with only productivity shocks is unable to account for high volatility in labor market flows. A lot of subsequent research has focused on mechanisms that lower firms' incentives to post vacancies in recessions and hence make the net hiring rate more cyclical; a prominent example is wage rigidities.[7] More recently, several authors have explored shocks to beliefs about the future – as incorporated for example into the stochastic discount factor used to evaluate future cash flows – as an alternative source of business cycle fluctuations, as yet with mixed success.[8]

An alternative approach emphasizes on-the-job search and match quality. Barlevy (2002) introduced the "sullying" effect of recessions: in bad times, low surplus matches persist longer, as there are fewer transitions by workers to better matches. Longer persistence of bad matches in an unfavorable environment is also an important force in our model; we emphasize its role for long-run level of misallocation as well as in the response to aggregate shocks. Recent studies have considered models of on-the-job search and variations in match quality with aggregate shocks to address the volatility of labor market flows over the business cycle (for example, Burgess and Turon, 2010; Menzio and Shi, 2011; Fujita and Nakajima, 2016; Gertler, Huckfeldt, and Trigari, 2016; Lise and Robin, 2017).

Other related papers abstract from cyclical fluctuations and instead ask how growth trends interact with the unemployment rate at the national level. Mortensen and Pissarides (1998) show that the theoretical effect of technological growth on unemployment depends crucially on whether the new technologies are only available for new jobs (a.k.a. embodied) or are shared with existing jobs (a.k.a disembodied). If new technologies increase the productivity of all jobs, a higher growth rate means that firms and workers expect the surplus of jobs to rise over time, which increases current labor demand, and thus decreases unemployment. This is often called the *capitalization effect*. If technologies are embodied, a higher growth rate means

[6] See Shimer (2012), but also Fujita and Ramey (2009); Elsby, Michaels, and Solon (2009); Yashiv (2007) for other views.

[7] See, for example, Hall (2005), Hall and Milgrom (2008), Gertler and Trigari (2009), Christiano, Eichenbaum, and Trabandt (2016).

[8] See, for example, Mukoyama (2009), Yashiv (2016), Hall (2017), Eckstein, Setty, and Weiss (2018) and Borovicka and Borovicková (2018).

that existing jobs become obsolete faster, which decreases the expected duration of a match and increases unemployment. This is often called the *creative-destruction effect*. Attempts at quantifying these effects have reached mixed conclusions.[9]

Our findings contribute to the theoretical literature in several ways. First, our results suggest that it is fruitful to disaggregate further than what is common in the literature. Once we split labor markets by city, we find that separation rates vary strongly over time in shrinking cities, a feature that our model captures. Moreover, cities differ in the relative importance of different flows in recessions. A quantitative strategy that focuses on aggregates will zero in on models that work for the average (growing) city, but may not be appropriate for shrinking cities where job losses are largest.

Second, our model integrates migration into a model of local labor markets. Data show that net migration flows are large and persistent at the city level, and are therefore important for understanding local labor markets. In contrast, when studying labor markets at the national level, it is plausible to ignore migration; after all, international net immigration flows are typically small relative to the labor force of countries. In the context of regional labor markets, migration is the only source of long-run differences in employment growth trends. This feature of our model highlights migration as another mode of reallocation, that is quantitatively important for growth at the national level.

Finally, we provide an explicit link between growth, reallocation rates, and the business cycle, which may be relevant more broadly. In particular, recent separate literature has documented a lack of dynamism in the US economy as well as a slowdown in growth, sometimes labeled the "Great Stagnation". Our model suggests the two phenomena may be related: Growing economies provide more opportunities for economic agents to reallocate resources, and therefore reduce misallocation.

3 Data and facts

In this section we provide new evidence on manufacturing labor flows in the cross section of US cities and over the business cycle. Our statistics are based primarily on a new data set of labor flows that we constructed. The raw data come from the Labor Turnover Survey (LTS). The LTS is an employer survey of labor demand conducted from 1930 to 1981.[10] Beginning in 1958, data on state and city level turnover rates were collected and reported as part of the BLS "Employment and Earnings" monthly publication.

Using these data we establish two new stylized facts. First, cities that are growing, i.e.

[9]See, for example, Prat (2007), Hornstein, Krusell, and Violante (2007), Pissarides and Vallanti (2007), Miyamoto and Takahashi (2011), Michau (2013).

[10]Carol M. Utter, "Labor turnover in manufacturing: the survey in retrospect," Monthly Labor Review (June 1982), p. 15-17, http://www.bls.gov/opub/mlr/1982/06/art3full.pdf. The survey was discontinued at the end of 1981 due to "severe budgetary cutbacks".

have a high employment growth over long periods of time, have on average more quits and fewer layoff than shrinking cities. The overall separation rate (quits plus layoffs) is mildly increasing with the growth trends of cities. Second, growing and shrinking cities differ in the way they experience business cycles. Growing cities exhibit large drops in hires and quits during recessions, while shrinking cities exhibit large layoff spike during some, but not all, recessions.

To construct the data set, we hand collected and digitized parts of the "Employment and Earnings" publication and formed a panel of state and local hiring, separations, quit, and layoff rates. These data cover the labor turnover rates in manufacturing for the majority of the largest statistical metropolitan statistical areas (SMSA), at a monthly frequency, over the period August, 1957 to November, 1981. For the sake of simplicity we often use the term "city" and SMSAs interchangeably.

The raw data is an unbalanced panel that covers 147 cities. The median city has 193 monthly observations (just over 16 years) and the mean is 176. We only include in the analysis cities that are observed for more than 24 months, which leaves 138 cities in our sample. The number of cities observed each month varies over time: from only 22 at the first observed month (September 1957) to 127 at the peak month (February 1966). However, between January 1964 and August 1981, which we consider as the main sample period, there are on average 96 cities observed each month. We also use a subsample of 71 cities that include more than 16 years of observations in the main sample period, which we then treat as a balanced panel.

The rest of this section presents the national trends in manufacturing employment in the US, the variation in manufacturing and other employment growth across cities, the cross section of labor market flows, and the business cycle properties of labor flows in growing and shrinking cities. Comparison with other data sets is also discussed.

3.1 Manufacturing employment growth in the US

Our study period is well known to exhibit a long-run decline in the relative importance of manufacturing to the US economy. Panel (a) of Figure 1 shows the share of manufacturing employment in the US. The share of manufacturing employment is declining steadily in this period, with an average decline of 1.4% per year. Despite the apparent decline in the relative employment in manufacturing, the absolute number of jobs in manufacturing is slowly *increasing* during this period. Panel (b) of Figure 1 shows the year-over-year employment growth in manufacturing employment. While employment growth in manufacturing dips in every recession, the average employment in manufacturing grows at an annual rate of 0.7% (dashed black line).

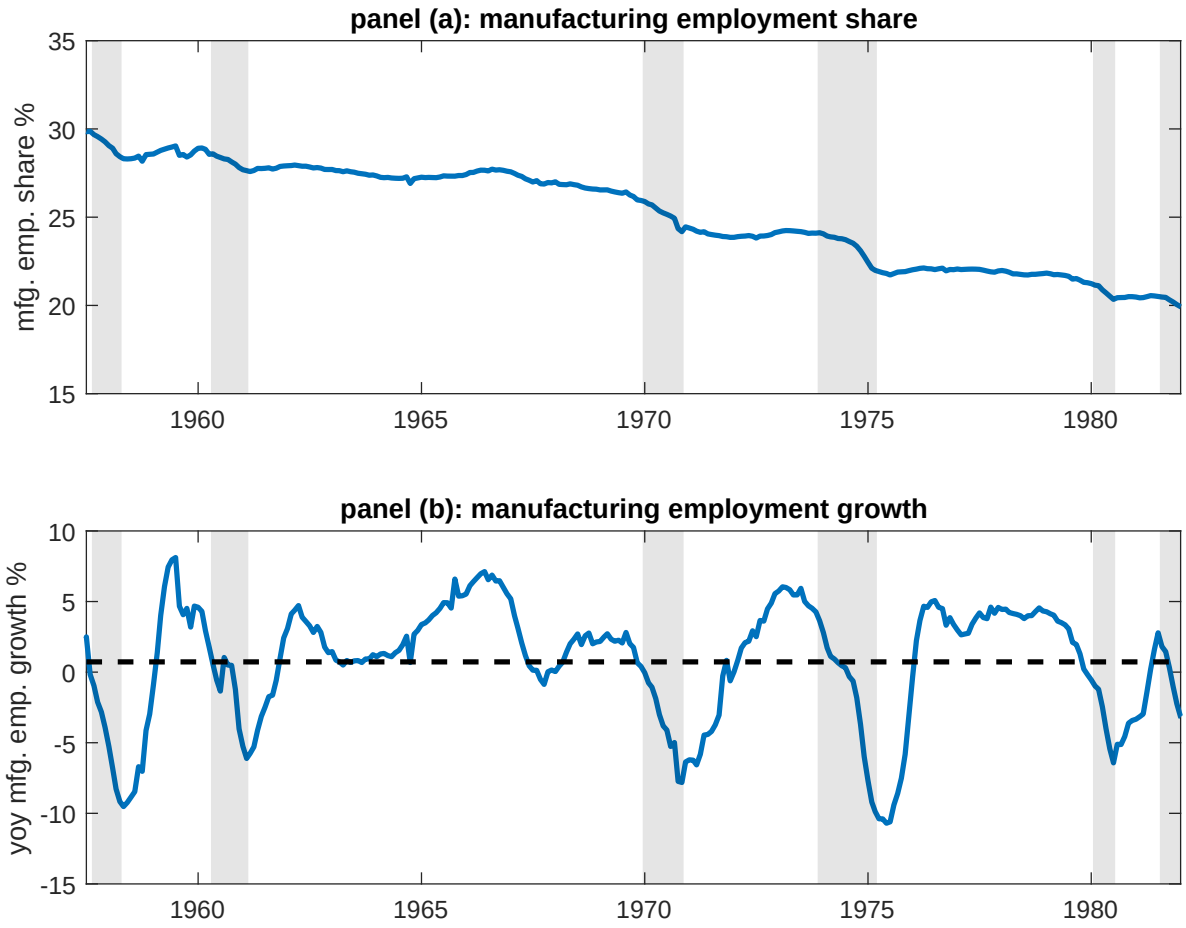


Figure 1: US manufacturing employment, 1957-1981

Source: Bureau of Labor Statistics via FRED – series 'MANEMP' and 'PAYEMS'.

The national-level trend masks remarkable regional variation in growth rates. To illustrate this variation, we calculate the mean employment growth rate for each city over all the available years. The mean employment growth rate is equal to the mean difference between the hiring and separation rates. Figures 2 and 3 present the mean manufacturing employment growth by city, based on LTS data. Each dot represents a city. The size of the dot represents the population of the city at 1980. The color of the dot represents the mean manufacturing employment growth in percentage annual terms. Colors are set so that red-yellow dots are above zero and dark-to-light blue dots are below zero. Figure 3 highlights the northeast region, in which cities are closer together. We also include dots for states that do not have any city in the sample to complete the geographical picture.[11]

[11]The states represented as dots on the map are Idaho, Montana, Nebraska, Nevada, and New Hampshire. Any subsequent analysis excludes these data points. The cities of California are presented by empty dots due to short sample period. See discussion of California data issues below.

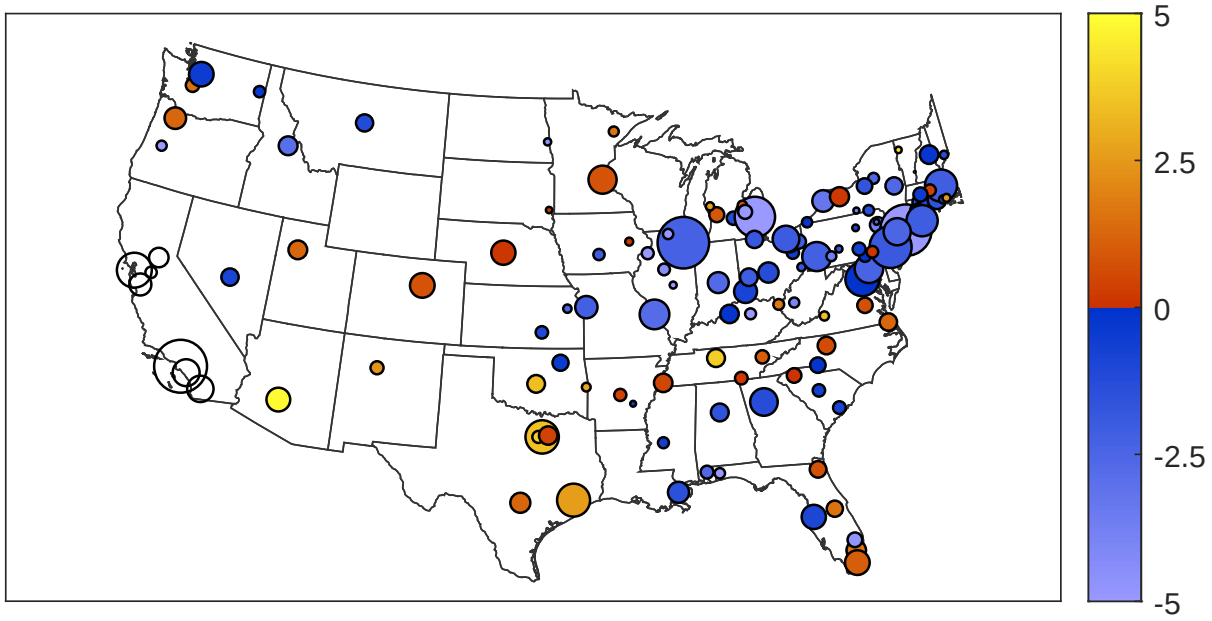


Figure 2: Mean manufacturing employment growth by city

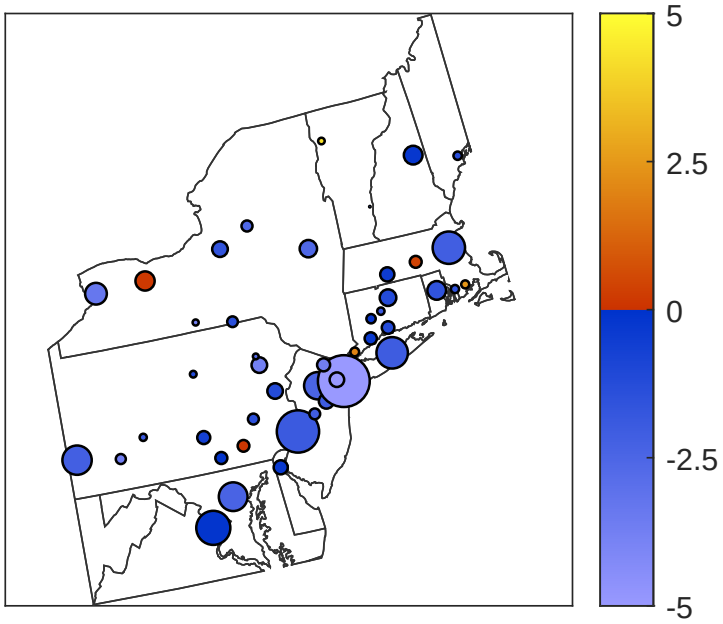


Figure 3: Net job-creation rates in manufacturing by location – northeast

The maps reveal two striking geographic patterns. The first pattern is the decline in manufacturing employment in the "Rust Belt": a series of cities that run from New York City in the east, through Pennsylvania, to the Midwestern cities of Ohio, Indiana, and Michigan. These cities experienced declines in manufacturing employment of almost 5% per year over the sample period. The second pattern is the growth in manufacturing employment in the "Sun Belt", which includes the major cities of South and North Carolina, Tennessee, and the south-western

states.[12] Cities such as Phoenix, Dallas-Fort Worth, and Houston experienced average manufacturing employment growth of more than 2.5% per year throughout the sample period. This geographical heterogeneity stands in stark contrast to the standard view of manufacturing as a declining industry.

3.2 Labor flows in the cross section of cities

We next consider how gross labor market flows vary across cities. We first compute the mean employment growth rate and the gross labor market flows for each city. To avoid a bias due to the difference sample periods across cities, we restrict this analysis to the 71 cities that are in our balanced panel (more than 16 years of observations between 1964 and 1981). We winsorize the sample by removing the cities with the highest and lowest mean employment growth.

Figure 4 reveals a remarkable relationship between the growth trend of cities and their average quit and layoff rates. Panel (a) shows the mean quit rate and mean employment growth in manufacturing for the cities in the balanced panel. The red line represents a linear projection. The figure reveals that growing cities have a substantially higher quit rate than shrinking cities. Based on the linear projection, a city with manufacturing employment that shrinks at a rate of 2.5% per year has on average a quit rate of only 18.6% per year. In contrast, cities that grow at a rate of 2.5% have an average quit rate of 32.9%. Panel (b) shows a similar picture for the layoff rate. Cities that shrink at a 2.5% rate have an average layoff rate of 27.9% while cities that grow at a rate of 2.5% have an average layoff rate of 20.5%. Due to the increasing quit rate with growth, the total separation rate (quits plus layoffs) is also increasing in the long-term employment growth rate.

[12]The California cities, which are not shown in Figure 2, are of surprisingly mixed character. Some metropolitan areas, such as San Jose and Orange Country grew extremely fast (6.8% and 3.7% manufacturing employment growth per year, respectively), but other cities such as San Diego and Sacramento had shrinking manufacturing employment. This is in part due to data limitation. California cities were included only until 1966, which makes their sample mean less informative on long-run trends. In constructing the sorted time series we overcome this issue by sorting cities into bins based on a fixed time windows around each month. See below for more details.

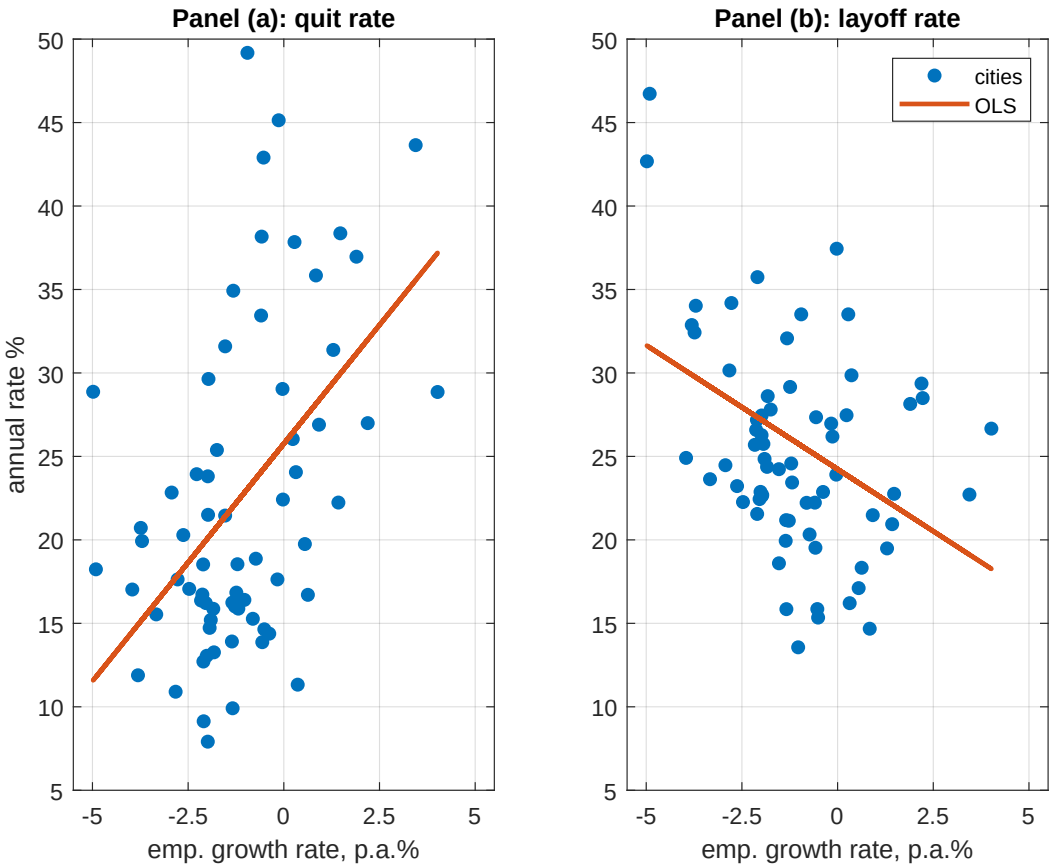


Figure 4: Manufacturing quit and layoff rates by city

3.3 A tale of three cities: Buffalo, Cinccinati, and Salt Lake City

To motivate studying the differences in business cycles experience across cities, we first focus on the histories of three cities . We pick three cities for which we have (almost) continuous observations over the main sample period. We picked two shrinking cities, Buffallo, NY (shrinking at rate -2.8% per year) and Cincinnati, OH (shrinking at a rate of -0.8% per year), and one growing city, Salt Lake City, UT (growing at a rate of 1.3% per year).

Figure 5 presents the gross separation flows in the three cities. Panel (a) shows the quit rates and Panel (b) the layoff rates. All rates are smoothed using a symmetric moving average of one year (6 months before, 6 month after) to remove seasonality. Buffalo, represented by a blue line, has persistently low quit rates over the sample period that exhibits little volatility. Its layoff rate is however is highly volatile and sharply increases on three occasions. The later two coincide with the recessions of 1974 and 1980. The first one seems to start during the recession of 1970, but peaks in 1972, after the recession has ended. Cinccinati (red line) has similar patterns but a slightly higher quit rate and noticeably less pronounced layoff spikes. The growing city, Salt

Lake City, has significantly higher quit rates which are also more volatile and procyclical. Salt Lake City's layoff rate is persistently low and does not move much with the business cycle.

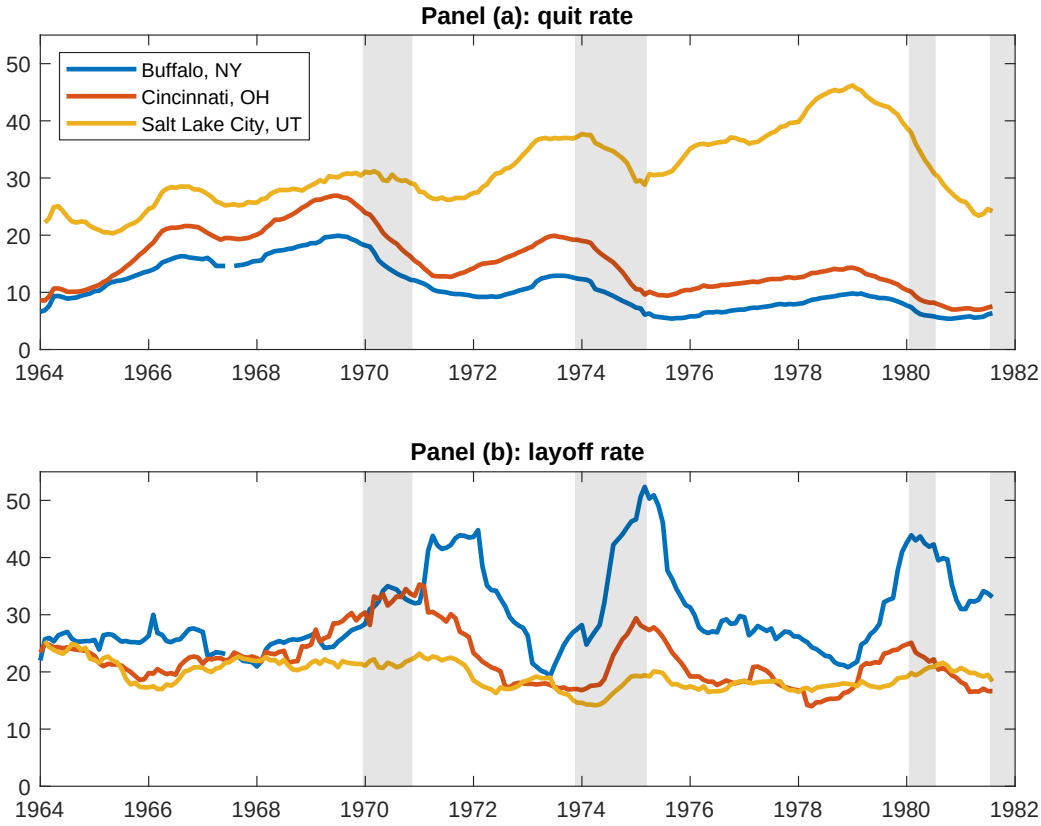


Figure 5: Labor market flows for three cities

While the focus on three selected cities limits the generality of the findings, it does provide a stark contrast between the business cycles experience of growing and shrinking cities. We will now continue to a systematic data analysis to establish stylized facts on the interaction of growth trends and business cycles across cities.

3.4 Business cycles and labor flows in growing and shrinking cities

Our main approach to documenting business cycles facts in the cross section of cities is based on sorting. We sort cities into "growth bins" and construct time series according to the following procedure. First, we sort all cities based on their mean employment growth over a symmetric six-year time window (three years before and three years after) for each month in our sample. This sorting captures the regional growth trend at the time of the observation. We then allocate cities into 5 bins of equal population size. Within each bin we calculate the mean hiring,

separation, quit, and layoff rates, across the included cities, weighted by total population. We end up with 5 sets of time series.

Table 1 summarizes the mean labor flows in all bins. The employment growth rate, the sorting variable, is -5% per year at the bottom bin and 2.2% per year at the top bin. This vast difference in growth rates is reflected in the composition of separations. The mean hiring and separation rates, however, both follow a u-shape pattern: They are higher at the top and bottom bin and lower in the middle bin. The stark patterns from the analysis of the cross section of cities reappear when decomposing the separation rate into quits and hires. In the top growth bin, the quit rate is 29% per year, and the layoff rate is 15% per year. In the bottom bin this relationship is reversed. The quit rate is 18% per year while the layoff rate is 29% per year. This highlights the importance for accounting for the type of separation.

Table 1: Mean manufacturing labor flows by employment growth bin

	bin				
	bottom	2	3	4	top
mean emp. growth rate	-5.00	-2.91	-1.75	-0.43	2.21
	(0.85)	(0.75)	(0.73)	(0.72)	(0.77)
mean hiring rate	51.99	45.42	44.25	47.35	55.53
	(2.07)	(1.13)	(1.47)	(1.38)	(1.62)
mean separation rate	56.99	48.32	46.00	47.79	53.32
	(2.25)	(1.12)	(1.34)	(1.50)	(1.68)
mean quit rate	17.80	18.99	20.03	22.94	29.01
	(1.47)	(1.63)	(1.32)	(1.44)	(2.21)
mean layoff rate	29.21	19.88	16.31	15.60	14.40
	(1.62)	(1.46)	(1.12)	(1.29)	(1.45)

Note: Flows are presented in percentage points at an annual rate. Standard errors in parentheses. All flows are calculated as a share of beginning of the period employment. For details on the construction of the bins see main text.

The labor flows by bin exhibit a considerable amount of seasonality and some mild trends. We therefore apply a band pass filter to remove seasonality and long-run trends from all time series. As is standard in the study of business cycles, we keep frequencies between 15 months and 12 years. Figure 6 presents the cycle component of the turnover rates in the bottom and the top bin. The hiring and quit rates of the top bin are remarkably cyclical and more volatile than the hiring and quit rates of the bottom bin. In contrast, the layoff rate in the bottom bin is more volatile and sharply spikes in the 1973-75 and the 1980 recessions.

Table 2 summarizes the business cycle volatility of labor flows by growth bin. The volatility

of the net flow into employment, the employment growth, declines with the trend employment growth of cities. The volatility of gross flows changes in opposite directions. The volatility of hiring and quit rates is increasing with growth: The volatility of quit rates in particular more than doubles from 2.66% at the bottom bin to 5.61% at the top bin. In contrast, the volatility of the layoff rate is decreasing with growth. The standard deviations of cyclical layoff rates is 5.70% at the bottom bin and only 3.00% at the top bin. The volatility of total separations, which adds up both quits and layoffs, is relatively stable across the growth bins.

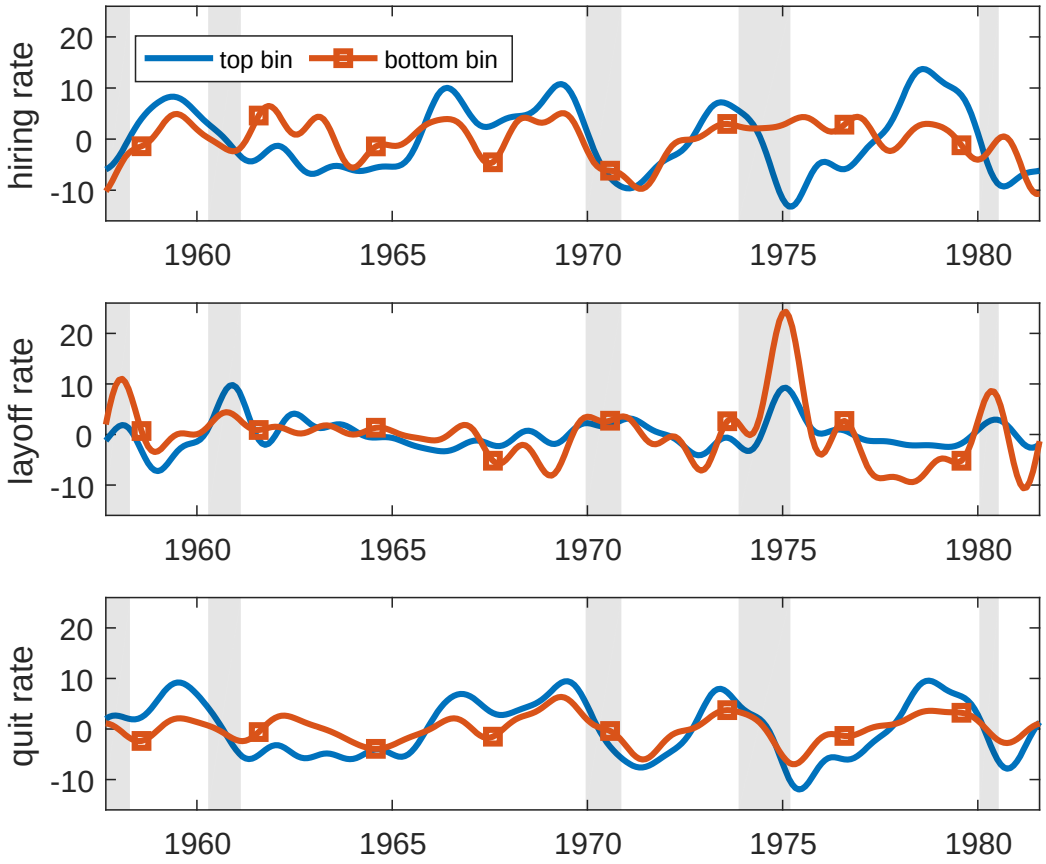


Figure 6: Cycle component of gross flows for top and bottom growth bins

This analysis establishes the following stylized fact: recessions in growing cities are characterized by a large decline in hires and quits and a relatively small decline in employment growth, while recessions in shrinking cities are characterized by large increases in layoffs.

Table 2: Volatility of manufacturing labor flows by employment growth bin

	bin				
	bottom	2	3	4	top
s.d. of emp. growth rate	5.44	5.32	5.08	4.63	4.26
	(0.62)	(0.70)	(0.59)	(0.60)	(0.40)
s.d. of hiring rate	3.83	4.00	4.55	5.35	6.50
	(0.42)	(0.38)	(0.52)	(0.48)	(0.49)
s.d. of separation rate	5.11	4.47	5.21	5.34	5.48
	(0.75)	(0.46)	(0.80)	(0.57)	(0.26)
s.d. of quit rate	2.66	3.38	3.88	4.51	5.61
	(0.29)	(0.40)	(0.39)	(0.61)	(0.27)
s.d. of layoff rate	5.70	4.41	4.57	3.75	3.00
	(1.18)	(0.51)	(0.67)	(0.60)	(0.46)

Note: Flows are presented in percentage points at an annual rate. Standard errors in parentheses. All flows are calculated as a share of beginning of the period employment. For details on the construction of the bins see main text.

3.5 Comparison with other data sets

This data set provides a unique opportunity to document facts and test theories of labor market dynamics at the local level controlling for industry effects. Local labor markets differ in industry compositions. If industries have different labor turnover characteristics, studying the cross section of cities without controlling for industry composition would confound interesting local effects and industry composition effects. Similarly, since industries are unevenly distributed across locations, measured differences across industries at the national level may be biased due to differences in their geographical distribution. Our focus is on labor turnover across locations and within manufacturing.

4 Model

This section proposes a "small open city" model to interpret the new stylized facts. The model has two building blocks: a *search and matching block* and a *population dynamics block*. The search and matching block is based on the baseline Diamond-Mortensen-Pissarides search and matching model with costly search on the job. It adds one new element: jobs that start out as "safe", that is, with a low rate of job destruction, may become "at risk", that is, with a higher rate of job destruction. Workers in these jobs have an incentive to search for safe jobs and, once they find a new vacancy, quit before being laid off.

The population dynamics block determines the migration flows into the home city based on its labor market prospects relative to a large benchmark city. Cities differ in their exogenous productivity growth trend. Cities that offer wages above the benchmark city attract more migrants who arrive as unemployed and search for jobs. A congestion externality in production ensures the existence of a balanced growth path in which wages in all cities grow at the same rate, but city-level population and employment diverge.

The key mechanism of the model is that in growing cities workers in jobs at risk face tighter labor markets that provide incentives to search harder on the job. Therefore worker in growing cities quit jobs at risk before being laid off, while workers in shrinking cities stay put and are more likely to be laid off. As a result, shrinking cities have fewer quits, more layoffs, and more misallocation, and are more exposed to mass layoffs during recessions.

4.1 Setup: search and matching block

Time is continuous and agents have an infinite horizon. A city is populated by a continuum of risk neutral workers and firms that discount time at rate r. The city-level output per employed worker is y_t. Unemployed workers derive a flow benefit of b_t. Firms create vacancies and search for workers at a flow cost κ_t.

Vacancies and searchers are matched according to a matching technology that has constant returns to scale in the measure of vacancies and the measure of effective searchers among workers. The measure of effective searchers accounts for on-the-jobs search, and is defined as the measure of unemployed, plus the measure of on-the-job searchers multiplied by their relative search intensity. The labor market tightness is θ_t and equals the number of vacancies per effective searcher. The matching technology can be summarized by a job finding rate by unemployed $f(\theta_t)$ that is increasing in tightness, and a vacancy filling rate $\phi(\theta_t)$ that is decreasing in tightness. As a result of homogeneity of the matching function, the job finding rate and vacancy filling rate satisfy the relationship $f(\theta_t) = \theta_t \phi(\theta_t)$.

All jobs are exposed to an idiosyncratic job destruction shock with a Poisson rate δ. This shock captures the exogenous separation of worker and firm for reasons that are unrelated to the aggregate state of the economy. In addition, jobs that start out as "safe" may become "at risk" at a Poisson rate σ. Both worker and firm know if the job is at risk or not. When a job is at risk, it is exposed to an additional job destruction shock with a Poisson rate ρ.

We also assume that workers in jobs that are destroyed by either shocks incur a one-time private cost $C_t > 0$. This cost captures, in a simple way, the recent evidence that losing a job involuntarily leads to a more lasting effect on the workers welfare.[13] We assume that private costs of job destruction is small enough so that jobs are still viable. It is sufficient to assume

[13] See, for example, Davis and Von Wachter (2011). There is additional evidence that job insecurity itself leads to deterioration in the health of workers, which can also be captured by this cost. See Caroli and Godard (2016).

that $(\rho + \delta)C_t < y_t - b_t - c(1,t)$, that is, the expected cost of layoff is lower than the the flow benefit of jobs minus their maximal value of the opportunity cost.

Since jobs at risk are inferior to safe jobs, workers have an incentive to engage in on-the-job search for safety. We assume that search when unemployed is free, but that on-the-job search is costly. Employed workers choose a search effort $e_t > 0$ and face an increasing and convex flow cost $c(e_t, t)$. Their job finding rate is $e_t f(\theta_t)$, which means that the search effort determines the ratio of job finding rate of the employed to the unemployed. Workers in safe jobs can also search, but since they have no benefit from switching employers they choose to stay put.

4.2 Optimal worker and firm behavior and bargaining

We can now write the optimality conditions for workers and firms. Workers take the wages of safe jobs w_t and wages of jobs at risk w_t^r as given, and maximize the present value of unemployment U_t, a safe job W_t, and a job at risk W_t^r based on the following set of Hamilton-Jacobi-Bellman equations:

$$rU_t = b_t + f(\theta_t)\left[P(\text{safe})(W_t - U_t) + P(\text{at risk})(W_t^r - U_t)\right] + \dot{U}_t, \tag{1}$$

$$rW_t = w_t - \delta(W_t - U_t) - \sigma(W_t - W_t^r) + \dot{W}_t, \tag{2}$$

$$rW_t^r = \max_{e_t}\left\{w_t^r - c(e_t,t) - (\delta+\rho)(W_t^r - U_t) - \rho C_t + e_t f(\theta_t)P(\text{safe})(W_t - W_t^r) + \dot{W}_t^r\right\}. \tag{3}$$

The notation $P(\text{safe})$ and $P(\text{at risk})$ are the probability that the vacancy they meet is safe and at risk respectively.

The first order condition for the choice of search effort e_t is

$$\frac{\partial c(e_t,t)}{\partial e_t} = f(\theta_t)(W_t - W_t^r). \tag{4}$$

Since $c(e_t, t)$ is strictly convex in effort, this equation implies that workers will search harder if it is easier to find a job, and if the gains from finding a job are larger. The Bellman equation for safe jobs implicitly assumes that workers exert no effort in on-the-job search.

Firm optimization is reflected in another set of Bellman equations for the present value of a vacancy V_t, a safe job J_t, and a job at risk J_t^r,

$$rV_t = \max\left\{-\kappa_t + \phi(\theta_t)(J_t - V_t) - \delta V_t - \sigma(V_t - V_t^r) + \dot{V}_t, 0\right\}, \tag{5}$$

$$rV_t^r = \max\left\{-\kappa_t + \phi(\theta_t)(J_t^r - V_t) - (\delta+\rho)V_t^r + \dot{V}_t^r, 0\right\}, \tag{6}$$

$$rJ_t = y_t - w_t - \delta(J_t - V_t) - \sigma(J_t - J_t^r) + \dot{J}_t, \tag{7}$$

$$rJ_t^r = y_t - w_t^r - (\delta+\rho)(J_t^r - V_t^r) - e_t f(\theta_t)(J_t^r - V_t^r) + \dot{J}_t^r. \tag{8}$$

Firms decide whether to keep searching or abandon the vacancy, which is reflected in the

maximization expression in the Bellman equations (5) and (6). In addition they decide whether to create more vacancies. It is costless to create new vacancies, and therefore the value of a vacancy is determined by free-entry conditions,

$$V_t = 0, \tag{9}$$

$$V_t^r = 0. \tag{10}$$

The flow cost of keeping a safe vacancy and a vacancy at risk active are equal, but the payoffs, under plausible restrictions, are higher for safe jobs. Since by the free-entry condition the value of a safe vacancy must be equal to zero, it must be that vacancies at risk are always abandoned and firms are indifferent between keeping or abandoning safe vacancies. Firm optimality then dictates that all active vacancies are safe, and that

$$P(\text{safe}) = 1 - P(\text{at risk}) = 1.$$

Another implication is that when a worker leaves a job at risk the firms abandons the vacancy. A direct interpretation is that quits by workers in jobs at risk trigger endogenous job destruction.

When a worker and a firm meet, they bargain over wages. The worker's outside option is unemployment (even when searching on the job), and the firm's outside option is to continue searching for workers. The wage is set by a surplus splitting rule that gives workers β share of the surplus, which we assume is one half.[14] Therefore the worker and firm surpluses from a safe job satisfy

$$W_t - U_t = J_t - V_t, \tag{11}$$

and the worker and firm surpluses from a job at risk satisfy

$$W_t^r - U_t = J_t^r - V_t^r. \tag{12}$$

4.3 Setup: population dynamics block

We now turn to describing the determinants of population dynamics in the model. The city is populated by a measure L_t of workers. We denote the number of employed workers as N_t, the share of employed workers in jobs at risk as s_t, and the unemployment rate as u_t. The

[14] We follow the literature in assuming that wages are set to split the total surplus from the job (see, for example, Pissarides (2000)). This assumption is consistent with a Nash bargaining solution under additional conditions that make sure that the wage splitting solution is Pareto efficient. As Shimer (2006) points out, in search models with on-the-job search, firms can prefer to pay a higher wage in order to reduce the incentives of workers to search on the job and leave. Since workers always prefer higher wages, this violates the Pareto efficiency of the solution. In our setup, wage splitting is Pareto optimal for safe jobs since the workers' search effort is zero. In the quantitative implementation we check that the present value of a job at risk for firms, J_t^r, is decreasing in wages to verify that the model is not subject to Shimer's criticism.

city is characterized by an exogenous productivity process A_t. The total output of the city is increasing in employed workers $A_t N_t^{1-\alpha}$, where $\alpha \in (0,1)$. This means that the output per worker is

$$y_t = A_t N_t^{-\alpha}. \tag{13}$$

The negative impact of the total employment on the output per worker captures a congestion externality that is not taken into account by workers or firms. Without this externality, workers should move to growing cities at an accelerating rate, and the only long-term stationary equilibrium would be one in which all workers reside in the most productive city.[15]

We model migration flows using a "small open city" approach: migration flows between a small "home city", which is the object of interest, and a much larger "benchmark city" that can be viewed as the aggregation of many cities that are each small relative to the total population. The idea is that migration flows into and out of the home city have negligible effects on the benchmark city and we therefore ignore them.

Migrating workers arrive in a new city without a job and immediately start to search for a job as unemployed workers. Let $\bar{U}_t$ denote the present value of unemployment at the benchmark city. The net population growth in the home city follows

$$\frac{\dot{L}_t}{L_t} = \gamma \left(\frac{U_t}{\bar{U}_t} - 1 \right) + \xi, \tag{14}$$

where γ and ξ are positive constants. The parameter γ determines the speed of population reallocation. A high γ means that migration flows are more sensitive to economic and therefore can reallocate workers quickly to a city with good economic conditions. The limit in which $\gamma \to \infty$ corresponds to static spatial equilibrium models without migration frictions. The parameter ξ captures natural population growth, which is also the rate of population growth in a city that offers the same expected wages as the benchmark city.

Equation (14) implies the following properties. First, all else equal, migration flows between cities are proportional to the size of the cities. This is consistent with observational evidence: There is more migration between New York and Los Angeles, then say, between Seattle and Orlando. The second is that the net migration between cities with identical economic conditions, as reflected in the present value of unemployment, would be exactly zero. Third, a constant population growth of a city is achieved only if the ratio of the present value of unemployment in the home and benchmark cities is constant over time. This is a key feature of the model for characterizing the economic conditions in cities from their long-run growth trends.

The implied population dynamics are the following. The change in the mass of employed

[15]This is sometimes referred to as the "centripetal force" in economic geography. Alternative specifications would capture similar externalities through non-traded amenities or factor immobility. See Helpman (1998) for theoretical foundations and Redding (2010) for empirical support.

workers is the inflow of workers from unemployment minus the outflow of employed workers through exogenous separation,

$$\dot{N}_t = f(\theta_t)(L_t - N_t) - \delta N_t - \rho s_t N_t.$$

The change in the mass of employed at risk is equal to the difference between the inflow from safe jobs minus the endogenous job destruction through OTJS and the exogenous job destruction.

$$(s_t \dot{N}_t) = \dot{s}_t N_t + \dot{N}_t s_t = \sigma(1 - s_t)N_t - e_t f(\theta_t) s_t N_t - (\delta + \rho) s_t N_t.$$

The change in the mass of unemployed is equal to the inflow from migration plus the inflow from exogenous job destruction minus the outflow into employment,

$$(u_t \dot{L}_t) = \dot{u}_t L_t + \dot{L}_t u_t = \dot{L}_t + \delta N_t + \rho s_t N_t - f(\theta) u_t L_t.$$

Combining the equations and rewriting them in growth rates gives,

$$\frac{\dot{N}_t}{N_t} = f(\theta_t)\frac{u_t}{1 - u_t} - \delta - \rho s_t, \tag{15}$$

$$\frac{\dot{s}_t}{s_t} = -\frac{\dot{N}_t}{N_t} + \sigma\frac{1 - s_t}{s_t} - e_t f(\theta_t) - (\delta + \rho), \tag{16}$$

$$\frac{\dot{u}_t}{u_t} = \frac{1 - u_t}{u_t}\left(\frac{\dot{L}_t}{L_t} - \frac{\dot{N}_t}{N_t}\right). \tag{17}$$

Finally, let v_t be the number of vacancies per worker in the home city. We can complete the model by expressing the labor market tightness as the ratio of v_t with the effective number of searchers per worker,

$$\theta_t = \frac{v_t}{u_t + (1 - u_t)s_t e_t}. \tag{18}$$

4.4 Balanced growth equilibrium

We analyze an equilibrium in which population and employment at the home city grow at a constant rate. Let the cost of keeping a vacancy κ_t, the flow benefit from unemployment b_t, the cost of OTJS $c(e_t, t)$, the cost of aggregate job destruction C_t, and the present value of unemployment at the benchmark city $\bar{U}_t$ all grow at a common rate $\bar{g}$.[16] The city specific productivity A_t grows at rate g^A.

A set of allocations $\{L_t, N_t, s_t, u_t, \theta_t, y_t, e_t\}$ and wages $\{w_t, w_t^r\}$ are a *balanced growth equi-*

[16]This means that the search cost $c(e_t, t)$ is the product of a time invariant function $\tilde{c}(e_t)$ and a time dependent term, so that $c(e_t, t) = \tilde{c}(e_t)\exp(\bar{g}t)$.

librium if tightness, search effort, the share employed in job at risk, and the unemployment rate are constant over time, output per worker and wages grow at rate $\bar{g}$, and population and employment grow at a constant rate g^N, and

1. Workers optimally search on the job according to equations (1)-(4).
2. Firms optimally choose to abandon vacancies and enter according to equations (5)-(10).
3. Workers and firms split the surplus from matches according to equations (11)-(12).
4. Output per worker, population dynamics, and the labor market tightness are consistent with choices of migrants, workers, and firms, expressed in equations (13)-(17).

If it exists, a balanced growth equilibrium implies that the growth rate of wages and output per worker in all cities is the same, yet cities in which productivity grows faster attract more inflows of migration and experience faster employment growth.

4.5 Growth, tightness, and on-the-job search

We turn the characterize an balanced path equilibrium. We denote equilibrium tightness θ^*, equilibrium search effort e^*, equilibrium share of jobs at risk s^*, and equilibrium unemployment u^*.

Proposition 1. *Suppose $r > \bar{g}$. A balanced growth path equilibrium satisfies the following:*

1. *Population growth is proportional to the difference between the home city productivity growth rate and the benchmark city growth rate,*
$$g^N = \frac{g^A - \bar{g}}{\alpha}.$$
2. *The present value of unemployment in the home city is proportional to that of the benchmark city and is increasing in the home city employment growth rate,*
$$U_t = \left(1 + \frac{g^N - \xi}{\gamma}\right) \bar{U}_t.$$
3. *The labor market tightness in the home city is increasing in the present value of unemployment,*
$$\theta^* = \frac{(r - \bar{g})U_t - b_t}{\kappa_t}.$$

Proof. The determination of output per worker in equation (13) and the condition that output per worker is increasing at rate $\bar{g}$ directly imply Part 1. The population equation (14) implies Part 2. The same equation also implies that the present value of unemployment grows

at rate $\bar{g}$. The firm's Bellman equation (5) and the free entry condition (9) imply $J_t = \kappa_t/\phi(\theta^*)$. Surplus splitting implies that $W_t - U_t = J_t$. Substitution into the worker Bellman equation (1) gives us Part 3 □

The intuition is the following. Suppose a growing city attracts migrants over a balanced growth path. In order to stay on the path, its employment level must grow at a rate that exactly offsets its productivity growth. To sustain that rate of migration, the relative present value of unemployment must be high enough relative to the present value of unemployment at the benchmark city. Due to free entry and surplus splitting, the present value of unemployment linearly increases with tightness. Therefore growing cities have tighter labor markets.

The same intuition also helps explain why output per worker in growing cities must be higher. This is because the only possible way for workers and firms to realize the higher surplus needed for tighter labor markets is if the output per worker is higher.

The relationship between growth and the search effort calls for more careful analysis. The key equation for understanding this relationship is (4). We have already established that growing cities have tighter labor markets. The direct effect of a tighter labor market is that finding a new job is easier, and therefore the payoff for search effort higher. Because search costs are convex, workers then have the incentive to exert more effort. There are also indirect effects that may potentially reduce the search effort. From a worker perspective, a tighter labor market makes the typical duration of an employment spell in jobs at risk shorter, and makes it more likely to end with a safe job rather than in unemployment. This shrinks the gap between the present value of safe jobs and jobs at risk, and therefore may reduce effort. There are, of course, additional equilibrium effects through wages and bargaining. Finding the exact relationship requires numerically solving a system of nonlinear equations numerically. However, in the quantitative implementation below, the direct effect dominates and therefore search effort is higher in growing cities than in shrinking cities.

4.6 Growth, quits, and layoffs

We now turn to characterize the unemployment rate, share of jobs at risk, and the labor flows in the balanced growth equilibrium given migration, tightness, and on-the-job search effort. The key equations are (15) to (17). On the balanced growth path,

$$\frac{\dot{N}_t}{N_t} = \frac{\dot{L}_t}{L_t} = g_N.$$

The share of jobs at risk satisfies the equation

$$s^* = \frac{\sigma}{g_N + e^* f(\theta^*) + \delta + \rho + \sigma} \ ,$$

which implies that the share of jobs at risk is lower in growing cities. The relationship between growth and the unemployment rate is more complicated. The unemployment rate satisfies the equation

$$u^* = \frac{\delta + \rho s^* + g^N}{\delta + \rho s^* + g^N + f(\theta^*)}.$$

Everything else equal, the unemployment rate declines in tightness. Similarly, a lower share of jobs at risk reduces the flow into unemployment and reduces the equilibrium unemployment rate. However, the equilibrium employment growth rate appears directly in the numerator and so it pushes the unemployment rate up. This is due to new migrants starting as unemployed. In the extreme case of free migration ($\gamma \to \infty$), the most productive city would attract all the unemployed. Even in the case that unemployment is decreasing in growth, the migration flows have a "flattening" effect on the relationship, which appears to indeed be weaker in the data.

5 Quantitative implications

This section builds a quantitative implementation of the model and evaluates its implication.

5.1 Parameterization

We select functional forms and pick parameter values to quantitatively evaluate the model. We choose a discount rate of $r = 0.03$ (3% per year) and the growth in expected real wages is $\bar{g} = 0.018$, or 1.8% per year, which matches the mean real compensation per hour growth in the US. We set the natural population growth rate to $\xi = 0.007$ to reflect the mean manufacturing employment growth in the US.

We follow the majority of the search and matching literature and pick a Cobb-Douglas matching function with elasticity 0.5, so that $f(\theta) = \chi\theta^{0.5}$, where χ is a scale parameter. We also apply a standard isoelastic functional form for the cost of on the job search,

$$c(e, 0) = c_0 \frac{e^{1+\eta}}{1+\eta},$$

with $\eta > 0$. This functional form means that workers can choose not to search and avoid any costs, $c(0, t) = 0$, and that the marginal cost of search is zero for non searchers, $c_e(0, t) = 0$. This means that any worker with an inferior job searches. To capture the range of layoff rates in the data, we set $\delta = 0.15$ and $\rho = 0.45$. This means that a city with no workers in jobs at risk would have a layoff rate of 15% per year, which is at the bottom of the observed city level layoff rate distribution, and a city that has all workers in jobs at risk would have 60% layoff rate, just above the top of the same distribution.

We then choose parameters to make sure that the benchmark city resembles the US average based on moments from the data and literature. We normalize the output per worker in the

benchmark city to $y_0 = 1$ and follow Shimer (2005) in setting the flow benefit of unemployment at $b_0 = 0.4$. We jointly set χ, σ, κ_0, and the total additional flow costs of jobs at risk $\bar{c} = c(e^*, 0) + \rho C_0$ in the benchmark city, to get a balanced growth equilibrium with 5.5% unemployment rate, unemployed job finding rate of 4 (equivalent to a mean unemployment duration of 3 months), mean quit rate of 26%, mean layoff rate of a ratio of vacancy to unemployment of 0.72 (Pissarides, 2009).

We get the following values. The scale parameter of the matching function is $\chi = 6.9$, which means that with labor market tightness of 1 an unemployed workers find new jobs in less than 2 months. $\sigma = 0.4$, which means, together with the job destruction rates of safe jobs and jobs at risk, that the expected duration of a new job, without on-the-job search is 3 years. While we do not have direct measures to check the duration, this number is within the range reported by the literature. The cost of keeping a vacancy open is $\kappa_0 = 1.48$, which is 48% higher than the output from a filled vacancy. This is higher than what is typically found in the literature, mostly because trend growth makes jobs more valuable. Finally, the total private flow cost of jobs at risk is $\bar{c} = 0.258$, which is just above 40 percent of flow payoff of a job – the difference between worker output and the flow benefit of unemployment. The the search effort on-the-job in the benchmark city is $e^* = 0.53$, which means employed searchers take double the time to find a new job compared to the unemployed.

We are then left with four parameters, that do not affect the benchmark city, but determine the shape of the cross section. These are the sensitivity of migration to wages γ, the private cost of being laid off C_0, and the cost of on-the-job search, c_0 and η. There are no consensus numbers on the sensitivity of migration to wages. Kennan and Walker (2011) study cross state migration and estimate that a 10% difference in wages leads to a 5% higher migration rate into that state. We therefore set $\gamma = 0.5$. We set $C_0 = 0.17$, $c_0 = 0.43$, and $\eta = 0.15$ to capture the the slopes of the quit rate and layoff rate in the cross section of cities, and make sure that the benchmark city quit rate matches the target value above. C_0 implies that a loss of a job through layoff in at risk jobs is equivalent to a loss of 2 months of output. c_0 means that searching on-the-job with the same intensity as unemployed costs 36 percent of the output per worker. The value of η is the inverse elasticity of search to the payoff. It implies that the job finding rate of workers in jobs at risk, around the benchmark city, will rise by 3.3% when the gap in present value of safe and at risk jobs rises by 1%.

5.2 Results: the cross section

Figure 7 shows how the model captures the mean gross flows by city. Each dot represents the means of the quit rate or layoff rate in a city in the balanced panel, which were also presented in Figure 4. The solid line captures the predictions of the model. The model is able to capture the difference between growing and shrinking cities with trend growth alone.

There is, however, considerable variation in the residual. We evaluate the share of the variation that the model explains as one minus the ratio of the variation in the model residuals to the variation in the mean rates. The model explains 25% of the variation in quit rates, and 11% of the variation in layoff rates in the data.

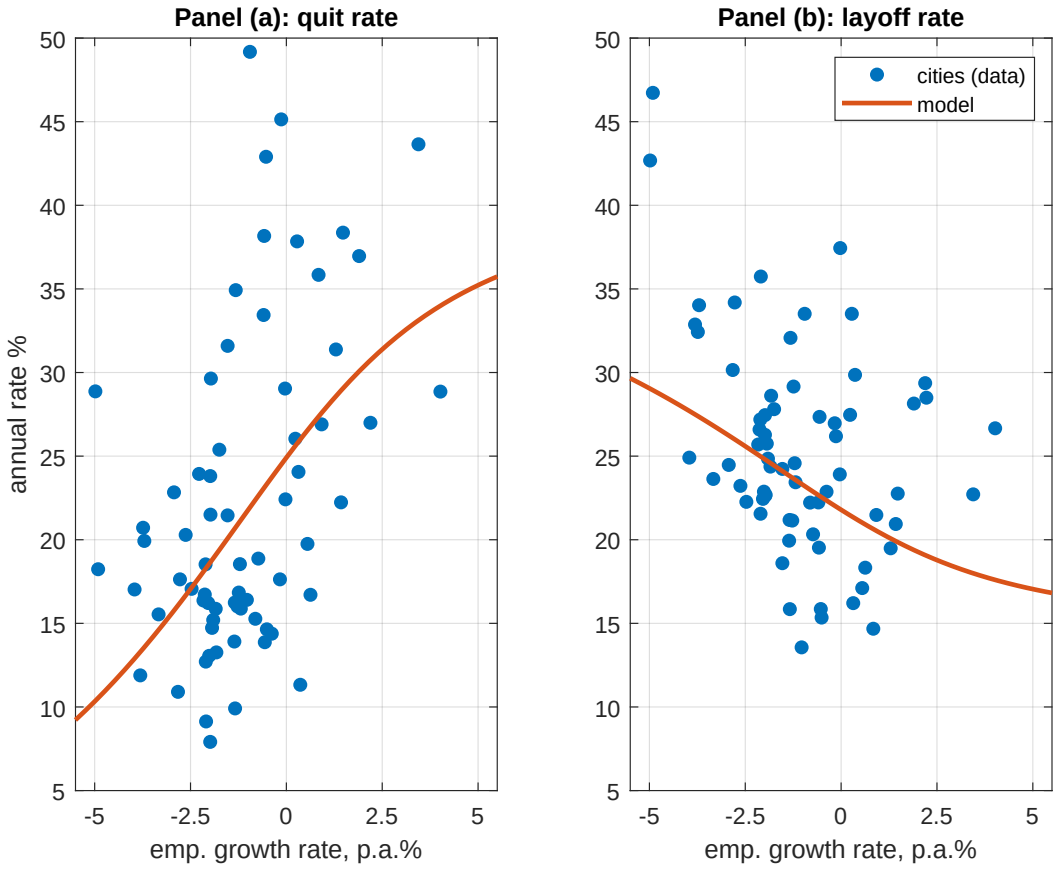


Figure 7: Manufacturing quits and layoff rates: data vs. model

Note: Each dot represents the mean flow rates in percentage annual terms by city. The sample features the 71 cities that have more than 16 years of observations between 1964-1981. The solid line represents the model prediction.

The model also explains why the labor flows are different across cities. Figure 8 uses a series of pictures to illustrate the equilibrium allocations at different growth rates. In each panel, the dashed lines represent the benchmark city (black), a "growing city" (red), and a "shrinking city" (blue). Panel (a) shows the labor market tightness. Cities are growing because they offer higher expected wages. In the bargaining environment in the model, the tightness is a sufficient statistic for the expected wages and therefore tightness is higher in growing cities.

Panel (b) shows the output per worker. Output per worker in growing cities is 4% higher

than the benchmark city, and in shrinking cities 6% lower. We emphasize that this is an equilibrium outcome: If output is higher then the equilibrium value, firms would post more vacancies, which will increase tightness and attract more workers. Then, the congestion externality would gradually reduce the output per worker relative to the benchmark city.

Panel (c) shows the job finding rate of the unemployed, which is mechanically increasing with tightness, and Panel (d) shows the amount that a worker in a job at risk gains from finding a safe job. In growing cities, it is both easier to find a new job by about 10%, due to the availability of many vacancies, and the gain from finding a new job is higher, by an additional 10%. Therefore the incentive to exert effort is higher. Indeed, workers in growing cities exert more effort. Panel (e) shows the on-the-job search effort of workers in jobs at risk. The effort measure the job finding rate of workers in jobs at risk relative to the unemployed. In shrinking cities, workers choose to exert low effort, quit their jobs slowly, and are likely to be laid off before finding a new employer. In growing cities, workers that want to quit search harder, and find new jobs almost as fast as unemployed workers, while in shrinking cities they take 5 times as much time to find a new job (roughly, a year and a half instead of 3.5 months). This is reflected in the share of jobs that are at risk. Panel (f) shows that this share is decreasing with growth. In shrinking cities almost a quarter of all employed workers are in jobs at risk, while in growing cities less than 10% of them are.

The equilibrium allocations also have implications for standard measures of misallocation of the state of the labor market. Panel (g) shows the unemployment rate. While there is a clear difference in the levels of unemployment between the cities, it is much less pronounced than the differences in flows. Shrinking cities have an unemployment rate of 6% and growing cities have an unemployment rate of 5%. This outcome is driven by migration. Growing cities have tighter labor markets that quickly reallocate unemployed labor to more efficient use, but they also attract incoming migration the increases the number of unemployed. Another variable that is often used as a proxy for tightness is the ratio of vacancies to unemployed. Panel (h) shows how there are more vacancies per unemployed in growing cities. However, this graph is much steeper then the actual tightness.

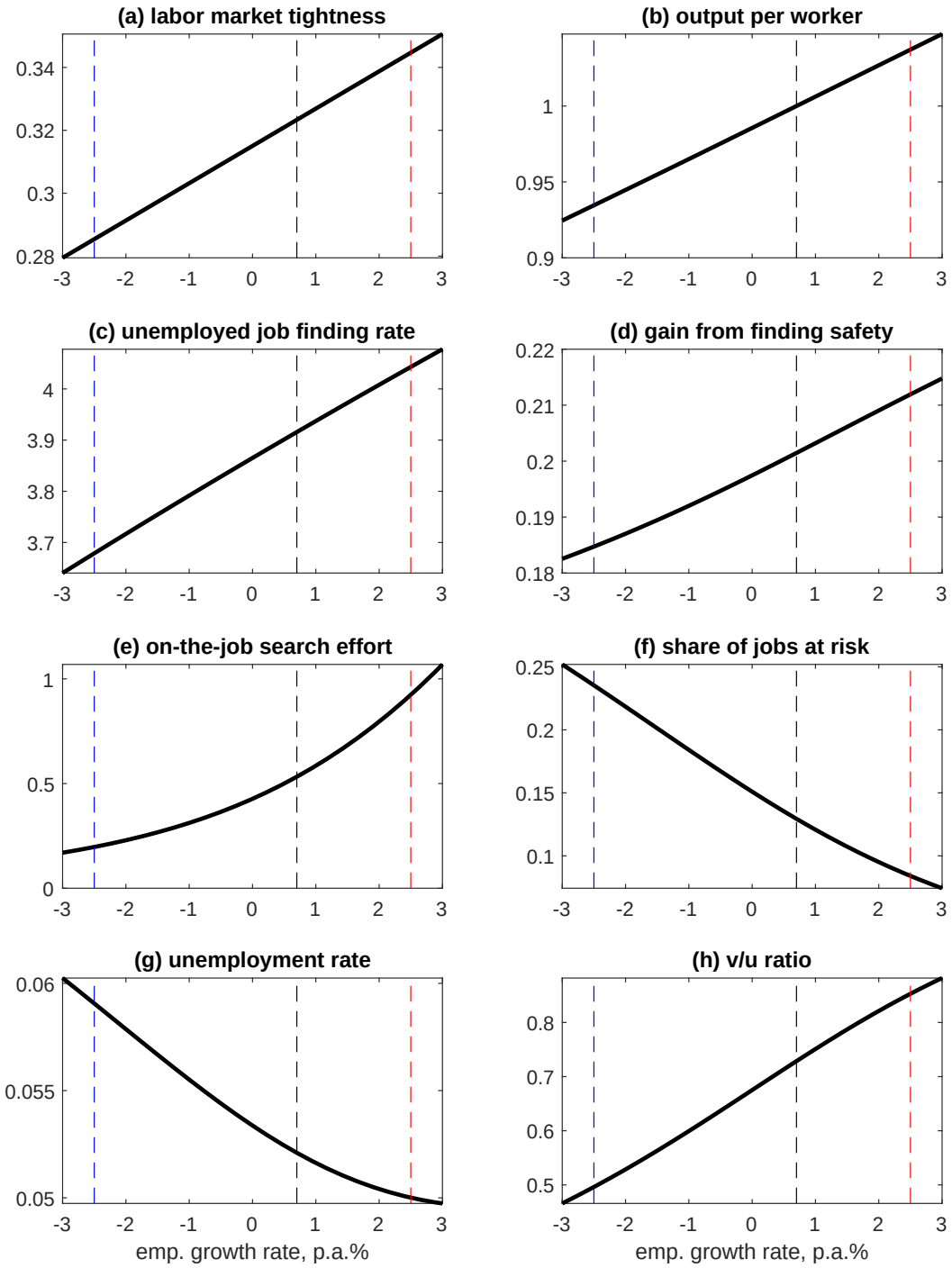


Figure 8: Balanced growth equilibrium allocations by employment growth

6 Conclusion

This paper studies how long-run trend, such as growth in productivity or employment, affect the rates of reallocation. Newly digitized data on manufacturing labor flows 1957-1981 show that growing cities have more quits and fewer layoffs. They also respond differently to recessions. In growing cities, recessions manifest as a decline in the quit and hiring rates, and in shrinking cities as layoff spikes.

We interpret the results through a small open city model with search on the job. A simple modification of the standard Diamond-Mortensen-Pissarides allows to model to account for the cross-sectional patterns with differences in trend growth. The key assumption is the jobs can become at risk: more likely to be destroyed soon. Workers in jobs at risk search on the job harder in growing cities, and quit their jobs rather than waiting to be laid off.

The variation growth trend alone accounts for roughly a quarter of the variation in quit rates, and one-seventh of the variation in layoff rates. The model is also consistent with the evidence on the differential response to business cycles. In recessions, productivity declines and the rate of job destruction of jobs at risk rise. Because more workers are in jobs at risk this leads to a spike in layoffs in shrinking cities. In growing cities, the incentives to search on the job decline at the same time that the pool of available vacancies shrinks, leading to a decline in hires and quits.

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A Appendix