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

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Abstract

This paper studies the connection between regional growth trends and labor market dynamics. New data on manufacturing worker flows for U.S. cities 1957-1981 show that growing cities see on average more new hires and more voluntary quits, but fewer forced layoffs. Moreover, recessions in growing cities are special in that hiring and quits are low, whereas their key feature in shrinking cities is a spike in layoffs. A model of migration and on-the-job search accounts for the common factor in growth, quits and layoffs in the cross section of cities. Its key feature is that jobs can become *at risk*: they have lower match surplus and are more likely to terminate. In growing cities, better prospects from on-the-job search lead workers to quit jobs *at risk* earlier, which reduces layoffs and misallocation.

1 Introduction

Reallocation of workers happens at different frequencies. There are strong regional growth trends that reflect movements of workers and jobs across locations over many decades. For example, between 1970 and 2000, manufacturing employment in the Northeast and Midwest regions of the U.S. gradually fell by 23%, while in the South and West regions it increased by 30%. At the same time, there is continual reallocation of workers in response to idiosyncratic shocks. These shocks generate large gross worker flows due to hiring, quits, and layoffs. The distribution of these shocks depends on the business cycle, so that the composition of these flows changes over the cycle. While there are large literatures on both regional change and labor market "churn", the two modes of reallocation are typically not studied jointly.

This paper argues that regional growth trends and gross worker flows are closely connected. We first use data on manufacturing worker flows for U.S. cities to document strong positive co-movement between average employment growth and average quit rates, as well as negative comovement between growth and layoff rates. The nature of recessions also varies by trend growth: while growing cities exhibit larger drops in hires and quits, shrinking cities exhibit larger layoff spikes. We then propose a search model of the labor market that generates co-movement of growth, quits, and layoffs in the cross section of cities. We calibrate the model to our data to show that our mechanism accounts quantitatively for the common factor in those series at reasonable parameter values.

The empirical part of the paper uses newly digitized archival records from the Bureau of Labor Statistics' Labor Turnover Survey (LTS), a precursor of the Job Opening and Labor Turnover Survey (JOLTS). The LTS reports new hires, quits and layoffs in manufacturing by Standard Metropolitan Statistical Area. In a balanced panel of 66 cities between 1969 and 1981, a 1 percentage point higher annual average employment growth rate goes along with a 4.5 percentage point higher annual quit rate and a 1 percentage point lower annual layoff rate. Employment growth was generally high in the Sun Belt and the West, whereas it was low in Rust Belt Cities in the Northeast and Midwest. For a concrete example, Salt Lake City grew at 4.3% per year with a quit rate of 34% and a layoff rate of 19%, whereas Buffalo shrank at 2.6% per year with a quit rate of only 10% but a layoff rate of 33%.

Our model relies on three main assumptions. First, cities differ in the surplus from a match between employer and worker. This could be due to differences in labor productivity, but also to regulation or amenities. The key is that high surplus cities attract more jobs and provide higher utility to local workers. Our second assumption is that migration responds gradually to cross-city differences in economic opportunities. As a result, workers arrive more slowly in growing cities than jobs, that is, the labor market in growing cities is tighter. Third, we assume that jobs can become *at-risk*: they then provide lower surplus and are more likely to terminate.

More formally, we study a small open city version of the standard Diamond-Mortensen-Pissarides search framework with heterogenous match quality and costly on-the-job search. The size of the labor force is determined by a migration equation that relates the net inflow of workers into a city to the ratio of indirect utility from living in the city relative to an exogenous outside option. Combined with the standard assumption of free entry by firms, gradual migration means workers move more slowly than jobs. We then interpret the cross section of employment growth, quits, and layoffs in our data as a balanced growth equilibrium: cities grow at different constant rates and exhibit different labor market churn, all driven by latent city-specific match surplus.

Our quantitative exercise shows that the model can account for the common factor in our three observables: hiring, quits, and layoffs. Indeed, workers gradually move to high surplus cities, which therefore exhibit higher employment growth than low surplus cities. Since labor markets are tighter in high surplus cities, it is easier to find a job there. Workers in at-risk jobs thus have a greater incentive to search on-the-job. As a result, quits and layoffs move in opposite directions: in growing cities, the quit rate is higher, but the pool of workers in at-risk jobs is lower, which leads to a lower layoff rate. Migration thus goes along with less misallocation of workers, either to unemployment or to at-risk jobs, within a city.

We do not take a stand on exactly what generates city differences in surplus. For concreteness, the quantitative exercise assumes differences in output per worker, or labor productivity. This is not essential, however: a model with workplace amenities that yield private benefits to employed workers is observationally equivalent in terms of growth, quits, and layoffs. The essence of the model is that a single factor generates the right variation in gross flows. We obtain this result because incentives to search on-the-job respond strongly to surplus relative to the response of migration. As a result, high surplus cities see high search effort and a higher job finding rate on-the-job; the quit rate is then higher even though migration lowers the relative share of at-risk jobs.

The feature that jobs can become at risk generates a connection between surplus and the layoff rate, and hence allows one factor to drive variation in all three series we target. If jobs only differed by match quality, higher surplus cities would still see more quits, but the layoff rate would be constant across cities. Moreover, while our calibration assumes that risk and match quality are perfectly correlated, and that all jobs start safe and become at risk over time, both features are not essential for the mechanism: an alternative model might have each job drawn up front from a flexible two-dimensional distribution.

While we do not have data on unemployment and vacancies by city for the period we study, the model also makes predictions about the cross section of those variables. At our parameter values, variation in surplus makes cities line up along a downward sloping Beveridge curve: high surplus cities have lower unemployment and higher vacancies as a share of the labor

force. In contrast to the standard search model with a fixed labor force, the presence of migration implies that high surplus cities not only have a higher job finding rate – which lowers unemployment – but also a larger pool of people looking for a job. Our calibration delivers a fairly flat relationship between employment growth and unemployment. At the same time, growing high surplus cities attract more jobs and hence vacancies per capita.

The model also suggests an explanation for the different impact of recessions on growing and shrinking cities. Suppose recessions are triggered by an aggregate shock that simultaneously lowers labor productivity and destroys a share of at-risk jobs in all cities. The main effect of the shock in shrinking cities with many jobs at risk is a large spike 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.

We add to a large literature on how local labor markets change over time; for a survey, see Moretti (2011). Most studies focus on wages and employment: a key fact is that cross sectional differences in those outcomes are very persistent, even though migration does respond to differences in local conditions. One strand of the literature interprets the data through the lens of static spatial equilibrium models, as in early work by Hall (1972) and Rosen (1979). Topel (1986) and Blanchard and Diamond (1990) instead focus on the dynamic relationship between migration and local conditions. Our paper follows this second approach, as does recent work by Redding (2016) and Amior and Manning (2018). However, the local conditions we study are statistics on gross worker flows, rather than wages or employment rates.

Detailed data on migration have been studied using models of location choice following Dahl (2002). Kennan and Walker (2011) developed a tractable choice model of job search and estimate the response of migration to local conditions, a key parameter also in our model. Schmutz and Sidibe (2019) estimate such a model with matched employer-employee data from France and show that workers respond to opportunities for better job-to-job transitions, in line with our mechanism. At the same time, there is little evidence on the details of gross worker flows (that is, new hires, quits, and layoffs) by geography over time. Hall (1972) compared layoff rates in 12 large cities in the 1960s and shows that tighter markets see fewer layoffs. Davis and Haltiwanger (2014) show that worker reallocation (hiring plus separation) moves with the employment rate across U.S. states since 1998. Our data allows us to distinguish quits and layoffs at the city level and relate them to regional growth at a time when migration rates were high.

There is an active literature on search models of local labor markets. Beaudry, Green, and Sand (2012, 2014), and Kline and Moretti (2014) embed a frictional labor market into a spatial equilibrium framework to study the relationship between amenities, policy and unemployment. Lkhagvasuren (2012) studies migration as an adjustment mechanism in a multi-city model.

Head and Lloyd-Ellis (2012), Nenov (2015), and Karahan and Rhee (2016) consider the effect of housing cost on migration. Our setup differs from these studies because we target quit rates and hence introduce on-the-job search, following Burdett and Mortensen (1998), Barlevy (2002), and Postel-Vinay and Robin (2002). Moreover, we generate a link between quit and layoff rates by assuming a connection between match quality and job risk as in Jarosch (2015).

The literature on job flows has studied reallocation and growth by industry and firm.[1] Foote (1998) notes that job creation and destruction are larger in growing sectors which also have a higher volatility of job creation than job destruction. He proposes an (S,s) employment adjustment model that qualitatively captures this relationship. Davis, Faberman, and Haltiwanger (2012) show that job reallocation rates are higher in retail and services than in manufacturing and higher at growing firms. While our focus is on worker flows by region, our mechanism could be relevant for thinking about sectoral growth and churn as well. Studying this connection would require a model with a richer distinction between job and worker flows, see for example Kiyotaki and Lagos (2007), Burgess and Turon (2010), or Borovičková (2016).

Our findings on worker flows in recessions relate to business cycle models with search. The typical approach studies labor reallocation at the national level. There has been some debate on the source of shocks: the relative importance of shocks to flow surplus and job destruction shocks depends on the relative cyclicality of job finding and separation rates (Shimer, 2012; Fujita and Ramey, 2009; Elsby, Michaels, and Solon, 2009; Yashiv, 2007). Our results suggest that these properties differ by region, and that a model with on-the-job search can account for differential exposure of regions to aggregate shocks. We thus add to a growing literature that explores the role of on-the-job search and variation in match quality to address the volatility of labor market flows over the business cycle (for example, Menzio and Shi, 2011; Fujita and Nakajima, 2016; Gertler, Huckfeldt, and Trigari, 2016; Lise and Robin, 2017; Moscarini and Postel-Vinay, 2018).

2 Data and facts

In this section we provide new evidence on manufacturing labor flows in the cross section of U.S. 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.[2] 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.

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[1]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. See Davis and Haltiwanger (2014) for a recent overview.

[2]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".

The geographical unit available in the LTS is the Standard Metropolitan Statistical Area (SMSAs). 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 SMSAs and cities are not technically identical, we use the term "city" to refer to these SMSAs.

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 SMSAs, at a monthly frequency, over the period August, 1957 to November, 1981.

To obtain information on the level of employment and industry composition, we supplement the LTS with data provided by the U.S. Bureau of Economic Analysis (BEA). The BEA publishes information on employment and income by industry at the metropolitan statistical area (MSA) and consolidated statistical area (CSA) level. The BEA data is annual and starts at 1969.

The raw LTS data include 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 there are on average 96 cities observed each month. We also use a sub-sample of 66 cities that include more than 8 years of observations in the period January 1969 and 1981 and have at least 20,000 employed workers in manufacturing in 1969 to connect with the BEA data.

The rest of this section presents the national trends in manufacturing employment in the U.S., 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.

2.1 Manufacturing employment growth in the U.S.

Our study period is well known to exhibit a long-run decline in the relative importance of manufacturing to the U.S. economy. Panel (a) of Figure 1 shows the share of U.S. manufacturing employment. 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).
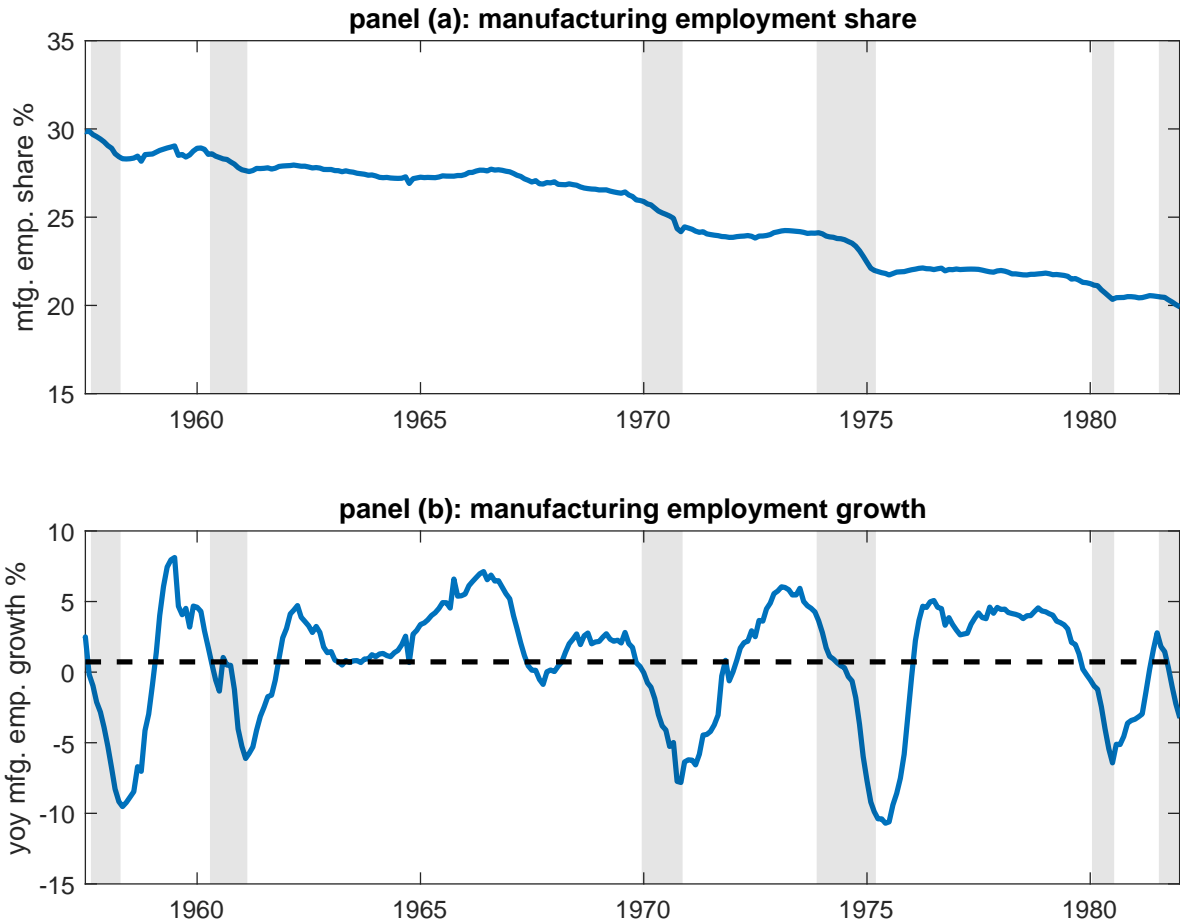
Figure 1: U.S. manufacturing employment, 1957-1981

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

The national-level trend masks remarkable regional variation in manufacturing employment growth rates. To illustrate this variation, we calculate the mean annualized employment growth in manufacturing over the period 1969-1981 based on the BEA data.

Figure 2 presents the manufacturing employment growth by city for 287 MSAs and CSAs. The color of each city is the growth rate in percentage annual terms. Colors are set so that red and yellow are growing cities and dark-to-light blue are shrinking cities.

The map reveals 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 around 2% per year over the sample period.[3] The second pattern is the growth in manufacturing employment in the "Sun Belt", which includes the cities of the Southern and Western regions of the United States.[4] Cities

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[3]For example, manufacturing employment in Detroit, MI declined by 2.2% per year, Chicago, IL by 1.8%, and Johnstown, PA by 3.5%.

[4]There are exceptions to the geographic classification. Manufacturing employment in the southern cities of

such as Phoenix, Dallas-Fort Worth, and Houston experienced average manufacturing employment growth of more than 3.5% per year throughout the sample period. This geographical heterogeneity stands in stark contrast to the standard view of manufacturing as a declining industry.
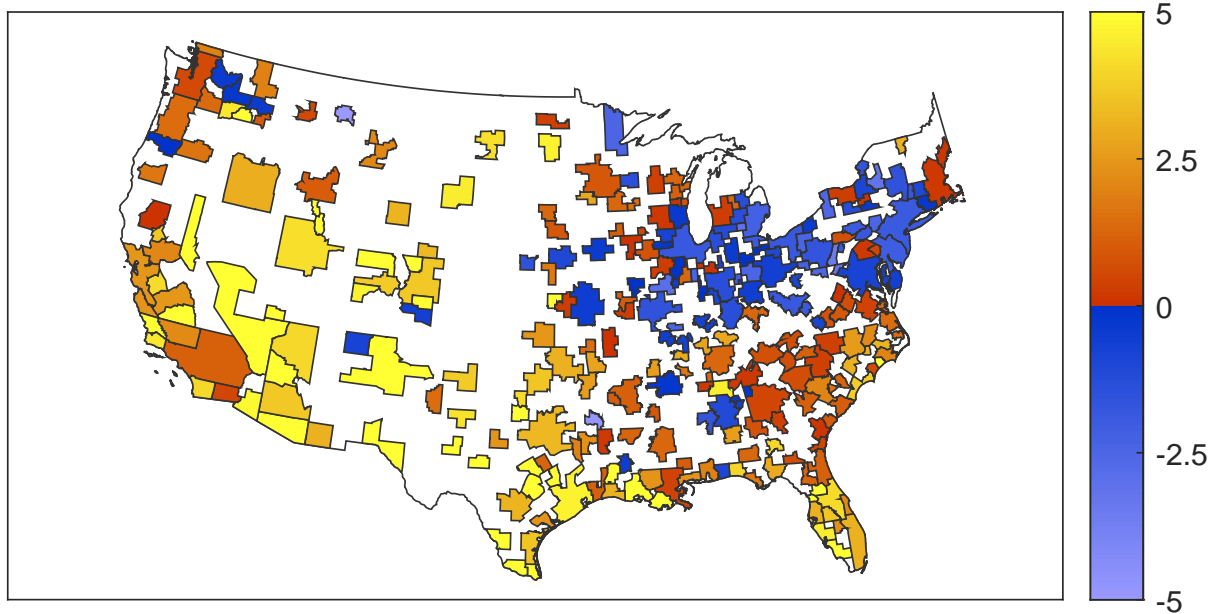

Figure 2: Manufacturing employment growth by city, p.a., 1969-1981

Note: Manufacturing employment growth rates in annualized percentage points over the period 1969-1981.

Source: BEA regional economic data.

2.2 Labor flows in the cross-section of cities

We next consider how gross labor market flows vary across cities. In particular we want to document the joint distribution of the mean manufacturing employment growth and the mean quit, layoff, and hiring rates. To conduct this analysis, we include only cities from the LTS with at least 96 monthly observations between January 1969 to November 1981 (the overlap period with BEA data) and with an employment in manufacturing exceeding 20,000 in 1969. We end up with a panel of 66 cities for which we have joint observation of the mean quit rate and layoff rate.

Figures 3 and 4 reveal a remarkable relationship between the growth trend of cities and their average quit and layoff rates. Figure 3 shows the mean quit rate and employment growth rate in manufacturing for the cities in the balanced panel. Each one out of the 9 Census divisions is represented by a different marker type. Colors represent the four Census regions: red is

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Birmingham, AL and Memphis, TN declined, despite strong growth in nearby Sun Belt areas. Similarly, cities in mid-western Minnesota and Wisconsin saw manufacturing employment growth despite being distant from the Sun Belt.

for northeast, blue is for mid-west, green is south, and orange is west. The black line is an OLS projection. The figure reveals that growing cities have a substantially higher quit rate than shrinking cities. As the map above shows, underlying this variation in growth rate is a strong geographical component, where west and south region cities grow quickly, while northeast and mid-west cities contract.

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 12.4% per year. In contrast, cities that grow at a rate of 2.5% have an average quit rate of 34.5%. Figure 4 shows a similar picture for the layoff rate. Cities that shrink at a 2.5% rate have an average layoff rate of 27.4% while cities that grow at a rate of 2.5% have an average layoff rate of 22.9%. 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.
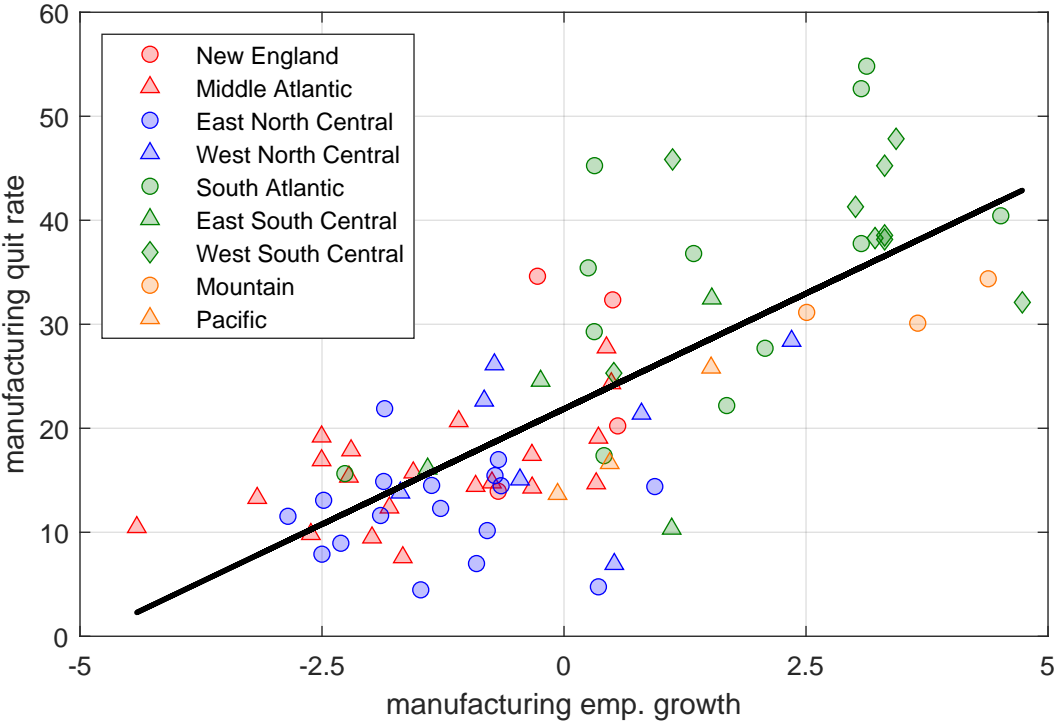

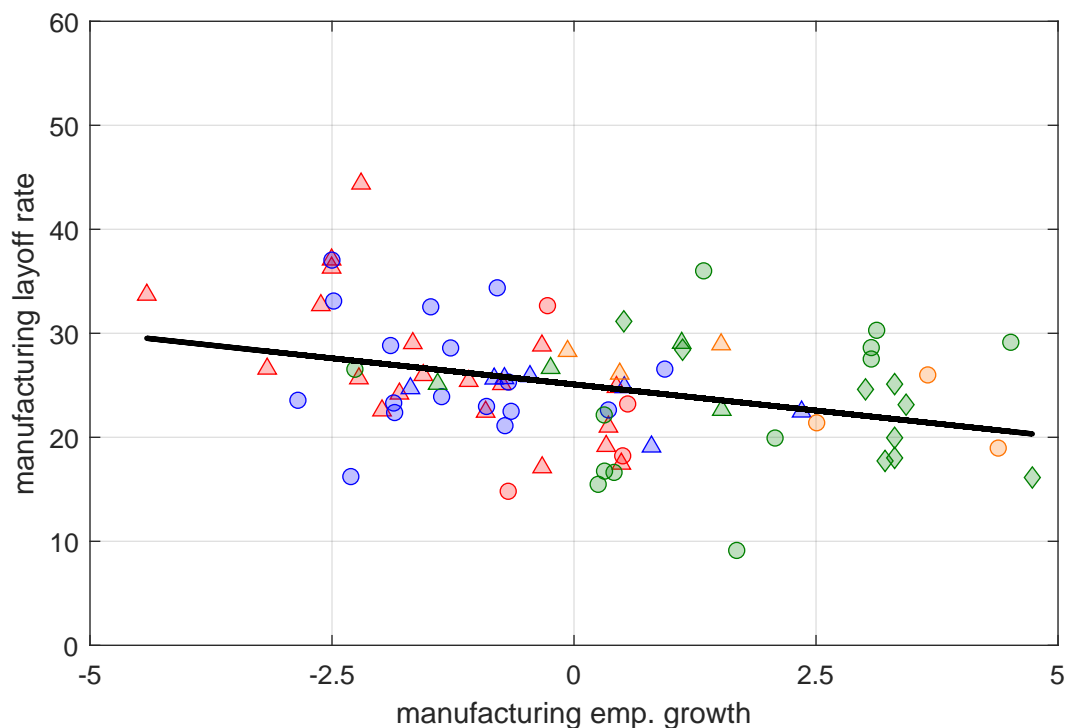Figure 3: Manufacturing quit rates by employment growth

Figure 4: Manufacturing layoff rates by employment growth

2.3 A tale of three cities: Buffalo, Cincinnati, 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, Buffalo, NY (manufacturing employment shrinking at rate -2.6% per year) and Cincinnati, OH (shrinking at -0.6% per year), and one growing city, Salt Lake City, UT (growing at 4.3% 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, 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.
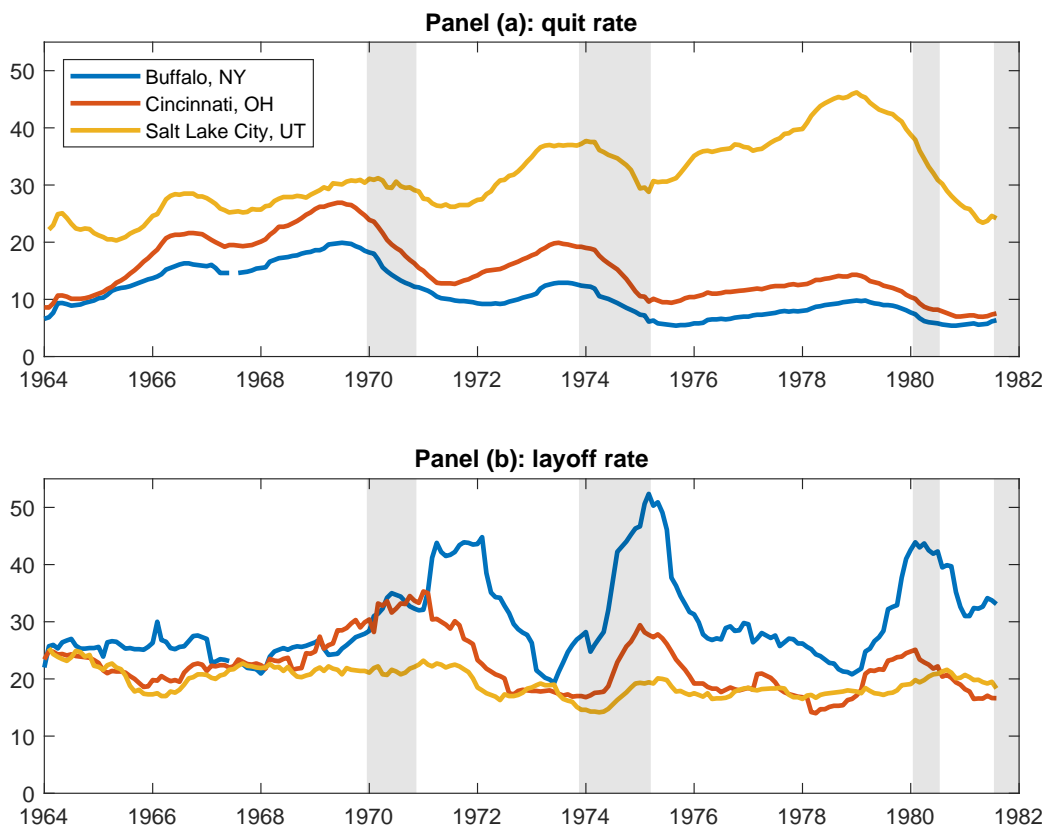
Figure 5: Labor market flows for three cities

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.

2.4 Business cycles and labor flows in growing and shrinking cities

We document business cycles facts for the cross section of cities by sorting cities into "growth bins" and plotting time series for each bin. For each month in our sample, we divide cities into 5 bins of equal population size, based on the net hiring rate over a symmetric six-year time window (three years before and three years after any given month). The net hiring rate, calculated as the difference between the hiring rate and the separation rate, is equivalent to the monthly employment growth, and so its mean over the six-year period captures the regional growth trend at the time of the observation. Within each bin, we then calculate the mean hiring, separation, quit, and layoff rates, weighted by total population. We end up with 5 sets of time series.

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.

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.

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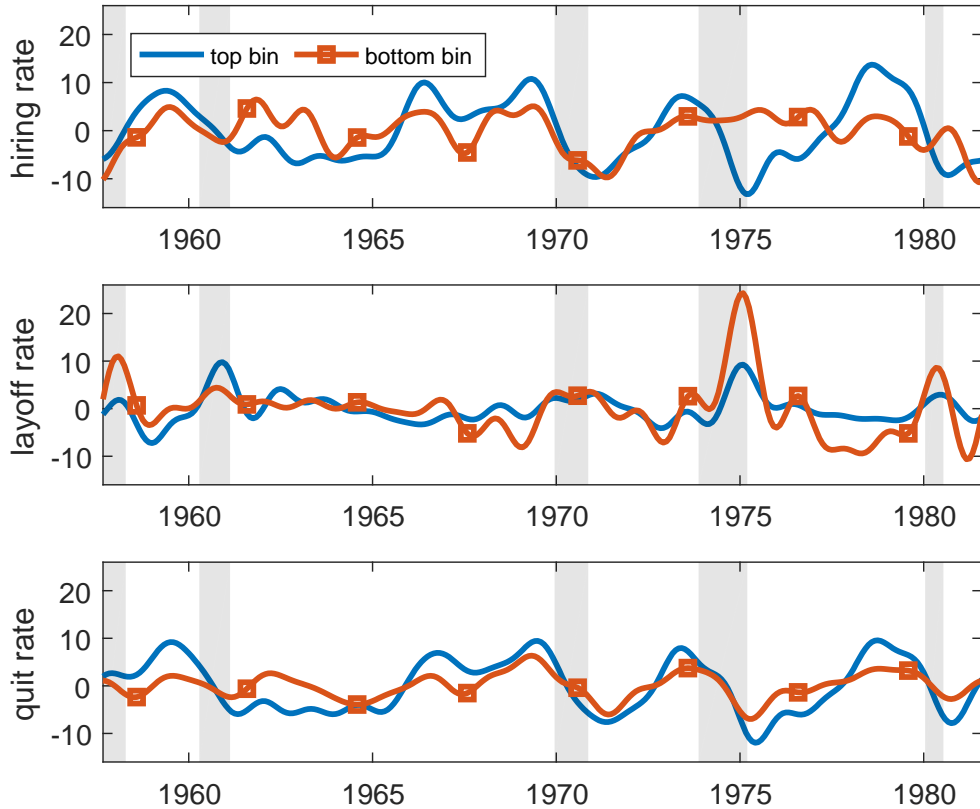
Figure 6: Cycle component of gross flows for top and bottom growth bins

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.

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.

2.5 Discussion: manufacturing employment growth and population growth

In the model section below we label the net inflows of workers into the status of seeking a job in a city-sector as "migration". This characterization is incomplete since workers can arrive at a

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.

city-sector in a variety of ways, most notably by switching from another sector within the same city. Labeling these inflows as migration is therefore only appropriate if cities that have a high employment growth in manufacturing are also the cities that are attracting more people.

Figure 7 shows the joint distribution of manufacturing employment growth and population growth across cities in our sample period, based on BEA data. The figure suggests that there is strong association between employment growth in manufacturing within a city, and migration into the city. Cities that add jobs in manufacturing are usually also cities that add population.
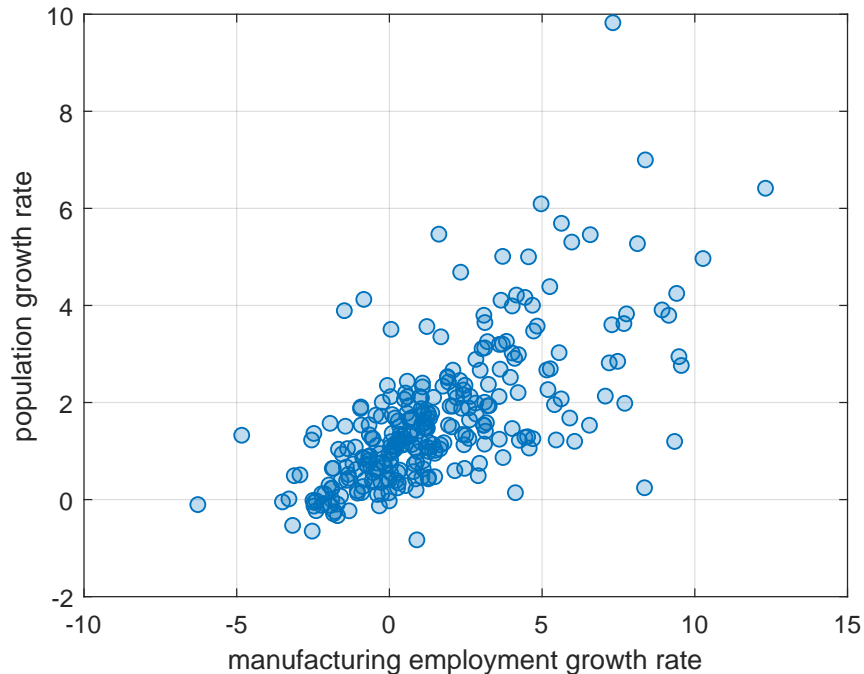
Figure 7: Employment growth in manufacturing and population growth, 1969-1981

3 Model

This section describes a model of a "small open city" to interpret the facts from the previous section. We start from the baseline Diamond-Mortensen-Pissarides (DMP) setup with costly search on-the-job. We add two new elements: first, jobs initially deliver high surplus and are destroyed at a low rate, but later may become "at-risk", that is, they yield lower surplus and are destroyed at a higher rate. Second, the size of the labor force is endogenous: migration responds gradually to differences in indirect utility between the small open city and the rest of the economy.

3.1 Setup

Time is continuous and agents live forever. Firms and workers are have linear utility and discount the future at rate r. Workers and firms search for each other to form matches. Unemployed workers search for free and receive a flow benefit b_t per unit of time. Firms create vacancies and search for workers at a flow cost κ. Employed workers can search for a different job by exerting effort $e_t > 0$ at flow cost $c_t \tilde{c}(e_t)$; the function $\tilde{c}$ is increasing and convex in effort and satisfies $\tilde{c}(0) = 0$.

When a firm and a worker meet, they can decide to form a match that produces output per

worker y_t. However, both the surplus from a match and its expected duration can deteriorate over time. When a match is first created, it is only exposed to an idiosyncratic job destruction shock with Poisson arrival rate δ. At rate σ, matches become "at-risk": workers then incur a nonpecuniary flow cost ρC_t while remaining in the match, which is now destroyed at the higher rate $\delta + \rho$. Both workers and firm know at all times whether a match is "at-risk" or "safe". They can walk away from a match at any time.

Firms and workers meet according to a matching function that is homogenous of degree one in the number of vacancies as well as the number of *effective searchers*, that is, unemployed workers plus on-the-job searchers multiplied by search intensity. The *tightness* of the labor market, denoted θ_t, is defined as the number of vacancies per effective searcher. The matching technology can then be summarized by the job finding rate of the unemployed $f(\theta_t)$, a strictly increasing function of tightness. The job finding rate of on-the-job searchers is $e_t f(\theta_t)$. The vacancy filling rate $f(\theta_t)/\theta_t$ is decreasing in tightness.

Wages are determined by bargaining. Importantly, an on-the-job searcher must decide to quit his old job before bargaining with the new employer: there is no renegotiation with the old employer with a new job opportunity in hand. As a result, the bargaining problem is the same regardless of how the match came about. We assume that the parties evenly split the total surplus from the match, as in Pissarides (2000). While surplus splitting need not generally be Pareto efficient – and hence reflect a Nash bargaining solution – with on-the-job search, we verify this property in our quantitative model below.[5]

The flow of workers into or out of the city reflects differences in utility relative to an outside option obtainable in a *benchmark city* that represents the rest of the economy. Let U_t denote the indirect utility of an unemployed worker in our small open city – since workers have linear preferences, it only depends on calendar time. Also denote utility in the benchmark city by $\bar{U}_t$. The city labor force L_t grows according to

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

The parameter $\gamma > 0$ determines the speed of population reallocation: if it is higher, migration flows are more sensitive to economic conditions. The parameter $\xi > 0$ captures population growth common to all cities: every period some new citizens start looking for jobs. We restrict parameters below such that the out-migration rate is always below the rate at which workers flow into unemployment. This is guaranteed for example if job destruction rates are large relative to migration rates. We can thus adopt the convention that only unemployed agents leave

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[5]Shimer (2006) points out that, in a model with on-the-job search, it may be beneficial for firms to pay a higher wage in order to reduce the incentives of workers to search on the job and leave. In our setup, wage splitting is Pareto optimal for safe jobs since the workers' search effort is zero. Moreover, we check that, at our parameter values, the present value of a job at risk for firms is decreasing in wages.

the city.

A city starts out with an initial labor force L_0, number of matches N_0 and share of at-risk matches s_0. An equilibrium allocation consists of paths for the labor force L_t, a distribution of matches described by N_t and s_t, posted vacancies $v_t L_t$ as well as wages w_t and w_t^r in safe and at-risk jobs, respectively, such that firms and workers optimize given tightness, wage bargaining splits the surplus, and aggregates reflect transition between individual states determined by agents' choices as well as idiosyncratic shocks.

As is common in DMP-based search models, equilibrium is characterized by a block-recursive system of differential equations. A first "search and matching block" determines wages, tightness and search effort, together with utility and profits, independently of unemployment or the distribution of matches. A second "population dynamics" block then determines the latter variables, in our case jointly with the size of the labor force that follows from endogenous migration. We now study these blocks in turn.

3.2 Search and matching block: optimal choices and wage bargaining

We consider equilibria such that both safe and at-risk jobs yield positive surplus. Optimal actions of workers and firms are then simple. In particular, all unemployed workers search, while employed workers search on the job if and only if their job is at-risk. All meetings between firms and workers result in the creation of a safe job. Finally, an at-risk job is terminated if and only if a destruction shock hits or the worker finds a new job. To guarantee existence of such equilibria, we assume that $y_t - b_t - \rho C_t > 0$ and that the cost of on-the-job search slopes up sufficiently quickly so surplus in at-risk matches at the optimal search effort is positive.

Consider workers' expected discounted utility in different states. We denote wages in safe and at-risk jobs by w_t and w_t^r, respectively. Workers' values in unemployment U_t, in a safe job W_t, and in a job at risk W_t^r satisfy the Hamilton-Jacobi-Bellman (HJB) equations

$$rU_t = b_t + f(\theta_t)(W_t - U_t) + \dot{U}_t, \tag{2}$$

$$rW_t = w_t - \delta(W_t - U_t) - \sigma(W_t - W_t^r) + \dot{W}_t, \tag{3}$$

$$rW_t^r = \max_{e_t} \left\{ w_t^r - c(e_t, t) - (\delta + \rho)(W_t^r - U_t) - \rho C_t + e_t f(\theta_t)(W_t - W_t^r) + \dot{W}_t^r \right\}. \tag{4}$$

The first order condition for search effort e_t chosen by a worker in an at-risk job equates the marginal cost of search to the expected gain from finding a job:

$$c_t \tilde{c}'(e_t) = f(\theta_t)(W_t - W_t^r). \tag{5}$$

Since $\tilde{c}(e_t)$ is increasing and convex, workers search harder if the expected gain is higher. In a tighter labor market, a higher job finding rate encourages higher effort. However, the expected

gain also depends on the endogenous utility gap between safe and at-risk jobs.

We denote firms' expected present values of profits by V_t when the firm posts a vacancy, and by J_t and J_t^r when the firm employs a worker in a safe and at-risk match, respectively. The HJB equations for the firm are

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

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

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

Free entry implies that in equilibrium the value of a vacancy must be zero.

In wage bargaining, the worker's outside option is unemployment. Since workers quit before bargaining, this is true for both unemployed and employed workers. The firm's outside option is to post a vacancy and therefore the same in both types of matches.

$$W_t - U_t = J_t - V_t, \tag{9}$$

$$W_t^r - U_t = J_t^r - V_t. \tag{10}$$

The 9 equations (2)-(10) together with the condition $V_t = 0$ describe a system of differential equations that characterizes the equilibrium dynamics for 10 unknowns: the six values, the two wages w and w_r, tightness and search effort. The system has no state variables. If the exogenous parameters y_t, C_t, c_t and κ_t grow at the same constant rate $\bar{g}$, then there is a solution such that wages and all values except V also grow at $\bar{g}$, and tightness as well as search effort are constant. We focus on such solutions from now on.

Comparative statics

The predictions of our model on growth and churn derive from comparative statics with respect to the initial level of output per worker, the key primitive that differs across cities. The relevant feature of the search and matching block is therefore how output per worker affects worker utility U_t, tightness, and search effort – those are the three variables that matter for growth and labor market flows. The effect on utility is straightforward: If one city has higher output per worker than another, surplus splitting implies that workers obtain some of the benefit, so U_t is also higher.

In addition, higher output per worker implies a tighter labor market. Indeed, the firm's Bellman equation (6) and the free entry condition imply $J_t = \kappa_t/\phi(\theta^*)$. Substituting surplus splitting $W_t - U_t = J_t$ into the worker Bellman equation (2), we have that tightness increases with the utility of the unemployed:

$$\theta_t = \frac{(r - \bar{g})U_t - b_t}{\kappa_t}.$$

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Intuitively, for any given size of the labor force, free entry always allows extra jobs to be created in order to chase some of the extra surplus.

The relationship between surplus and search effort is more subtle. Consider the effect of a tighter labor market, and hence a higher job finding rate on the effort decision (5). Holding fixed the gap between utilities of safe and at-risk jobs, a higher job finding rate encourages search effort, since the search cost is convex. At the same time, a higher job finding rate lowers the duration of employment spells in at-risk jobs and the risk of job destruction, and thereby shrinks the gap between utilities. There are also additional equilibrium effects through wage bargaining, so the direction is generally ambiguous. In the quantitative implementation below, the direct effect dominates, and therefore search effort is higher in higher surplus cities.

3.3 Population dynamics block: growth and labor market flows

We now turn to the dynamics of an equilibrium allocation. For given utility U_t, the labor force grows according to (1). The change in the number of employed workers is given by 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 number of matches at risk is

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

The inflow comes from safe matches that make up $1 - s_t$ of employment and become at-risk at rate σ. Outflows are due either to on-the-job searchers who find jobs at the rate $e_t f(\theta_t)$ – the first negative term – or to exogenous job destruction at the rate $\delta + \rho$.

Let u_t denote the unemployment rate, that is, the number of unemployed divided by the size of the labor force. The change in the mass of unemployed is then

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

Migration $\dot{L}_t$ enters because both in- and out-migration occur to or from a state of unemployment. In addition, there is inflow from exogenous destruction of jobs. Outflow reflects job finding by the unemployed at rate $f(\theta_t)$.

Finally, the number of vacancies per worker v_t is derived from the definiton of tightness as vacancies per effective searcher: per worker,

$$\theta_t = \frac{v_t}{u_t + (1 - u_t)s_t e_t}. \tag{11}$$

The total number of vacancies in the city $v_t L_t$ scales with the labor force. We also note that the dynamics of s_t directly determines the layoff rate $l_t := \delta + \rho s_t$ as well as the quit rate $q_t := s_t e_t f(\theta_t)$.

To understand the dynamics, it is helpful to combine equations and rewrite the evolution of employment, the share of at-risk matches and the unemployment rate as

$$\frac{\dot{N}_t}{N_t} = f(\theta_t)\frac{u_t}{1 - u_t} - \delta - \rho s_t, \tag{12}$$

$$\dot{s}_t = \sigma(1 - s_t) - \left(\frac{\dot{N}_t}{N_t} + e_t f(\theta_t) + \delta + \rho\right) s_t, \tag{13}$$

$$\dot{u}_t = (1 - u_t)\left(\frac{\dot{L}_t}{L_t} - \frac{\dot{N}_t}{N_t}\right). \tag{14}$$

For any initial condition (L_0, N_0, s_0 and paths for utility U_t, tightness θ_t and search effort e_t from the first block above) equations (11)-(14) determine the evolution of employment and the distribution of matches, as well as the layoff and quit rates.

3.4 Balanced growth

For our quantitative analysis, we consider cities that grow at constant rates. We thus assume that the benchmark city utility $\bar{U}_t$ grows at the same constant rate $\bar{g}$ as all parameters of the search and matching block, that is, output per worker and the search costs. The growth rate of the labor force in a small open city, g^*, say, is then determined from (1) by the constant ratio of utilities in the city relative to the benchmark city. From (12)-(14), employment and the labor force grow at the same rate; the unemployment rate and the share of at-risk matches are constant.

This "balanced growth" approach to comparing cities makes heavy use of the "small open city" assumption. In a closed economy with many cities and reallocation due to differences in surplus, the growth rate of the outside option $\bar{U}_t$ would change over time as more workers flow into high surplus cities; this would in turn create time variation in the cross section of city growth rates. We find the balanced growth approach useful for understanding magnitudes because it yields simple tractable formulas. It will give a good approximation for dynamics in the medium run as long as reallocation is not very large.

The goal of our quantitative exercise is to generate differences in growth, quits and layoffs from underlying variation in surplus, captured by initial output per worker. From the search and matching block, we know that higher output per worker implies higher utility and a tighter labor market. It thus follows directly from (1) that high surplus cities grow faster. We further focus on the case where search effort increases, so the job finding rate on-the-job $e^* f(\theta^*)$ is also higher.

Labor market flows depend on the share of at-risk jobs. Along a balanced growth path, it is given by

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

(15)

where stars indicate constant values along the path. Higher surplus cities have a smaller share of at-risk jobs. With a fixed labor force, this would follow simply from the fact that the outflow rate due to search on-the-job is higher, while the inflow rate per safe jobs is the same. In our model, the share further declines with migration: new workers first obtain a safe job, and so increase the denominator.

Quit and layoff rates now depend on primitives via growth g^*, and on-the-job finding rate $e^* f(\theta^*)$:

$$q^* = s^* e^* f(\theta^*) = \frac{\sigma e^* f(\theta^*)}{\sigma + \delta + \rho + e^* f(\theta^*) + g^*} \qquad l^* = \delta + \rho s^*.$$

(16)

Layoff rates vary in the cross section only because at-risk jobs are destroyed more quickly. Higher surplus cities thus have lower layoff rates because of more successful on-the-job search and higher growth.

Cross sectional variation in quit rates reflects both the share of at-risk jobs and the outflow rate due to search on-the-job. The presence of migration implies that the effect is generally ambiguous. With a fixed labor force, a higher surplus cities would only see more successful on-the-job search which always increases the quit rate. At the same time, however, higher surplus cities also see more in-migration and hence more safe jobs in which workers do not search on-the-job. In our quantitative analysis, the second effect is relatively small: it comes from net worker flows which are an order of magnitude smaller than gross flows.

Finally, consider the relationship between growth and the unemployment rate, which is given by

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

Unemployment is lower when the labor market is tighter. Moreover, a lower share of jobs at risk reduces the flow into unemployment and reduces the equilibrium unemployment rate. Both effects suggest that unemployment is lower in high surplus cities. However, unemployment also increases with the growth of the labor force. Migration thus "flattens" the effect of surplus on unemployment. In our quantitative exercise, the effect is negative but has a small slope.

4   Quantitative implications

In this section, we first show that the model can be calibrated to match the common factor in the cross section of growth, quits, and layoffs. We then provide a simple comparative statics

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exercise to illustrate how the model can help think about recessions.

4.1 Parameterization

Following much of the existing literature, we work with a Cobb-Douglas matching function with elasticity 0.5; the job finding rate is therefore $f(\theta) = \chi \theta^{0.5}$, where χ is a scale parameter. We also use a standard isoelastic functional form for the cost of on-the-job search,

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

with $\eta > 0$. While workers can choose not to search and avoid any costs, the marginal cost of search at zero effort is zero. Any worker with an inferior job therefore exerts positive search effort. Moreover, the elasticity of search effort with respect to the job finding rate of the unemployed is equal to η.

The calibration proceeds in three steps. We first set a number of parameters up front to values from the data or the literature. Second, we determine the two job destruction rates and the match quality transition rate from the population dynamics block only; here we match moments of high and low growth cities. For the final step, we define the *benchmark city* as a city where the indirect utility of an unemployed worker is equal to the outside option. We then use the two model blocks jointly to find the latent output per worker for each city together with the remaining parameters by (i) matching exactly the cross section of growth rates and (ii) equating statistics for the benchmark city to national averages.

In the first step, we set the common growth rate of workers' outside option, output per worker, and all cost parameters to $\bar{g} = 0.018$, the growth in mean real compensation per hour in the United States. The natural population growth rate is $\xi = 0.007$, the average annual growth rate of U.S. manufacturing employment over our sample period. The discount rate is $r = 0.03$. We normalize output in the benchmark city to one and follow Shimer (2005) in setting the flow benefit of unemployment to $b_0 = 0.4$. There are no consensus numbers on the sensitivity of migration to local economic conditions. Kennan and Walker (2011) study cross-state migration and estimate that a 10% difference in wages leads to a 5% higher migration rate. We therefore set $\gamma = 0.5$.

For the second step, we note that (16) implies a tight link between the layoff rate l^*, the quit rate q^* and the employment growth rate g^*:

$$l^* = \delta + \rho \frac{\sigma - q^*}{\delta + \rho + \sigma + g^*}. \tag{17}$$

Since layoff rates vary only with the share of jobs at risk and the latter also matters for the

quit rate, the three exogenous transition rates need to allow the right extent of cross sectional variation. The transition rate σ serves as an upper bound for quit rates the model can deliver. We set $\sigma = 0.457$, the 95th percentile of the observed mean quit rates in our cross section.

For given σ, we can now pin down job destruction rates ρ and δ by making (17) hold exactly for two city triples (q^*, l^*, g^*). We start from growth rates of $\pm 2.5\%$ and form the two triples by computing, for each growth rate, the fitted values from the regressions of quit rate and layoff rate on growth in Figures 3 and 4, respectively. We arrive at $\delta = 0.209$ and $\rho = 0.154$. The mean duration of a job at risk until it is destroyed by an exogenous shock is 2.8 years, for a safe job – taking into account the transition to at-risk job – the number is 3.4 years. Of course actual duration is shorter as it also depends on search on-the-job.

The third step jointly determines the remaining parameters – the scale parameter χ, the vacancy creation cost κ, the parameters of the search cost function c_0 and η as well as the loss of surplus in an at-risk match ρC_0, together with output per worker for each city. We target growth in each city and match four moments of the benchmark city to national moments. In particular we target an unemployment rate of 5.5%, a ratio of vacancies to unemployed of 0.72 as in (Pissarides, 2009), a quit rate of 26.5%, and a layoff rate of 24.5%.

The cost function parameters are $c_0 = 0.41$ and $\eta = 4.4$, and a surplus loss in jobs at risk equal $\rho C_0 = 0.06$. The elasticity of search effort with respect to the job finding rate η is somewhat lower than what Krause and Lubik (2006) choose in a model with search on the job. However, in their model the difference between jobs is only in productivity, and so the gain from switching jobs is less sensitive than in this model to changes in tightness. The cost of maintaining a vacancy is $\kappa_0 = 1.39$, which is similar to what Miyamoto and Takahashi (2011) find in a search model with trend growth. In the benchmark city, the share of jobs at risk is 0.24, and on-the-job search effort is 0.26; an employed worker takes roughly 4 times longer to find a new match than an unemployed worker. The share of jobs at risk is consistent with the finding by Faberman, Mueller, Şahin, and Topa (2017) that a quarter of employed workers report searching on the job. The on-the-job search cost chosen by workers in the benchmark city equals 6.4% of match output. The ratio of vacancies to unemployment and the unemployment rate pin down the tightness of the benchmark city at 0.35, and the scale parameter $\chi = 7.32$. This implies a mean unemployment duration of 2.8 months, slightly longer than what Shimer (2005) finds. The cross section of output per worker is plotted in panel (b) of Figure 9 below.

4.2   Results: the cross section

Figure 8 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 Figures 3 and 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.
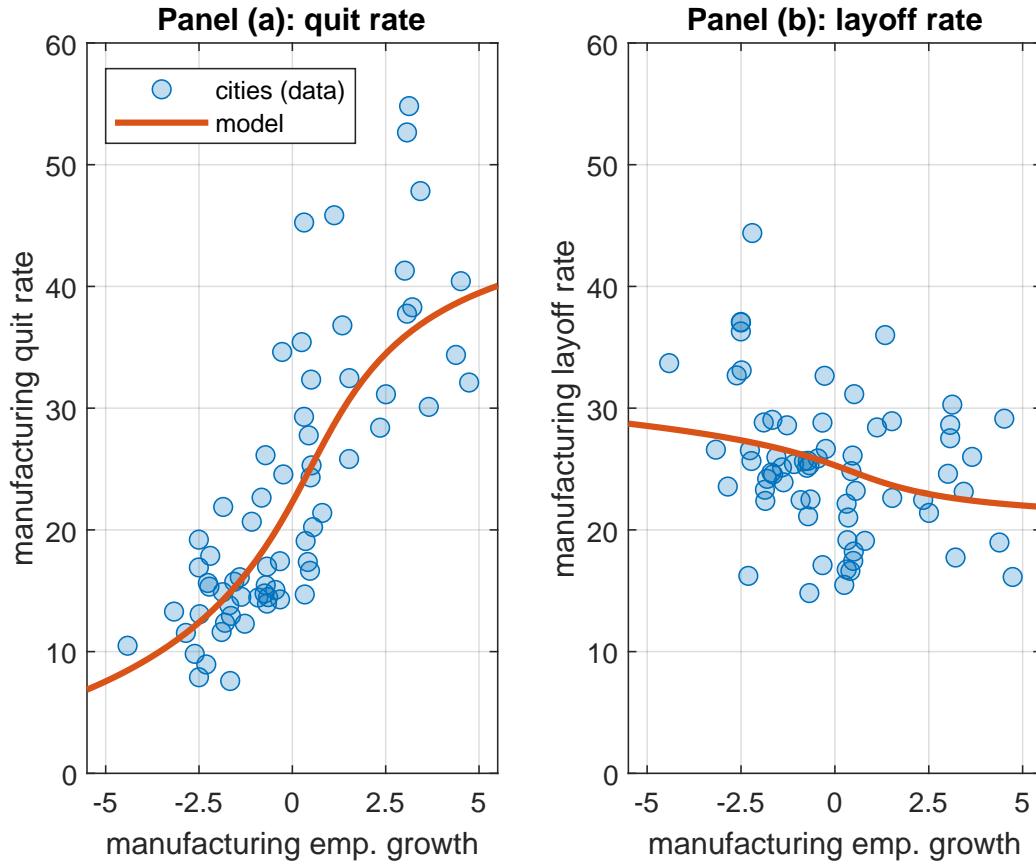
Figure 8: Manufacturing quits and layoff rates: data vs. model

Note: Each dot represents city in the sample. The vertical axis is the mean quit (left) or layoff (right) rate over all observations between 1969-1981. The horizontal axis is the annualized employment growth over the sample period based on BEA data. Included in the sample are cities that have at least 96 flows observations in that sample period and have at least 20,000 workers employed in manufacturing in 1969 (66 cities). The solid line represents the model prediction.

The model also explains why the labor flows are different across cities. Figure 9 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 5% higher than the benchmark city, and in shrinking cities 8% lower.
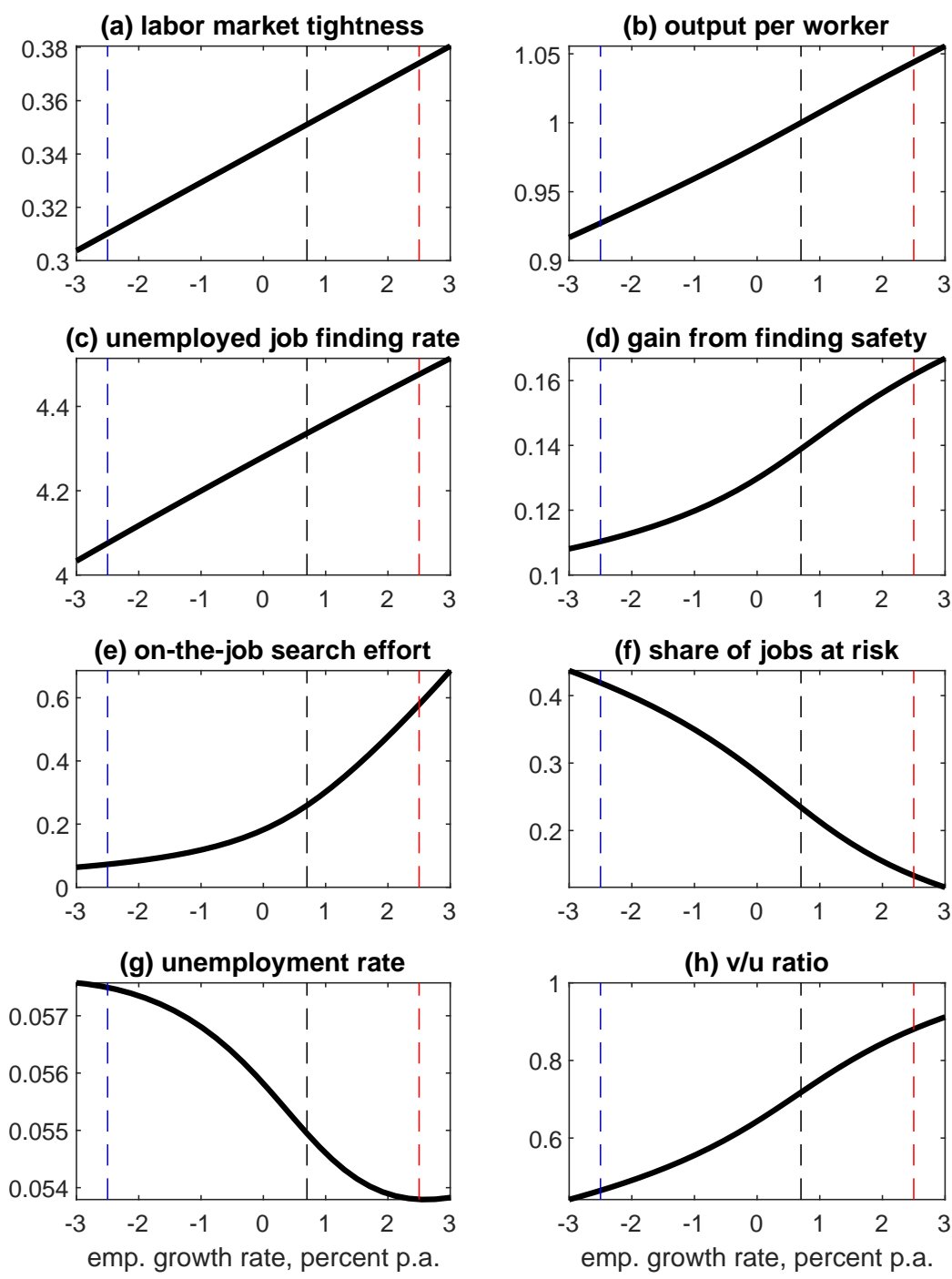
Figure 9: Balanced growth equilibrium allocations by employment growth

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 bigger by 50%. Therefore the incentive to exert effort is much 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 about two and a half the time as unemployed workers, while in shrinking cities they take 15 times as much time to find a new job. 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 roughly 40% of all employed workers are in jobs at risk, while in growing cities just above 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 5.8% and growing cities have an unemployment rate of 5.4%. 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.

4.3 Recessions in growing and shrinking cities

We run a simple exercise to gauge how the model responds to aggregate shocks. We consider the outcome of an aggregate shock that simultaneously reduces the productivity level of all cities in the same proportion, and increases the rate at which jobs at risk are destroyed. This captures both the decline in job creation and the increase in layoffs in recessions.

City-specific shocks that lower productivity will have a strong impact on migration flows by changing its indirect utility relative to the outside option value. In contrast, aggregate shocks that lower the productivity in all cities simultaneously also lower the outside option of migrants, and therefore have a much smaller effect on migration flows. To determine migration flows in this exercise, we first solve for the utility in the benchmark city when its productivity level is lower, and then use its indirect utility as the outside option that determines migration flows in all other cities. These adjustments turn out to be negligible.

We consider a 7% decline in output per worker y_t, and a 0.40 increase in the destruction

rate of jobs at risk, ρ (reduces the expected duration of the match from 2.8 years to 2 years) that are unexpected and lasts forever. Figure 10 shows the long-run impact of this shock based on comparative statics. The blue lines are the equilibrium quit and layoff rates as before. The red lines are the balanced growth equilibrium quit and layoff rates at the city following the shock. The left panel shows the response of the quit rate. The quit rate declines, but mostly for the cities that are growing faster. The right panel shows the response of the layoff rate. The layoff rates increase less in faster growing cities. In a city growing at 2.5% the layoff rate goes up by 7%, and in a city shrinking at 2.5% it goes up by 10%. This effect is relatively modest. This is because the aggregate shock lowers search effort in growing cities more than in shrinking cities, and as a result, the share of jobs at risk in those cities goes up. This is the sullying effect studied by Barlevy (2002). In shrinking cities, the increased job destruction lowers the share of jobs at risk, acting as a cleansing effect.
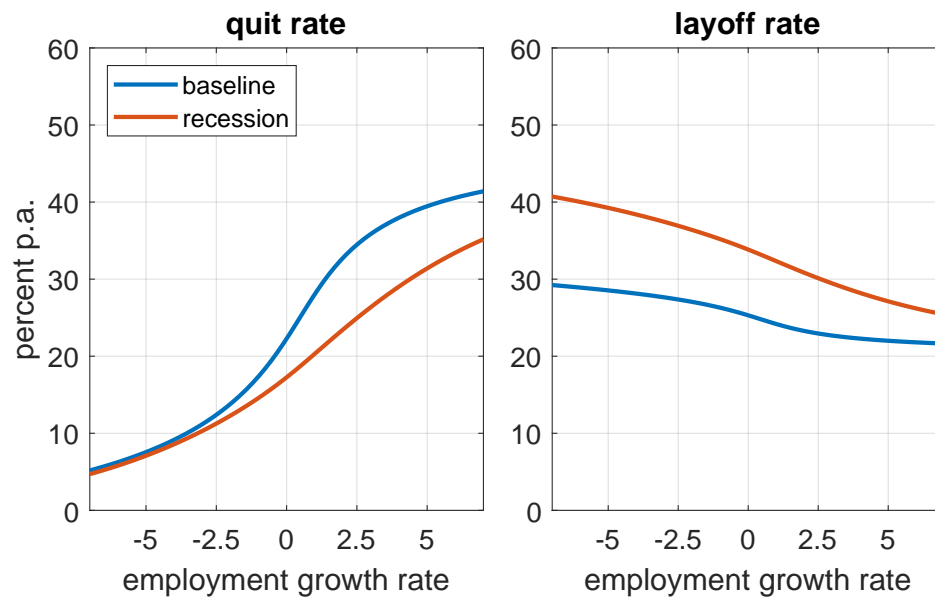

Figure 10: Comparative statics exercise: response to shock by growth rate

References

Amior, M. and A. Manning (2018, July). The persistence of local joblessness. *American Economic Review 108*(7), 1942–70.

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

Beaudry, P., D. A. Green, and B. Sand (2012). Does industrial composition matter for wages? a test of search and bargaining theory. *Econometrica 80*(3), 1063–1104.

Beaudry, P., D. A. Green, and B. Sand (2014). Spatial equilibrium with unemployment and wage bargaining: Theory and estimation. *Journal of Urban Economics 74*, 2–19.

Blanchard, O. and P. Diamond (1990). The cyclical behavior of the gross flows of u.s. workers. *Brookings Papers on Economic Activity 21*(2), 85–156.

Borovičková, K. (2016). Job flows, worker flows and labor market policies.

Burdett, K. and D. T. Mortensen (1998). Wage differentials, employer size, and unemployment. *International Economic Review*, 257–273.

Burgess, S. and H. Turon (2010). Worker flows, job flows and unemployment in a matching model. *European Economic Review 54*(3), 393–408.

Davis, S. J., J. R. Faberman, and J. Haltiwanger (2012). Labor market flows in the cross section and over time. *Journal of Monetary Economics 59*, 1–59.

Davis, S. J. and J. Haltiwanger (2014, September). Labor market fluidity and economic performance. Working Paper 20479, National Bureau of Economic Research.

Elsby, M. W., R. Michaels, and G. Solon (2009). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics 1*(1), 84–110.

Faberman, R. J., A. I. Mueller, A. Şahin, and G. Topa (2017). Job search behavior among the employed and non-employed. Technical report, National Bureau of Economic Research.

Foote, C. (1998). Trend employment growth and the bunching of job creation and destruction. *Quarterly Journal of Economics 113*, 809–834.

Fujita, S. and M. Nakajima (2016). Worker flows and job flows: A quantitative investigation. *Review of Economic Dynamics 22*, 1–20.

Fujita, S. and G. Ramey (2009). The cyclicality of separation and job finding rates. *International Economic Review 50*(2), 415–430.

Gertler, M., C. Huckfeldt, and A. Trigari (2016). Unemployment fluctuations, match quality, and the wage cyclicality of new hires. Technical report, National Bureau of Economic Research.

Hall, R. E. (1972). Turnover in the labor force. *Brookings Papers on Economic Activity 3*.

Jarosch, G. (2015). Searching for job security and the consequences of job loss.

Kennan, J. and J. R. Walker (2011). The effect of expected income on individual migration decisions. *Econometrica 79*(1), 211–251.

Kiyotaki, N. and R. Lagos (2007). A model of job and worker flows. *Journal of political Economy 115*(5), 770–819.

Kline, P. and E. Moretti (2014). People, places and public policy: Some simple welfare economics of local economic development programs. *Annual Review of Economics 6*(1), 629–662.

Krause, M. U. and T. A. Lubik (2006). The cyclical upgrading of labor and on-the-job search. *Labour Economics 13*(4), 459 – 477. Special Issue: European Association of Labour Economists, 2nd World Conference SOLE/EALE, Fairmont Hotel San Francisco, USA, 2âĂŞ5 June 2005.

Lise, J. and J.-M. Robin (2017). The macrodynamics of sorting between workers and firms. *American Economic Review 107*(4), 1104–35.

Lkhagvasuren, D. (2012). Big locational unemployment differences despite high labor mobility. *Journal of Monetary Economics 59*(8), 798 – 814.

Menzio, G. and S. Shi (2011). Efficient search on the job and the business cycle. *Journal of Political Economy 119*(3), 468–510.

Miyamoto, H. and Y. Takahashi (2011). Productivity growth, on-the-job search, and unemployment. *Journal of Monetary Economics 58*(6-8), 666–680.

Moretti, E. (2011). Local labor markets. Handbook of Labor Economics.

Moscarini, G. and F. Postel-Vinay (2018). On the job search and business cycles. Working Paper, Yale.

Pissarides, C. A. (2000). *Equilibrium unemployment theory.*

Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica 77*(5), 1339–1369.

Postel-Vinay, F. and J.-M. Robin (2002). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica 70*(6), 2295–2350.

Schmutz, B. and M. Sidibe (2019). Frictional labour mobility. *Review of Economic Studies 86*(4), 1779–1826.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American economic review 95*(1), 25–49.

Shimer, R. (2006). On-the-job search and strategic bargaining. In *Structural Models of Wage and Employment Dynamics*, pp. 37–59. Emerald Group Publishing Limited.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics 15*(2), 127 – 148.

Topel, R. H. (1986). Local labor markets. *Journal of Political Economy 94*(3), 111–143.

Yashiv, E. (2007). Us labor market dynamics revisited. *Scandinavian journal of Economics 109*(4), 779–806.