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ABSTRACT

This paper estimates how effects of shocks to local labor demand on local labor market outcomes vary with initial local economic conditions. The data are on U.S. metro areas from 1979 to 2011. The paper finds that demand shocks to local job growth have greater effects in reducing local unemployment rates if the local economy is initially depressed than if the local economy is booming. Demand shocks have greater effects on local wage rates if the local unemployment rate is initially low, but lesser effects if local job growth is initially high. These different effects of local demand shocks imply that social benefits of adding jobs are two to three times greater per job in more depressed local labor markets, compared to more booming local labor markets.

JEL Classification Codes: R23, H43, J64

Key Words: Local labor markets, labor demand, social benefits of job creation

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This paper estimates how effects of local labor demand shocks vary with local labor market conditions. Effects examined are changes in local labor force participation, unemployment, and real wages. The local labor markets examined are 23 large U.S. metro areas, using annual data from the Current Population Survey from 1979 to 2011. Labor demand shocks are measured by changes in local employment due to national demand for the metro area's industrial specializations. The initial labor market conditions that are allowed to alter the effects of labor demand shocks include the area's preexisting unemployment rate and job growth.

Why should we care how effects of labor demand shocks vary with local conditions? One reason is that these labor market effects interest local policymakers. Much local politics is concerned with economic development: how to promote local prosperity via job growth (Molotch 1976; Peterson 1981). Promoting job growth—for example, by business tax incentives—has fiscal costs. Are these costs justified by local labor market benefits? How do such benefits vary in different local circumstances? These estimates shed light on these questions.

A second reason for caring is these estimates' relevance to how local economic development should be addressed by national policy. Local competition for jobs is often called a zero sum game. If local economic development policies only redistribute jobs across locations, with no national job gain, national benefits appear minimal. This leads to calls for this competition to be constrained by national policy (Rolnick and Burstein 1994). But if benefits of job growth vary across local areas, then job redistribution toward areas with higher benefits will be in the national interest. National policy should allow or even promote such job redistribution.

A third reason for caring is that these estimates can help measure social benefits or costs of job gains or loss. Benefit-cost analyses often must consider how to value effects on jobs. For example, if an environmental regulation will cost jobs, what is the dollar value of that job loss (Bartik 2012)? Local labor markets are a natural laboratory for estimating benefits and costs of job changes. Do such estimates fit the conventional wisdom that social benefits or costs of job changes can be ignored when the economy is near full employment? Do job changes have higher benefits or costs when the local economy is initially more depressed?

This paper's estimates find that local labor demand shocks have stronger effects in reducing unemployment in more distressed metro areas. Labor demand shocks also have stronger effects on real wage rates in low unemployment metro areas, but weaker effects on real wage rates in high-growth metro areas.

Based on these estimates, the benefits of job growth are large and persistent. These benefits are sizable even when the local economy is booming. However, benefits are much greater when the local economy is depressed.

The next section of the paper explains why local labor demand shocks might have persistent effects. This section also summarizes how to value jobs in benefit-cost analysis.

Following the theory section, the paper reviews previous empirical literature on labor demand shocks. This literature has reached varied conclusions on whether effects of demand shocks persist. The main limitation of this literature is overreliance on modeling assumptions.

The paper then describes the data and estimation approach. The methodology is innovative in choosing the model specification based on statistical tests rather than assumption. Estimates are then presented and used to calculate benefits of labor demand shocks.

THEORY

If mobility was instantaneous and information was perfect, local demand shocks would not affect labor market outcomes. Any improvement or deterioration in a local area's employment rates or real wage rates would be instantly eliminated by migration. Demand shocks would be completely capitalized into changes in local property values.[1]

A less extreme position is that U.S. mobility is quick enough and extensive enough that local demand shocks cannot have effects on local labor market outcomes that are large and persistent. Marston (1985) defends this position.

The counterargument is that moving costs and effects of labor market experiences allow labor demand shocks to have effects that are large and persistent. Moving costs, both financial and due to ties to home, cause migration responses to be reduced. As a result, in the short run, local labor demand shocks affect whether some individuals are employed, and the quality of their jobs. These labor market experiences affect job skills. Labor market experience also affects workers' self-confidence and reputation with employers. Changes in job skills, self-confidence, and reputation may all have persistent effects on wage rates and employment rates.

This argument was eloquently made by Nobel Prize–winning economist Edmund Phelps (1972):

> Of [the changes caused by a boom], job experience, with its opportunities for learning by doing and on-the-job training, is possibly the most important. When people are engaged in sustained work of a kind with which they have not had any similar experience, they become different for it in a number of ways that are relevant for the equilibrium unemployment rate. Getting to work on time is just about the most important habit a worker can have in nearly every kind of job . . . For many of the people who comprise the hard-core, most frequently unemployed group, getting to be "reliable" and learning to work with other people are necessary attributes for continuation in the job.

[1] This can easily be shown, for example, in a Roback-style model in which the labor demand shock is described by a shock to amenities valued only by firms (Roback 1982).

> For other people, the opportunity to acquire skills at more demanding jobs in the skill hierarchy than they could ordinarily quality for under normal always-equilibrium aggregate demand behavior may be the more important aspect . . . The upgrading of many workers that results from a disequilibrating rise of aggregate demand may gradually lead to a true upgrading in the average quality of the labor force. (p. 79)

This argument was applied to local labor markets in Bartik (1991). A once-and-for-all increase in local employment will increase local residents' employment rates and wages in the short run, due to limited migration. This enhanced employment will increase local workers' skills, boosting long-run employment rates and wages. A similar argument applies to reductions in local employment. Short-run labor demand shocks may have long-run "supply-side" effects.

Labor market effects of local demand shocks will differ over time and space. Whether residents or in-migrants get jobs depends on the local and national economies. Higher local unemployment may increase the share of short-run job openings that are filled by local residents versus in-migrants. An extra job may not help local workers as much if many jobs were already being created. Any feature of the national economy that reduces mobility—cultural trends, underwater mortgages, the affordability of moving costs—may reduce the share of new local jobs that go to in-migrants, which means more jobs go to local residents.

Local labor market effects are relevant to putting a value on job creation or destruction in benefit-cost analyses. How to include job effects in benefit-cost analysis is a longstanding issue.[2] If there is full employment, and all workers who want jobs can instantly get jobs that reflect their productivity, then job gains or losses have no net social benefit or cost. The marginal worker's opportunity cost of her time is equal to the wage. If a new job is created, the worker hired would otherwise have been employed at similar wages, or would have been voluntarily at leisure. With

[2] For a classic discussion of this issue, see Haveman and Krutilla (1967). For more recent treatments in benefit-cost textbooks, see Boardman et al. (2011) and Mishan and Quah (2007). For another recent discussion, see Haveman and Farrow (2011).

full employment, workers at leisure could have easily obtained jobs, and leisure's value must be close to the wage rate. New jobs generate earnings, but workers' opportunity costs offset this gain. A similar argument can be applied to job losses.

But in the real world, there frequently is involuntary unemployment and underemployment. Workers do not instantly get jobs that match the worker's productivity potential. Labor demand shocks, by altering how easy it is to get jobs, may result in changes in earnings that exceed the opportunity cost of workers' time.

Bartik (2012, 2013) argues that social benefits of job gains and losses can be measured from an ex post perspective. After a labor demand shock, we can compare workers' earnings and unemployment to the counterfactual world without the shock. Suppose that the shock is a job gain. Then workers gain increased earnings due to more employment at better jobs. The cost for workers is reduced nonwork time. The net cost of reduced nonwork time depends upon workers' valuation of nonwork time, which depends on the stigma effects of unemployment. In addition, there is a social cost from the increase in wage rates for employers.

Large stigma effects of unemployment are found in the life satisfaction literature (Blanchflower and Oswald 2004; Frey and Stutzer 2002; Helliwell and Huang 2011; Knabe et al. 2011; Tella, MacCulloch, and Oswald 2001). Unemployment reduces life satisfaction by more than the resulting increase in earnings. For example, Knabe et al. (2011) suggests that unemployment reduces life satisfaction by 150 percent of the earnings loss, whereas being out of the labor force reduces life satisfaction by 110 percent of the earnings loss.

Bartik (2013) argues that local labor market effects can measure the social benefits of labor demand shocks. Any actual labor demand shock takes place in one or more local labor markets. Changes in local earnings measure the local worker benefits of demand shocks.

Changes in one local area's earnings due to its job growth do not reflect social benefits or costs due to migrants attracted to this labor market. But such benefits and costs are small. Migrants' well-being is not substantially affected, because these workers would have otherwise had similar labor market opportunities elsewhere (Bartik 1991). Furthermore, the evidence suggests that migration shocks to local labor markets have little effect on local labor market outcomes; for example, this is shown in the immigration literature (Card 1990; Greenwood and Hunt 1984). Out-migration from a local economy probably destroys about as many jobs as the reduction in local labor supply (Greenwood and Hunt 1984; Muth 1971).

The main difference between the local perspective and the national benefit-cost perspective is the treatment of wage effects. From a local perspective, most real wage gains are a benefit. The costs of this wage change to employers will mostly be a cost to outside employers. (Wage changes to local employers will be reflected in local prices, and hence not much in real wages.) The national benefit-cost perspective will see more of these wage gains as redistribution from some employers to some workers, with little net benefit.

The traditional view in benefit cost analysis is that the social benefits or costs of job changes will be low when the local economy is near full employment. When the local economy is depressed, social benefits or costs of job changes might be much larger. This paper's estimates allow this traditional view to be empirically tested.

REVIEW OF LITERATURE

Short-Run and Long-Run Effects of Local Labor Demand Shocks

Researchers often relate changes in local labor market outcomes or migration to local job growth. Bartik (1991, 1993) reviews dozens of examples. But researchers often do not distinguish between labor demand and supply shocks to job growth. These different shocks have different effects. If job growth occurs because of a shock to labor supply, the increased local labor supply will increase local unemployment and lower wages. This greater availability and lower cost of local labor will attract job growth. Job growth's correlation with wages or employment/population ratios will be negative.

Labor demand shocks make an area more desirable for job growth, due to some factor other than labor supply that increases local profitability (e.g., changes in local taxes or services, national demand). This boost to local job growth will increase employment rates and wages. Job growth's correlation with wages or employment rates will be positive.

In addition, researchers often do not examine the dynamics of the short-run and long-run effects of labor demand shocks. Short- and long-run responses might differ, for example, because migration responses may increase over time.

Two highly cited studies of dynamic effects of local labor demand shocks are Bartik (1991) and Blanchard and Katz (1992). These studies' different models reach diverse conclusions. Both models impose some untested assumptions that will be discussed below. Both models also are hard to adapt to allow differential effects of labor market conditions.

Both Bartik (1991) and Blanchard and Katz (1992) use as dependent variables average labor market outcomes in local area/year cells. These labor market outcomes are estimated as a function of current and lagged local area job growth, and various other control variables.

Bartik (1991) regresses the one-year-to-the-next change in labor market outcomes in a metro area on current job growth and several lags in growth, and national year dummies.[3] This estimating equation can be written as:

[3] This oversimplifies somewhat the models actually estimated in Bartik (1991), as some models look at levels of labor market outcomes versus levels of employment and include local area fixed effects.

(1) $LMO_{mt} - LMO_{mt-1} = B_0 + B(L)G_{mt} + F_t + e_{mt}$.

LMO_{mt} is the level of some labor market outcome variable for metro area *m* in year *t* (e.g., the unemployment rate, the labor force participation rate, the real wage rate). G_{mt} is job growth for MSA *m* from year $t-1$ to *t*. $B(L)$ indicates that a set of coefficients is applied to current values of growth and lags in growth. F_t is a fixed effect for each year. e_{mt} is the disturbance term.

The year fixed effect means that we are focused on local labor market effects by controlling for any national trend.[4] Dynamic effects of short-run versus long-run growth shocks are controlled for by including several lags in growth. The cumulative effect on the level of labor market outcomes of a one-time growth shock (a once-and-for-all shock to the employment level) after *k* years is the sum of the coefficients on the growth variables up to the *k*th lag.

The Bartik (1991) model imposes the assumption that dynamic effects of job growth do not change after the included lags. The model is made more general by choosing an optimal lag length, based on the Akaike Information Criterion, among models with up to a relatively large number of lags (eight years in Bartik [1991]).

Bartik (1991) is one of the first attempts to distinguish between local labor demand shocks and supply shocks. Labor demand shocks are distinguished by treating job growth as endogenous and using instrumental variables. The instrumental variables used are the job growth predicted if the local area's industries all grew at each industry's national growth rate. As the appendix to Bartik (1991) shows, this instrument proxies for the change in national demand for the area's export-base industries.

Bartik (1991) finds significant short- and long-run effects of local demand shocks on labor market outcomes. Effects are most persistent for labor force participation rates and wages.

[4] Local area fixed effects can also be controlled for, but in practice these fixed effects do not make much difference to results, probably because the labor market outcome variable is first-differenced.

For these variables, long-run effects are similar to short-run effects. Long-run effects are also found on unemployment, although much below short-run effects.

Labor demand instruments do not make a statistically significant difference for labor force outcome variables, but do sometimes make a statistically significant difference for real wages. Differences are in the expected direction: demand-induced growth has a larger impact on real wages (and employment rates, although not significantly) than growth in general.

Blanchard and Katz (1992) reach different conclusions from Bartik (1991) on growth shock effects in the long-run; the models differ in how they capture dynamics. Blanchard and Katz regress the level of labor market outcomes in a U.S. state in a particular year on lagged levels of labor market outcomes, current and several lags in growth, and controls for national year effects and state fixed effects.

The Blanchard/Katz (1992) model can be written as

(2) $LMO_{st} = B_0 + B_L(L)LMO_{st-1} + B_G(L)G_{st} + F_s + F_t + e_{st}$.

LMO_{st} is the level of a labor market outcome for state s in year t (e.g., rates of unemployment, labor force participation rate, wages). G_{st} is job growth for MSA m from year $t - 1$ to t. $B_L(L)$ indicates that coefficients are applied to lagged values of the state labor market outcome variable. $B_G(L)$ indicates that coefficients are applied to current growth and lags in growth. F_s is a fixed effect for each state. F_t is a fixed effect for each year. e_{st} is the disturbance term.

Some Blanchard/Katz models use the industry mix instruments proposed by Bartik (1991) to proxy for labor demand shocks. The dynamics of the Blanchard/Katz model depend on both the coefficients on growth, and the coefficients on lagged labor market outcomes. The model dynamics are revealed by simulating the model over some time period.

For the Blanchard/Katz model to be stable, the long-run effects of a growth shock on labor market outcomes have to at some point return to zero. However, the empirical estimates found by Blanchard/Katz do not come close to showing a model that is unstable.

Blanchard/Katz find short-run effects similar to Bartik (1991), but much lower long-run effects. Blanchard/Katz conclude that while labor demand shocks have short-run effects on labor force participation and unemployment rates, these effects return to zero after five or six years. For wages, the estimates also imply modest effects on real wages that return to zero in the long run. The adjustment is more prolonged for real wages.

Bartik (1993) reexamines the Blanchard/Katz results. He finds that the different results are not due to Blanchard/Katz using states or Bartik using metros. Rather, the different long-run results are driven by the different model specifications.

Both the Bartik and Blanchard/Katz models have limitations. First, both models impose limitations on dynamic effects in the long run that are not fully empirically tested. The Bartik model assumes that demand shock effects on labor market outcomes do not change after the number of included lags. The Bartik "changes" dependent variable can be seen as equivalent to a Blanchard/Katz "levels" model with an assumption that the coefficient on the lagged dependent variable is one, which precludes gradual reduction in growth effects after the number of included lags. The dynamics are made more general by testing for optimal lag lengths, but there are limitations to how many lags can be included.

The Blanchard/Katz model also imposes its own assumptions about dynamics. If the model is stable, then growth effects must converge to zero. The model does not allow permanent effects of growth shocks on labor market equilibria, as theorized by Phelps (1972).

One special problem with the Blanchard/Katz model is that the estimated coefficients on the lagged labor market outcome variables may be biased toward zero, for several reasons. Such bias will also bias toward zero the long-run effects of growth shocks.

One issue is measurement error. The lagged labor market outcome variables are estimated by relatively small sample sizes in each area. The resulting measurement error will bias the coefficients on the lagged dependent variables toward zero.

Another reason for bias is the Blanchard/Katz model's relatively short time dimension. With a short time dimension, panel data models with fixed cross-section effects and a lagged dependent variable will understate the lagged dependent variable's effects. Some of the true persistence due to effects of the lagged dependent variables will be mistakenly attributed to the cross-sectional fixed effects (Nickell 1981).

A final reason for bias is that treating the lagged dependent variables as exogenous prevents the estimates from revealing the dynamic effects of labor demand shocks. The model estimates rely in part on the effects of any shock to lagged labor market outcomes on current outcomes. Shifts in lagged outcomes due to demand shocks may have effects that are different from shifts due to supply shocks. This requires instrumenting for the lagged outcomes as well as job growth to isolate the effects of labor demand shocks.

Several previous studies have addressed some but not all of these issues in the Blanchard/Katz model (Bartik 1993; Partridge and Rickman 2006; Rowthorn and Glyn 2006). These studies have found larger long-run effects than Blanchard/Katz. Bartik (1993) modifies the Blanchard-Katz model by adding lags in growth. The resulting estimates still show unemployment effects of demand shocks returning rapidly to zero but evidence for long-run effects on labor force participation for at least 17 years. Rowthorn and Glyn (2006) correct for measurement error in state employment rates and find that shocks to employment rates take a century to dissipate. Partridge and Rickman (2006) estimate vector autoregressive models of employment, migration, and wages in U.S. states that do not restrict long-run responses to labor demand shocks, and find long-run equilibrium effects on employment rates. Although these studies make the Blanchard-Katz model more general by dealing with measurement error, or allowing additional growth lags, none of these studies address the endogeneity of lagged labor market outcomes. This paper addresses this issue.

Another problem with the Bartik and Blanchard/Katz models is the inclusion of multiple lags. Multiple lags in job growth and labor market outcomes create serious problems in allowing growth's effects to be interacted with lagged levels of some labor market outcome such as local unemployment. For example, suppose the level of some local labor market outcome was a function of current job growth and four lags in job growth, along with four lags in the labor market outcome. To allow lagged labor market outcomes to flexibly alter the effects of job growth, we would have to interact our four lags in the labor market outcome with the five job growth variables, resulting in 20 interaction variables. To identify effects of labor demand shocks, all the lagged growth and labor market outcome variables, and their interactions, would have to be instrumented for with demand shock instruments. Accurately estimating such a model, with 29 endogenous variables, is challenging. Simulating such a model to determine dynamic effects would be messy.

How Local Conditions Alter the Effects of Local Demand Shocks

Perhaps because of the complexity of interacting local demand shocks and local economic conditions, relatively few studies allow for labor demand shocks to have different effects with local economic conditions. For example, there are no studies that allow a demand shock's effects to vary with local unemployment. Yet benefit-cost analysis commonly assumes that the benefits of job growth are higher when unemployment is high.

Some studies allow local growth shocks to have nonlinear effects by adding growth squared as an explanatory variable. Blanchard and Katz (1992); Notowidigdo (2013); Partridge and Rickman (2006); and Partridge et al. (2012)do not find evidence of nonlinearity in growth's effects on employment rates or real wages.[5] Bartik (1991) finds greater short-run effects of job growth in reducing unemployment in initially slow-growing metro areas.

How National Conditions Alter the Effects of Local Demand Shocks

Some recent studies examine how local growth shock effects vary with national circumstances. Partridge et al. (2012) find that over time, local demand shocks have had have smaller migration effects and greater effects on employment rates.

Saks and Wozniak (2011) find that U.S. internal migration rates are procyclical, which suggests that if the national economy is booming, in- and out-migration might be more sensitive to local growth shocks. As a result, employment to population ratios will be less responsive.

Implications of Past Research Literature for Needed New Research Work

Based on this past literature, there is a lack of studies that examine how local unemployment alters the effects of local labor demand shocks. New studies should also control for nonlinear effects of growth. High unemployment and slow growth are correlated, and we want to distinguish between their influences.

Studies of local demand shocks should explicitly test their modeling strategies. Prior research has adopted dynamic models that assume what should be estimated.

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[5] Notowidigdo (2013) finds nonlinear effects of his predicted growth term on employment and population as separate dependent variables, but not on their ratio.

If possible, studies should adopt simpler models with fewer lags, if these models can capture the dynamics. Simpler models can more easily include interaction terms.

This paper will address all of these issues, as developed in the next section.

DATA AND MODELS

Summary

The regressions use pooled time series/cross sections of mean data for metro area/year cells. The dependent variables used are levels or changes in adjusted means of labor market outcomes from the Current Population Survey for 23 metro areas in 33 years, from 1979 to 2011. The labor market outcome variables are the logarithm of the real wage, the logarithm of the employment to labor force ratio, and the logarithm of the labor force to population rate. The means are adjusted for differences in education and demographics across metro area/year cells. The dependent variables are related to current and lagged levels of metro area employment growth. Some specifications also include lags of adjusted labor market outcomes. Preliminary estimates test possible specifications: regressing levels of labor market outcomes on lagged labor market outcomes and job growth, and regressing changes in labor market outcome on job growth. These tests determine what specification is used for subsequent estimation.

Once the functional form of the equation is determined, the estimation adds interactions between lags in adjusted employment to labor force ratios and growth, to allow an area's initial unemployment rate to alter the impact of growth on labor market outcomes. Some specifications allow for growth to have nonlinear effects. Some specifications allow for growth effects to vary over time or with national economic conditions.

All specifications include metro area and year dummies to control for metro area or national effects. Most specifications treat the growth variables and lagged labor market outcome variables as endogenous. The instruments are predictions of job growth or level of the metro area in a given year based on past industry mix and national growth in different industries.

Data Description

The 23 metro areas used are those for which one can obtain consistent time series data on inflation rates for all years from 1979 to 2011, and for which it is possible to combine data in the Current Population Survey data to get reasonably consistent metro area definitions over time. The local price levels are adjusted to 2011 national price levels. These price adjustments are based in part on Aten (2006), who reports local area price comparisons for 2003. These data are combined with BLS local inflation data for all years. The 23 metro areas are large: Atlanta, Boston, Chicago, Cincinnati, Cleveland-Akron, Dallas-Fort Worth, Denver-Boulder, Detroit, Houston, Kansas City, Los Angeles-Long Beach-Santa Ana-Riverside-San Bernardino, Milwaukee, Minneapolis-St-Paul, New York-Newark, Philadelphia, Pittsburgh, Portland-Vancouver (OR-WA), St. Louis, San Diego, San Francisco-Oakland-San Jose, Seattle, Washington-Baltimore. Metro areas in past CPS data were combined to match as closely as possible the current metro area definitions.

The adjusted mean data are derived from preliminary regressions and logit calculations using individual data from the Merged Outgoing Rotation Group of the Current Population Survey.[6] The preliminary regressions/logits predicted the natural logarithm of the individual's

[6] The wage was calculated as the reported wage per hour for workers paid by the hour, and as usual earnings divided by usual hours for other workers. If usual hours vary, actual hours are used. The nominal wage data was combined with price data to restate all nominal wage rates in real national prices as of 2011. Outliers in real wages (less than $3 per hour or more than $250 per hour in 2011 dollars) were dropped from the sample. Employment to labor force ratios and labor force population ratios were zero-one variables for individuals based on official CPS definitions. Observations were treated as missing if they were "allocated" by BLS due to nonresponse.

real wages, zero-one variables for labor force participation status, and employment versus unemployment status. Separate regressions/logits were estimated for each of the 33 years from 1979 to 2011. Each regression/logit controlled for demographic and education categories.[7]

To calculate the adjusted means, the regression/logit coefficients for each year were combined with the 2011 national sample. For each year and metro area, the regression/logit coefficients were used to calculate for each person in the 2011 national sample the predicted ln(real wage), the predicted probability of being in the labor force, and the predicted probability of being employed if in the labor force, if that person had been in a particular metro area in a particular year. For each metro/year cell, the mean value of these predictions was then calculated. The mean ln(real wage) prediction was used as is in subsequent regressions looking at effects of local demand shocks. Natural logarithms of predicted mean labor force participation rate and employment to labor force ratios were used in subsequent regressions.

These large metro areas have large samples for metro/year cells. Table 1 reports the cell sizes in these regressions. These large sample sizes increase the precision of other estimates.

Table 2 provides statistics on the distribution of MSA/year adjusted means. It describes the statistical distributions of both the levels of these variables, and of their first difference, which is the change from last year to this year. The data show a wide variation across the sample in both levels and changes in labor market outcomes.

The job growth data are derived by combining BEA county data to match the most recent official metro area definition for each metro area. Table 2 also shows that local job growth has large variations across the sample.

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[7] These demographic/education controls were MSA dummies; a quartic in age; dummies for education level (high school dropout, high school graduate, some college, college or more); dummies for race/ethnicity (white, black, Hispanic, other); a dummy for marital status; a dummy for gender; gender interacted with all other right-hand-side variables except MSA dummies. The regressions/logits were weighted regressions using the CPS person weights.

Most regressions used as instruments predicted metro year job growth or metro job levels. Metro job growth was predicted by using the metro area's industry mix the previous year at the 3-digit NAICS industry level, and national growth rates from last year to this year by 3-digit NAICS. Metro job levels were predicted by taking the metro area's actual number of jobs in 1969 and adding in predicted growth for each subsequent year.

A variety of sources were used for the 3-digit NAICS data. The employment data from 1969 to 1989 was based on 2-digit SIC data from Regional Economic Models Incorporated. These SIC industries were converted to NAICS industries using a conversion table published by BLS. For 1990 to 2003, the industry data were derived from BEA and BLS data, with industry suppressions overcome by various interpolations and extrapolations and exploitation of adding-up constraints. From 2004 to 2011, the 3-digit NAICS shares of overall BEA metro area employment were derived from the Isserman and Westervelt (2006) data and software, which overcome suppressions in County Business Patterns data.

Modeling Strategy

The challenge in estimating how local labor demand shock effects on labor market outcomes vary with initial local market conditions is that estimated models can quickly become difficult to estimate and explain. With many lags in both job growth and labor market outcomes, and a full set of interactions, the model would have many coefficients to estimate and a complex simulation task. The complexity is even greater if it is necessary, as has been argued, to treat all these variables as endogenous.

The strategy in the current paper for each labor market outcome is to first identify an appropriate simple model. This is done testing simple models that omit interaction terms between job growth and lagged local labor market conditions. These simple models use no more than one lag. The strategy is to statistically choose between two alternative models: 1) a Blanchard-Katz model, where the dependent variable is the levels of labor market outcomes, which implies an exponential decay in growth effects; and 2) a Bartik model, where the dependent variable is the change in labor market outcomes, which implicitly assumes a lagged coefficient of one on the dependent variable, and effects of growth on outcomes that are unchanging after some point. For each labor market outcome dependent variable, the model chosen will then be compared with more complicated versions of the Bartik and Blanchard models to see if the simple model reasonably captures the dynamics. For each dependent variable, it proves possible to do so. These simpler models will then be reestimated with interactions with lagged unemployment rates, and then the modeling will proceed to also considering the effects of growth squared.

ESTIMATES

Initial Estimates and Tests

The starting model for estimation is a simpler version of the Blanchard-Katz model:

(3) $$LMO_{\mathrm{mt}} = B_0 + B_L LMO_{mt-1} + B_G G_{mt} + F_m + F_t + e_{mt}\ .$$

The only difference in the specification from Blanchard-Katz is that the model only has one lag in labor market outcomes and zero lags in job growth, whereas the original Blanchard-Katz model had multiple lags. However, the estimation is quite different in that Blanchard-Katz only treated job growth as endogenous. The new estimation treats both job growth and the lagged labor market outcome variables as endogenous. The instruments used are predicted metro job growth and predicted metro job levels based on the metro area’s industry mix and national growth rates by industry.[8] Lags in these predictions were also included as instruments.[9] The purpose of including demand-shock instruments for both job growth and lagged labor market outcomes is so that the dynamics capture the effects of labor demand shocks rather than other types of shocks to job growth. The demand-shock instruments also correct for measurement error in the lagged labor market outcomes, and for possible short-time series biases in panel data models with a lagged dependent variable and metro fixed effects.[10]

Table 3 shows the coefficient estimates using OLS and 2SLS. The test statistics show that the instruments are highly statistically significant.[11] The 2SLS estimates are significantly different from OLS for the labor force participation and wage dependent variables.

For the wage and labor force participation dependent variables, the 2SLS estimates push the coefficients on the lagged dependent variable up to close to one. At conventional levels of statistical significance, the lagged dependent variable coefficients are insignificantly different from one.[12]

Because these confidence intervals include coefficients on lagged dependent variables that exceed one, simulated effects of a growth shock reveal the model to be dynamically unstable. Random draws from the 2SLS coefficient vector frequently draw a value greater than

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[8] For predicted job levels, the instrument is constructed by starting with each metro area's 1969 employment, taking its natural logarithm, and then adding in predicted logarithmic growth for each subsequent year based on industry mix in each year $t-1$ and national employment growth in each year from $t-1$ to year t.

[9] The instruments used were predicted logarithmic employment growth from year $t-1$ to t, and four lags from $t-1$ to $t-4$ in the predicted logarithm of metro area employment. The inclusion of lags is rationalized by multiplier effects that occur over time, as shown in Bartik (1991, p. 283). The inclusion of metro fixed effects means that the predicted metro employment instruments are measuring predicted employment relative to each metro's average, and so the size of each metro area does not drive the results.

[10] As mentioned above, measurement error may not be a big issue given the large cell sample sizes. Furthermore, short-time-series biases will be limited because the time series for each metro area is 32 years.

[11] This is also true of the individual test statistics. The F-statistics for the first stage are 15.95 (p = 7.14e-15) for lagged labor force participation rates, 23.45 (p = 9.00e-22) for lagged employment to labor force participation rates, 5.304 (p = 8.64e-5) for lagged log wage, and 26.88 (p = 7.81e-25) for growth.

[12] Unit root tests find nonstandard distributions of t-test statistics. But in this case, the hypothesis is not that wages or labor force participation have a unit root. Rather, the hypothesis is that for demand shocks, the effect of the lagged dependent variable is one. The overall distribution of the wage and labor force participation rate may not follow a random walk. In the current case, it seems appropriate to use customary distributions for t-statistics.

one for the lagged dependent variable for the labor force participation and wage equations. As a result, the estimated effects and their standard errors blow up over time.[13]

The conclusion is that a simple but stable specification of the dynamics of wages and labor force participation in response to labor demand shocks should constrain the coefficient on the lagged dependent variable to equal one. This is equivalent to specifying the dependent variables as changes in labor force participation and wages. In contrast, the empirical evidence is more consistent with specifying the employment to labor force ratio equation in levels form.

The chosen models are shown in Table 4. The change in wages and labor force participation are estimated as a function of current job growth. The employment to labor force ratio is specified as a function of its lag and current growth. All models also control for metro area and year fixed effects. All models are estimated via 2SLS, using as instruments predicted current metro job growth and four lags in the log of predicted metro job levels.

How well do these simplified models compare with the dynamics of the Bartik (1991) and Blanchard-Katz (1992) specifications? Using the current database, estimates were done of the full Blanchard-Katz specifications: in the employment/labor force and labor force participation equations, two lags for both the lagged dependent variables and the job growth variable; in the wage equation, four lags for both the lagged dependent variable and job growth. Using the current database, estimates were done of Bartik (1991) specifications: changes in all labor market outcomes regressed on various lags in growth. All possible lags from 0 to 10 lags

[13] For example, in the simulations, from year 10 to year 20, the effect on labor force participation increases from 0.298 to 0.778, and the standard deviation across 1,000 simulations increases from 0.274 to 2.386. For wages, from 10 years to 20 years, the average effect across 1,000 simulations increases from 0.332 to 0.891, and the standard deviation of these effects increases from 0.642 to 5.318.

were tested, and 3 lags were chosen as optimal.[14] The estimated dynamics with this current database were quite similar to the dynamics in the original Blanchard-Katz and Bartik papers.

Figures 1, 2, and 3 compare the simplified models in Table 4 to the Blanchard-Katz and Bartik models. For the employment to labor force ratio, Figure 1 shows that the Table 4 model closely matches the more complex Blanchard-Katz model. The Bartik model also shows a large decay in effects on the unemployment rate over time. The simplified model, which assumes exponential decay from the initial effect, may not be a bad match to reality.

For the labor force participation rate, Figure 2 shows that the simplified model of Table 4 is a good match for the more complex Bartik (1991) model. Assuming that short-run effects of labor demand shocks on labor force participation equal long-run effects is a reasonable simplification. The Blanchard-Katz model instead estimates fairly rapid decay, but this model restricts the number of job growth lags and treats lagged dependent variables as exogenous.

Similar conclusions are reached for the real wage rate in Figure 3. The simple model that short-run demand shock effects equal long-run effects is a good match for the more complex Bartik (1991) model. The Blanchard-Katz model exaggerates exponential decay by combining limited growth lags with exogenous lagged dependent variables.

The bottom line is that the Table 4 models, with constant demand effects over time for labor force participation and real wages, and exponential decay for unemployment, are reasonable simplifications. The workability of these simplifications is fortuitous, as it allows the model dynamics to be captured with only current job growth, and no more than one lag in the

[14] Appendix A, available upon request, reports more details.

dependent variable.[15] These simple models make it easy to estimate specifications with interactions with lagged unemployment, which is examined in the next section.

Growth Shock Effects at Different Initial Unemployment Rates

The next models explore how growth effects vary with lagged local unemployment rates. Lagged local unemployment is allowed to moderate the effects of growth by including it as an interaction term with growth. To ensure that these represent true interaction effects, lagged unemployment is also included by itself.

These specifications are estimated by 2SLS using instruments derived from local industry mix and national industry growth. Demand shock instruments are also included for the interaction terms. This interaction term would have many potential additional instruments: all possible interactions between the five original instruments (predicted job growth and four lags in predicted employment levels), and all possible interactions between these instruments and the MSA dummies and year dummies. But this would result in too many instruments, overfitting the first stage. To avoid this problem, preliminary regressions on demand shock instruments were done to construct fitted values for growth and lagged unemployment, and the interaction of these fitted values was added as an instrument.

Table 5 presents the coefficient estimates. Tables 6, 7, and 8 present simulation results of effects of a growth shock after various years. Effects are shown at two different initial adjusted ln(employment to labor force ratios): the 10th and 90th percentiles of adjusted employment to labor force ratios across the 23 metro areas and 33 years in the sample. These percentiles correspond to unemployment rates of 10.0 percent and 4.2 percent. To simulate the distribution of the estimates, the model is simulated 1,000 times using random draws from the variance-

[15] This good fortune may be due to the reality that this year's outcome, conditional on last year, should be predictable using variables from last year and this year. More remote effects reflect reduced form influences.

covariance matrix for the estimated coefficients. Tables 6, 7, and 8 report the mean effects on labor market outcomes to a once-and-for all demand shock of 0.01 to ln(local employment). To gauge statistical significance, Tables 6–8 report the proportion of the 1,000 simulations that have the opposite sign from the mean estimated effect. This is a "one-tailed test" for the statistical significance of that particular mean estimated effect.[16]

Table 6 and Figure 4 show how effects of local demand shocks on the employment to labor force ratio vary at high versus low unemployment. Table 6 and Figure 4 show that although demand shocks reduce unemployment even when unemployment is already low, demand shocks have about twice as great an effect when unemployment is high. These differences are statistically significant and large. If some local job growth creates 1,000 jobs in a low-unemployment area, 276 of those jobs would result in reduced local unemployment, whereas if the area has high unemployment, 555 of those jobs would reduce local residents' unemployment.

Table 7 shows how effects of local demand shocks on labor force participation vary at high versus low unemployment rates. Effects are higher when initial unemployment is high, but the difference is not as great as for unemployment and is not statistically significant.

Table 8 and Figure 5 show how effects of local demand shocks on the real wage vary at high versus low unemployment rates. Real wage benefits for local workers are greater when local unemployment is initially low. If unemployment is high, a demand shock has no significant effects in raising real wages, but if unemployment is initially low, a demand shock of 0.01 to ln(employment) will raise wages a little less than 0.3 log points. This initial difference is somewhat statistically significant. Over time, the differential in demand shock effects narrows and becomes statistically insignificant.

[16] An alternative would be reporting the standard deviation of the estimated effects across the 1,000 draws from the distribution of coefficient estimates. But the distribution of the estimated effects is not symmetric, so this would not reveal whether the estimated effects are statistically distinguishable from zero.

The qualitative differentials in demand shock effects at different initial unemployment rates make sense. If there is a large pool of local unemployed labor, a labor demand shock will be accommodated to a greater extent from the local unemployed and will not require a large wage increase to induce sufficient in-migration or labor force participation to fill the new jobs. But these new estimates reveal the quantitative magnitude of these differentials, which are considerable. Furthermore, although these differentials might be as expected, these expectations have not in the past been backed by empirical work.

Table 9 uses these estimated effects of growth shocks to generate measures of the "social benefits" of job growth under different initial local unemployment rates. Three different possible definitions of social benefits are examined. The first definition assumes that only the increase in earnings due to employment to labor force ratio increases counts as social benefits. The second definition adds to the first definition the additional increase in earnings due to increases in labor force participation rates. The final definition assumes that all earnings increases, including real wage increases, count as social benefits. For all three definitions, the present value of these social benefits is calculated over a 20-year period, as a percentage of the present value of the earnings associated with this job growth, with present value calculated using a 3 percent discount rate.

The second definition seems the most reasonable. As discussed above, previous research suggests the net opportunity cost of nonemployed labor is zero or negative. But wage increases have costs for employers that should be considered. Readers can easily adjust the numbers to reflect their views of the opportunity costs of reduced time unemployed or outside the labor force, or their views of the net social benefits from real wage increases.

As Table 9 shows, social benefits of job growth go up with higher unemployment. However, social benefits are still large even at low unemployment rate numbers. The second definition finds social benefits of a labor demand shock of 25 percent of the associated earnings, even when initial unemployment is 4.2 percent. Social benefits almost double when unemployment is 10 percent, to 48 percent of earnings.

Nonlinear Effects of Growth Shocks

To test whether local growth's effects on local labor markets are nonlinear, growth squared is added to the specification, and growth squared interacted with lagged local unemployment. Predicted growth squared and three lags in predicted growth squared were added as instruments. In addition, preliminary regressions predicted growth squared and lagged local unemployment using all the exogenous variables including instruments. The fitted values from these preliminary regressions were interacted and used as an instrument in the final equation.

Before considering these results, it might seem difficult to separate the influence of initial local unemployment and initial local growth rates. Aren't these two variables too highly correlated? It turns out that this is not so. The sample of MSA/year cells is divided into quintiles of initial lagged local unemployment and current local growth. Table 10 shows the number of MSA/year cells in each of the 25 possible combinations of quintiles. Although there is some slight tendency for high (low) current growth and low (high) lagged unemployment to go together, there are also many metro areas with low lagged unemployment and low current growth, or high lagged unemployment and high current growth. Cyclical lows or highs in local unemployment can be followed by reversals in growth trends. In addition, high (low) growth is compatible with high (low) unemployment if offset by migration.

Table 11 shows the coefficient estimates for the growth squared model. The growth squared terms are statistically significant in the employment to labor force and wage equations. Growth interactions with unemployment are statistically significant in the real wage equation.

Simulations of the model confirm that growth effects differ significantly with initial growth only for the employment to labor force and real wage variables, and differ significantly with initial unemployment only for the real wage variable. Tables 12–14 report these simulated differences that are statistically significant.

This more complex model suggests that it is initial growth, rather than initial unemployment rates, that has the greater influence of whether new jobs go to the local unemployed. When initial local job growth is low, extra local jobs have a tendency to benefit the local unemployed more than when local job growth was already high. The initial unemployment rate does not matter. The more complex model still suggests that a low initial unemployment rate tends to increase the effect of local demand shocks on local real wage rates. Finally, the interaction model suggests that demand shocks increase real wages by less when initial local job growth was high. Perhaps high growth results in lower-quality job matches, with more marginal workers and jobs being matched.

Table 15 reports various measures of social benefits of job growth based on the Table 11 matter. Using the second definition of social benefits (earnings increases due to lower unemployment and higher labor force participation), social benefits of growth are much greater if unemployment is high and growth is low, compared to high growth and low unemployment. Benefits go from 31 to 90 percent, almost a threefold increase.

National Variables' Influence on Growth Effects

Some specifications tested for national variations in effects of demand shocks. No statistically significant differentials were found when time trend interactions with local job growth were added. However, the point estimates were compatible with Partridge et al.'s (2012) finding that demand shock's effects on employment rates have increased over time.

Another specification added interactions with the national unemployment rate. No statistically significant interaction effects were found. However, the point estimates were consistent with Saks and Wozniak (2011) in suggesting that higher national unemployment may be associated with somewhat larger effects of local demand shocks on labor force participation rates.

CONCLUSION

Consistent with other research, this paper finds persistent effects of local labor demand shocks on labor force participation rates and wage rates. This paper also finds important short-run effects on local unemployment rates.

The effects of local labor demand shock vary a great deal with prior labor market conditions. Growth shocks are more powerful in reducing local unemployment when preexisting local labor market conditions are more depressed. Growth shocks are more powerful in raising real wages when prior local unemployment is low. However, growth appears to have diminishing returns in raising wages as prior growth increases.

Under reasonable estimates of social benefits of increasing employment rates, the social benefits of an additional job can vary by a factor of two or three when comparing a distressed local labor market with a booming local labor market. This is relevant to benefit-cost analyses of many policies that create or destroy jobs. This would include local and national job creation policies, as well as environmental regulations.

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Table 1 Description of Cell Sizes for Different Labor Market Outcomes in This Study's CPS Data

Variable	Mean sample size for MSA/year cells	Standard deviation	Minimum cell size	Maximum cell size	10th percentile of cell size	Median cell size	90th percentile of cell size
log(wage)	1,722	1,419	274	9,276	647	1,155	3,580
Employment to labor force status	2,707	2,232	488	12,294	1,007	1,799	5,861
Labor force participation rate status	3,575	3,089	670	17,386	1,297	2.368	7,883

NOTE: These data calculate average cell size in regressions/logits for each metro area/year cell in this study's data. The number of metro area/year cells is 759: 23 metro areas by 33 years from 1979 to 2011. The two labor force variables are zero-one variables for individual's labor force status. Cell size for employment to labor force status is lower because those out of labor force are "missing" for this variable. Log(wage) has lower cell size because: only defined if employed; observations dropped if allocated, and higher percentage allocated for earnings variable used to calculate earnings per hour; observations dropped if outliers on wage (less than $3 per hour or more than $250 per hour in 2011 national dollars).
SOURCE: Author's calculations.

Table 2 Descriptive Statistics for Labor Market Outcome Variables, for Both MSA/Year Cell Means, and Year-to-Year Changes in MSA/Year Cell Means

Variable	Mean	Standard deviation	Minimum	Maximum	10th percentile	Median	90th percentile
ln(employment to labor force ratio)	−0.0697	0.0249	−0.2025	−0.0252	−0.1053	−0.0639	−0.0428
ln(labor force to population ratio)	−0.2666	0.0380	−0.4010	−0.1761	−0.3213	−0.2645	−0.2165
ln(wage)	2.8659	0.0771	2.6602	3.0663	2.7530	2.8711	2.9642
Change in ln(employment to labor force ratio)	−0.0017	0.0169	−0.1009	0.0462	−0.0223	−0.0001	0.0173
Change in ln(labor force to population ratio)	−0.0005	0.0204	−0.0780	0.0829	−0.0228	−0.0013	0.0221
Change in ln(wage)	−0.0021	0.0334	−0.1453	0.1305	−0.0406	−0.0017	0.0339
Job growth(change in ln)	0.0143	0.0209	−0.0673	0.0833	−0.0121	0.0154	0.0398

NOTE: The levels variables are MSA/year cell means. The number of MSA/year cells is 759 (23 metro areas by 33 years, 1979 to 2011). The changes variables are changes in mean variables from last year to this year for each metro area. There are 736 observations (23 metro areas by 32 pairs of years, 1979–1980 to 2010–2011).
SOURCE: Author’s calculations.

Table 3 Simplified Blanchard/Katz model: How Estimates Change if Lagged Dependent Variables are Treated as Endogenous

	OLS			2SLS		
	Labor force participation	Employ/labor force	Wage	Labor force participation	Employ/labor force	Wage
Lag(lfpr)	0.596***	0.0983***		0.925***	0.253*	
	(17.95)	(4.33)		(5.31)	(1.96)	
Lag(emp/lf)	0.265***	0.541***		0.174	0.449***	
	(6.46)	(18.66)		(0.86)	(3.05)	
Growth	0.0800**	0.427***	0.0833	0.153	0.489***	0.460***
	(1.98)	(12.72)	(1.38)	(1.60)	(6.86)	(3.02)
Lag(wage)			0.735***			0.871***
			(27.74)			(6.41)
Probability of LM stat for first-stage				0.0050	0.0050	0.0003
Probability of test stat for endogeneity				0.0003	0.1460	0.0120

NOTE: Each of the six columns of numbers shows a different equation, with the dependent variable at the top. The independent variables for which coefficients are reported are listed in leftmost column. Estimated coefficients are reported, with t-statistics in parentheses. Asterisks indicate statistical significance at 10%, 5%, and 1%. All models include metro and year dummies. Number of observations is 736: 23 metro areas by all years from 1980 to 2011. The 2SLS estimates treat both growth and all lagged labor market outcome variables as endogenous. Instruments are based on predicted growth from one year to the next for each metro area based on the previous year's metro industrial mix, and national growth rates by industry from last year to this year. The instruments used are predicted current growth, and four lags in predicted employment. Predicted employment begins with 1969, and adds in predicted growth for each subsequent year to get predicted employment levels. All dependent variables and lagged labor market outcome variables are specified as natural log of adjusted labor market outcome. Descriptive statistics for these variables are in Table 2. Growth is logarithmic job growth. In additional to the overall first-stage LM stat being highly significant, individual F-tests are large. The F statistic for lagged growth is 26.88 (p = 7.81e-25); lagged lfpr F is 15.95 (p = 7.14e-15); lagged emp/lf F is 23.45 (p = 9.00e-22); lagged wage F is 5.304 (p = 8.64e-5).
SOURCE: Author's calculations.

Table 4 Simplified Dynamic Model of Effects of Local Labor Demand Shocks

	Change in labor force participation	Level of employ/labor force	Change in real wage
Growth	0.202**	0.405***	0.538***
	(2.17)	(8.01)	(4.13)
Lagged employment to labor force		0.705***	
		(15.59)	
Probability of endogeneity test stat	0.497	0.717	0.005

NOTE: Each of the 3 columns of numbers is a different estimated equation, with the dependent variable listed at the top. The independent variables for which coefficient estimates are reported are listed in left-most column. Numbers in table are coefficient estimates, with t-statistics in parentheses. Asterisks indicate statistical significance at 5% and 1%. All three equations are estimated by 2SLS. See text for instruments, which involve industry mix predicted job growth and levels. Overall LM test for first stage has probability of 2.37e-14 for two changes equation, 2.83e-16 for levels equation. F-test for predicted growth is 32.45 (p = 9.04e-25), and F-test for lagged employment to labor force ratio is 61.09 (p = 1.48e-52). All equations also include complete set of metro area and year dummies.
SOURCE: Author’s calculations.

Table 5 Estimated Model Parameters Including Growth Interactions with Lagged Employment to Labor Force Ratio

	Change in labor force participation rate	Level of employment to labor force ratio	Change in real wages
Growth	0.0633	0.0893	0.459**
	(0.38)	(0.67)	(2.35)
Lagged employment to labor force ratio	0.0948	0.791***	0.121
	(1.31)	(14.20)	(1.13)
Growth times lagged employment to labor force ratio	−1.219	−4.387**	4.436*
	(−0.65)	(−2.42)	(1.84)
Probability of endogeneity test	0.806	0.883	0.976

NOTE: Each of the 3 columns of numbers is a different estimated equation, with the dependent variable listed at the top. The independent variables for which coefficient estimates are reported are listed in left-most column. Numbers in table are coefficient estimates, with t-statistics in parentheses. Asterisks indicate statistical significance at 10%, 5%, and 1%. All equations also include full set of metro area and year dummies. Estimated using 2SLS. All terms involving growth and lagged employment to labor force ratio treated as endogenous. F-tests for first stage of 2SLS have F values of: growth, 29.78 (p = 1.50e-47); lagged employment/labor force, 30.96 (p = 2.84e-49); interaction term, 290.07 (p = 1.66e-46). The overall LM stat has a probability of 2.44e-14.
SOURCE: Author's calculations.

Table 6 Simulated Implications of Interaction Model for Effects of Local Demand Shock on Employment to Labor Force Ratio at High and Low Initial Unemployment Rates

	Effects at various lengths of time after once and for all demand shock		High UR – Low UR	
	High UR effects	Low UR effects	Point estimate	Prob opp. sign
Immediate effect (year 1)	0.555 (0.000)	0.276 (0.000)	0.279	0.006
Year 2	0.414 (0.000)	0.204 (0.000)	0.210	0.006
Year 3	0.310 (0.000)	0.152 (0.000)	0.158	0.006
Year 4	0.233 (0.000)	0.113 (0.000)	0.120	0.006
Year 5	0.176 (0.000)	0.085 (0.000)	0.091	0.006
Year 10	0.045 (0.000)	0.021 (0.000)	0.024	0.006

NOTE: All estimates are based on simulation of equation system whose coefficients are reported in Table 5. Effects reported are means from 1,000 draws from distribution of coefficient estimates. Numbers below in parentheses are proportion of times out of 1,000 draws that the estimated effect has the opposite sign from the mean estimated effect. This can be viewed as a one-tail test for statistical significance of the estimate. High initial UR and low initial UR are defined as 90th percentile and 10th percentile of mean adjusted unemployment rate across 759 metro area/year cells. High UR is 10.0% unemployment. Low UR is 4.2% unemployment. The next to rightmost column reports point estimate of high UR effect minus low UR effect (i.e., the first column minus the second column), and the number in rightmost column is proportion of times out of 1,000 simulations that this difference had the opposite sign from this point estimate.
SOURCE: Author’s calculations.

Table 7 Simulated Implications of Interaction Model for Effects of Demand Shock on Labor Force Participation Rate at High and Low Initial Unemployment Rates

	Effects at various lengths of time after once and for all demand shock		High UR – Low UR	
	High UR effects	Low UR effects	Point estimate	Prob opp. sign
Immediate effect (year 1)	0.194 (0.024)	0.113 (0.137)	0.081	0.266
Year 2	0.240 (0.006)	0.134 (0.105)	0.106	0.227
Year 3	0.275 (0.004)	0.151 (0.083)	0.124	0.197
Year 4	0.303 (0.002)	0.164 (0.068)	0.139	0.183
Year 5	0.325 (0.001)	0.174 (0.065)	0.151	0.172
Year 10	0.382 (0.001)	0.200 (0.053)	0.182	0.155

NOTE: All estimates are based on simulation of equation system whose coefficients are reported in Table 5. Effects reported are means from 1,000 draws from distribution of coefficient estimates. Numbers below in parentheses are proportion of times out of 1,000 draws that the estimated effect has the opposite sign from the mean estimated effect. This can be viewed as a one-tail test for statistical significance of the estimate. High initial UR and low initial UR are defined as 90th percentile and 10th percentile of mean adjusted unemployment rate across 759 metro area/year cells. High UR is 10.0% unemployment. Low UR is 4.2% unemployment. The next to rightmost column reports point estimate of high UR effect minus low UR effect (i.e., the first column minus the second column), and the number in rightmost column is proportion of times out of 1,000 simulations that this difference had the opposite sign from this point estimate.
SOURCE: Author's calculations.

Table 8 Simulated Implications of Interaction Model for Effects of Demand Shock on Real Wage Rates at High and Low Initial Unemployment Rates

	Effects at various lengths of time after once and for all demand shock		High UR – Low UR	
	High UR effects	Low UR effects	Point estimate	Prob opp. sign
Immediate effect	−0.004	0.267	−0.271	0.041
(year 1)	(0.499)	(0.017)		
Year 2	0.088	0.311	−0.223	0.102
	(0.259)	(0.010)		
Year 3	0.159	0.345	−0.187	0.159
	(0.150)	(0.005)		
Year 4	0.214	0.372	−0.158	0.212
	(0.118)	(0.005)		
Year 5	0.257	0.392	−0.136	0.251
	(0.096)	(0.005)		
Year 10	0.365	0.443	−0.078	0.343
	(0.076)	(0.003)		

NOTE: All estimates are based on simulation of equation system whose coefficients are reported in Table 5. Effects reported are means from 1,000 draws from distribution of coefficient estimates. Numbers below in parentheses are proportion of times out of 1,000 draws that the estimated effect has the opposite sign from the mean estimated effect. This can be viewed as a one-tail test for statistical significance of the estimate. High initial UR and low initial UR are defined as 90th percentile and 10th percentile of mean adjusted unemployment rate across 759 metro area/year cells. High UR is 10.0% unemployment. Low UR is 4.2% unemployment. The next to rightmost column reports point estimate of high UR effect minus low UR effect (i.e., the first column minus the second column), and the number in rightmost column is proportion of times out of 1,000 simulations that this difference had the opposite sign from this point estimate.
SOURCE: Author's calculations.

Table 9 Social Benefits of Labor Demand Increases at Different Initial Unemployment Rates

	Low unemployment (4.2%)	Median unemployment (6.2%)	High unemployment (10.0%)
Social benefit measure based on:			
Unemployment	6.5%	8.9%	13.4%
Unemployment & labor force participation	25.0%	32.8%	48.3%
Earnings	66.1%	70.2%	78.2%

NOTE: These estimates are based on labor market model whose coefficient estimates and selected simulations are reported in Tables 5 through 8. Unemployment rates considered are 10th percentile, median, and 90th percentile of adjusted unemployment rates across 23 metro areas and 33 years. Social benefits calculated are for once and for all shock that increases metro area employment. Social benefits are calculated as present value of social benefits as percentage of present value of earnings associated with this employment increase. First row social benefit measure is based on earnings increase associated with reduced unemployment due to demand shock. Second row adds in earnings increase from increased labor force participation due to demand shock. Final row simply looks at local change in real earnings due to demand shock, which adds in real wage increase to the previous two numbers.
SOURCE: Author's calculations.

Table 10 Distribution of Metro Area/Year Cells by Quintiles of Last Year's Unemployment and This Year's Employment Growth

	Quintiles of lagged unemployment				
	<4.9%	4.9% to <5.7%	5.7% to <6.7%	6.7% to <8.2%	Ge 8.2%
Quintiles of current growth					
LE −1.6%	23	22	32	36	35
>−1.6% to 1.2%	24	32	23	32	36
>1.2% to 2.0%	33	35	26	25	28
>2.0% to 3.0%	28	28	35	29	27
>3.0%	39	30	31	25	22

NOTE: This divides up the 736 metro area/year cells (23 metro areas by 32 years) according to values of the previous year's adjusted unemployment and logarithmic growth from last year to this year. Growth is stated in logarithmic percentage points. Quintiles are calculated in lagged unemployment and current growth, and each MSA/year cell is counted in the appropriate quintile combination. An even distribution would have an average of a little over 29 metro area/years in each of these possible quintile combinations.
SOURCE: Author's calculations.

Table 11 Estimated Model with Growth Squared Added

	Change in labor force participation rate	Level of employ/labor force	Change in real wages
Growth	−0.147	0.409	1.739***
	(−0.34)	(1.50)	(2.65)
$Growth^2$	5.287	−1.858	−27.33*
	(0.51)	(−0.31)	(−1.72)
Lagged(emp/lf)	0.0835	0.690***	0.0952
	(1.02)	(12.06)	(0.73)
Growth*lagged(emp/lf)	−3.730	−1.201	18.84***
	(−0.75)	(−0.39)	(2.51)
$Growth^2$* lagged(emp/lf)	33.85	69.88	−186.9
	(0.30)	(1.01)	(−1.13)
Prob. of $growth^2$ terms	0.706	0.001	0.021
Probability of two growth terms interacted with lagged(emp/lf)	0.570	0.469	0.010
Probability of all growth terms	0.135	7.97e-20	0.021
Probability of endogeneity stat	0.948	0.019	0.063

NOTE: Each of the 3 columns of numbers is a different estimated equation, with the dependent variable listed at the top. The independent variables for which coefficient estimates are reported are listed in left-most column. Numbers in table are coefficient estimates, with t-statistics in parentheses. Asterisks indicate statistical significance at 10%, 5% and 1%. All regressions also include complete set of metro area and year dummies. All estimates use 2SLS demand shock instruments for all growth and lagged (emp/lf) variables. The overall LM statistic for the first stage has a probability of 0.012, and all the individual F tests are also sizable. The smallest first stage F-test is for growth squared interaction term, which has F-test of 5.057, with probability of 1.29e-7.
SOURCE: Author's calculations.

Table 12 Simulated Implications of Growth Squared Interaction Model for Effects of Demand Shock on Employment to Labor Force Ratio at Low and High Initial Growth Rates

	Effects at various lengths of time after once and for all demand shock		Low growth minus high growth difference	
	Low initial growth	High initial growth	Point estimate	Prob opp. sign
Immediate effect	0.633	−0.017	0.650	0.005
(year 1)	(0.000)	(0.450)		
Year 2	0.454	−0.018	0.472	0.003
	(0.000)	(0.450)		
Year 3	0.331	−0.017	0.347	0.000
	(0.000)	(0.450)		
Year 4	0.245	−0.015	0.260	0.000
	(0.000)	(0.450)		
Year 5	0.184	−0.013	0.197	0.000
	(0.000)	(0.450)		
Year 10	0.054	−0.006	0.060	0.006
	(0.000)	(0.450)		

NOTE: All estimates are based on simulation of equation system whose coefficients are reported in Table 11. Effects reported are means from 1,000 draws from distribution of coefficient estimates. Numbers below in parentheses are proportion of times out of the 1,000 draws that the estimated effect has opposite sign from mean effect across 1,000 draws. Low initial growth rate and high initial growth rate are defined as intervals from 0.5% below to 0.5% above 10th percentile and 90th percentile of mean adjusted growth rate across 736 metro area/year cells. Low growth rate starts at −1.7%. High growth rate starts at 3.5%. Growth shock considered is once-and-for-all increase in employment in one year of 1%, which brings growth from 0.5% below a percentile to 0.5% above. The labor market outcome effects are evaluated at the mean initial unemployment rate of 6.2%. The next-to-rightmost column reports the effect of a demand shock at low initial growth minus the effect at high initial growth (first column minus second column). The right-most column reports proportion of time out of 1,000 draws that this difference has opposite sign from mean difference.
SOURCE: Author's calculations.

Table 13 Simulated Implications of Growth Squared Interaction Model for Effects of Demand Shock on Real Wages at Low and High Initial Growth

	Effects at various lengths of time after once and for all demand shock		Low growth minus high growth difference	
	Low initial growth	High initial growth	Point estimate	Prob opp. sign
Immediate effect	0.893	−0.686	1.579	0.008
(year 1)	(0.003)	(0.030)		
Year 2	0.695	−0.707	1.402	0.014
	(0.002)	(0.042)		
Year 3	0.564	−0.725	1.289	0.016
	(0.003)	(0.061)		
Year 4	0.477	−0.740	1.217	0.019
	(0.004)	(0.072)		
Year 5	0.419	−0.753	1.172	0.024
	(0.006)	(0.079)		
Year 10	0.314	−0.792	1.106	0.031
	(0.049)	(0.091)		

NOTE: All estimates are based on simulation of equation system whose coefficients are reported in Table 11. Effects reported are means from 1,000 draws from distribution of coefficient estimates. Numbers below in parentheses are proportion of times out of the 1,000 draws that the estimated effect has opposite sign from mean effect across 1,000 draws. Low initial growth rate and high initial growth rate are defined as intervals from 0.5% below to 0.5% above 10th percentile and 90th percentile of mean adjusted growth rate across 736 metro area/year cells. Low growth rate starts at −1.7%. High growth rate starts at 3.5%. Growth shock considered is once-and-for-all increase in employment in one year of 1%, which brings growth from 0.5% below a percentile to 0.5% above. The labor market outcome effects are evaluated at the mean initial unemployment rate of 6.2%. The next-to-rightmost column reports the effect of a demand shock at low initial growth minus the effect at high initial growth (first column minus second column). The right-most column reports proportion of time out of 1,000 draws that this difference has opposite sign from mean difference.
SOURCE: Author's calculations.

Table 14 Simulated Implications of Growth Squared Interaction Model for Effects of Demand Shock on Real Wages at High and Low Initial Unemployment Rates

	Effects at various lengths of time after once and for all demand shock		High UR minus low UR difference	
	High UR effects	Low UR effects	Point estimate	Prob opp. sign
Immediate effect	−0.485	0.331	−0.815	0.001
(year 1)	(0.021)	(0.015)		
Year 2	−0.420	0.413	−0.833	0.003
	(0.058)	(0.012)		
Year 3	−0.374	0.472	−0.846	0.007
	(0.084)	(0.008)		
Year 4	−0.341	0.514	−0.855	0.009
	(0.118)	(0.005)		
Year 5	−0.317	0.544	−0.861	0.012
	(0.144)	(0.005)		
Year 10	−0.267	0.607	−0.875	0.014
	(0.209)	(0.005)		

NOTE: All estimates are based on simulation of growth squared equation system whose coefficients are reported in Table 11. Effects reported are means from 1,000 draws from distribution of coefficient estimates. Numbers below in parentheses are proportion of times out of the 1,000 draws that the estimated effect has opposite sign from mean effect across 1,000 draws. High initial UR and low initial UR are defined as 90th percentile and 10th percentile of mean adjusted unemployment rate across 759 metro area/year cells. High UR is 10.0% adjusted unemployment. Low UR is 4.2% unemployment rate. Differences across different unemployment rates are all calculated around median growth rate of 1.5% across 736 cells, with one-time increase in growth rate from 1.0% to 2.0%, whereupon growth rate reverts back to 1.0%. The next-to-rightmost column reports mean effect at high UR minus effect at low UR, or column 1 minus column 2. The rightmost column reports the proportion of times out of 1,000 draws that this difference has opposite sign from average difference.
SOURCE: Author's calculations.

Table 15 Social Benefits Based on Growth Squared Interaction Model, Various Combinations of Initial Growth and Unemployment

	High UR		
	Low growth	Median growth	High growth
UR only	19.7%	5.0%	-5.2%
UR+LFPR	89.8%	38.1%	29.9%
Earn	34.4%	7.6%	-94.9%
	Median UR		
	Low growth	Median growth	High growth
UR only	15.0%	5.7%	-0.8%
UR+LFPR	47.9%	28.5%	30.9%
Earn	88.9%	55.3%	-46.4%
	Low UR		
	Low growth	Median growth	High growth
UR only	12.6%	6.1%	1.4%
UR+LFPR	26.6%	23.6%	31.4%
Earn	116.7%	79.6%	-21.7%

NOTE: These social benefits are based on the Table 11 model that interacts growth and growth squared with initial unemployment rates. All effects shown are based on 1% once-and-for-all shock to employment. Low growth, median growth, and high growth are starting initial points that start 0.5% below 10th percentile, median, and 90th percentile of growth in sample (starting points of −1.7%, 1.0%, and 3.5%). High unemployment, median unemployment, and low unemployment are 90th percentile, median, and 10th percentile of unemployment (10.0%, 6.2%, and 4.2% unemployment). Social benefits are calculated three different ways. First way is increased earnings due to reduced unemployment. Second way adds in increased earnings due to increased labor force participation. Third way simply looks at change in real earnings. Social benefits are calculated as percentage of earnings associated with new jobs.
SOURCE: Author's calculations.

Appendix Table A1 Short-run and Long-run Effects of Local Labor Demand on Labor Market Outcomes, Bartik-Style Specification

	Employ/labor force		Labor force participation		Wage	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Year 1	0.428***	0.611***	0.0942	0.155	0.199***	0.558***
(Immediate effect)	(9.08)	(6.04)	(1.62)	(1.20)	(2.65)	(3.09)
Year 2	0.319***	0.262***	0.166***	0.208*	0.292***	0.612***
	(6.62)	(2.66)	(2.71)	(1.72)	(3.46)	(3.47)
Year 3	0.230***	0.315*	0.196**	0.319*	0.118	0.742***
	(4.71)	(2.48)	(3.08)	(1.94)	(1.25)	(2.83)
Long-run	0.167***	0.143	0.170**	0.259**	0.354***	0.488***
(3-lag spec)	(3.25)	(1.47)	(2.79)	(2.07)	(3.71)	(2.64)
Long-run	0.122*	0.170	0.222*	0.219	0.376**	0.581*
(10-lag spec.)	(1.73)	(1.09)	(2.06)	(1.05)	(2.80)	(2.13)
Probability 2SLS=OLS	0.238		0.917		0.036	

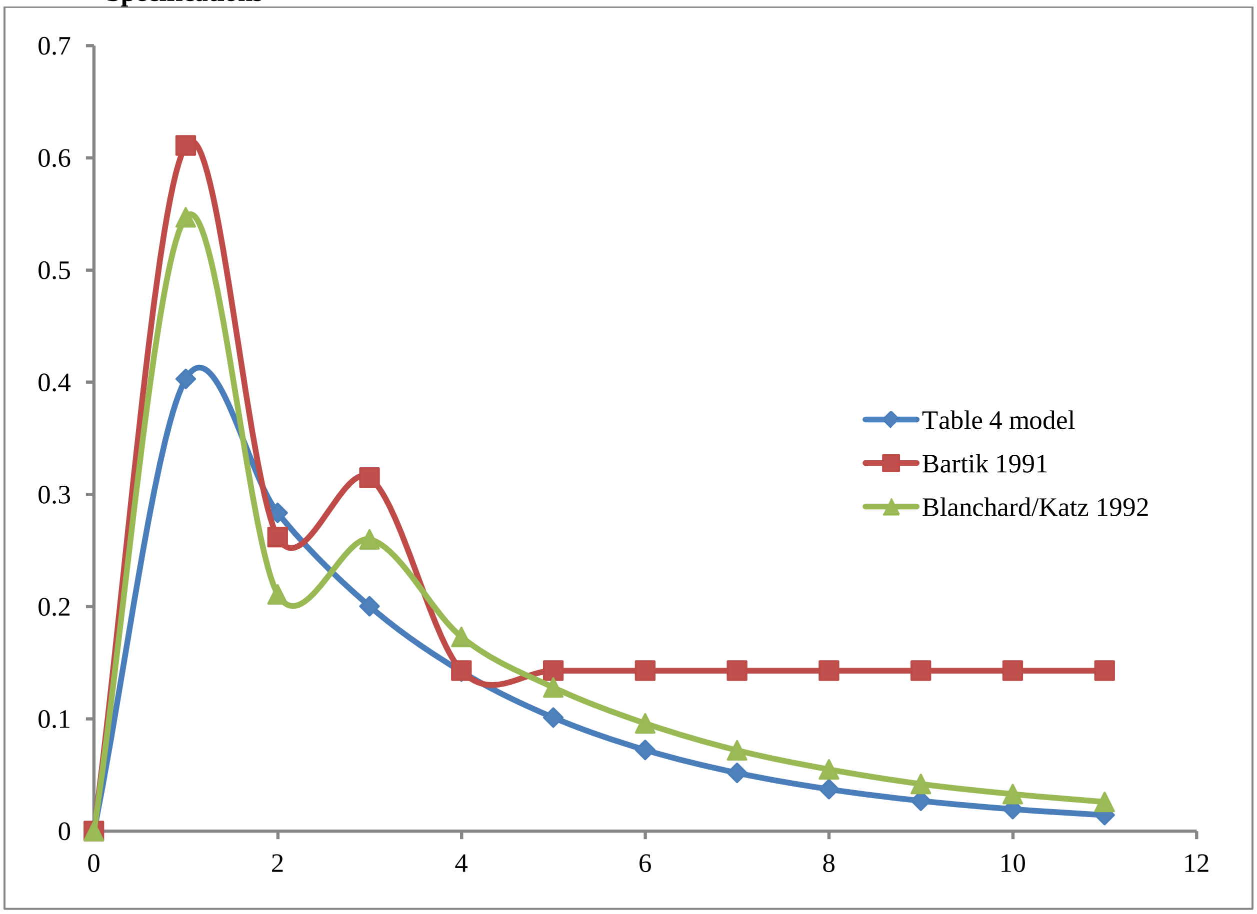
NOTE: t-statistics are in parentheses. Asterisks designate statistical significance at 10%, 5%, 1%. Each column reports all results for demand shock effects in 3-lag specification, and long-run effects from a separate 10-lag specification. Dependent variable is change from last year to this year in natural log of the three labor market outcome variables. Growth variable is change in natural log of employment. All growth effects shown are cumulative effects after growth shock. All specifications also include complete set of metro area dummies and year dummies. 2SLS treats employment growth as endogenous and uses as instruments predicted growth based on local industry mix and national industry growth rates. F-tests in first stage are large, and overall LM test for first stage (Kleibergen-Paap) is highly significant with probability of 1.15 times 10 to the (−8). For 2SLS, report probability of endogeneity test, which tests probability that 2SLS estimates are same as OLS estimates. 3-lag specification is chosen in OLS by AIC among all specifications from zero lags to 10 lags. For 2SLS, sequential F-tests also suggest that 2-lag or 3-lag specification is optimal.
SOURCE: Author’s calculations.

Appendix Table A2 Short-run and Long-run Effects of Local Demand Shocks on Labor Market Outcomes, Blanchard-Katz Style Specification

	Labor force partic.		Employ/labor force		Wage	
	Effect	Pseudo-t	Effect	Pseudo-t	Effect	Pseudo-t
Immediate Effect						
Year 1	0.074	1.32	0.404	9.65	0.077	0.98
Year 2	0.161	2.84	0.273	7.02	0.164	2.08
Year 3	0.163	3.39	0.188	5.98	−0.012	−0.14
Year 4	0.166	4.93	0.136	7.22	0.110	1.35
Year 5	0.149	4.58	0.099	5.80	0.259	3.85
Year 10	0.060	2.73	0.026	2.47	0.066	2.75

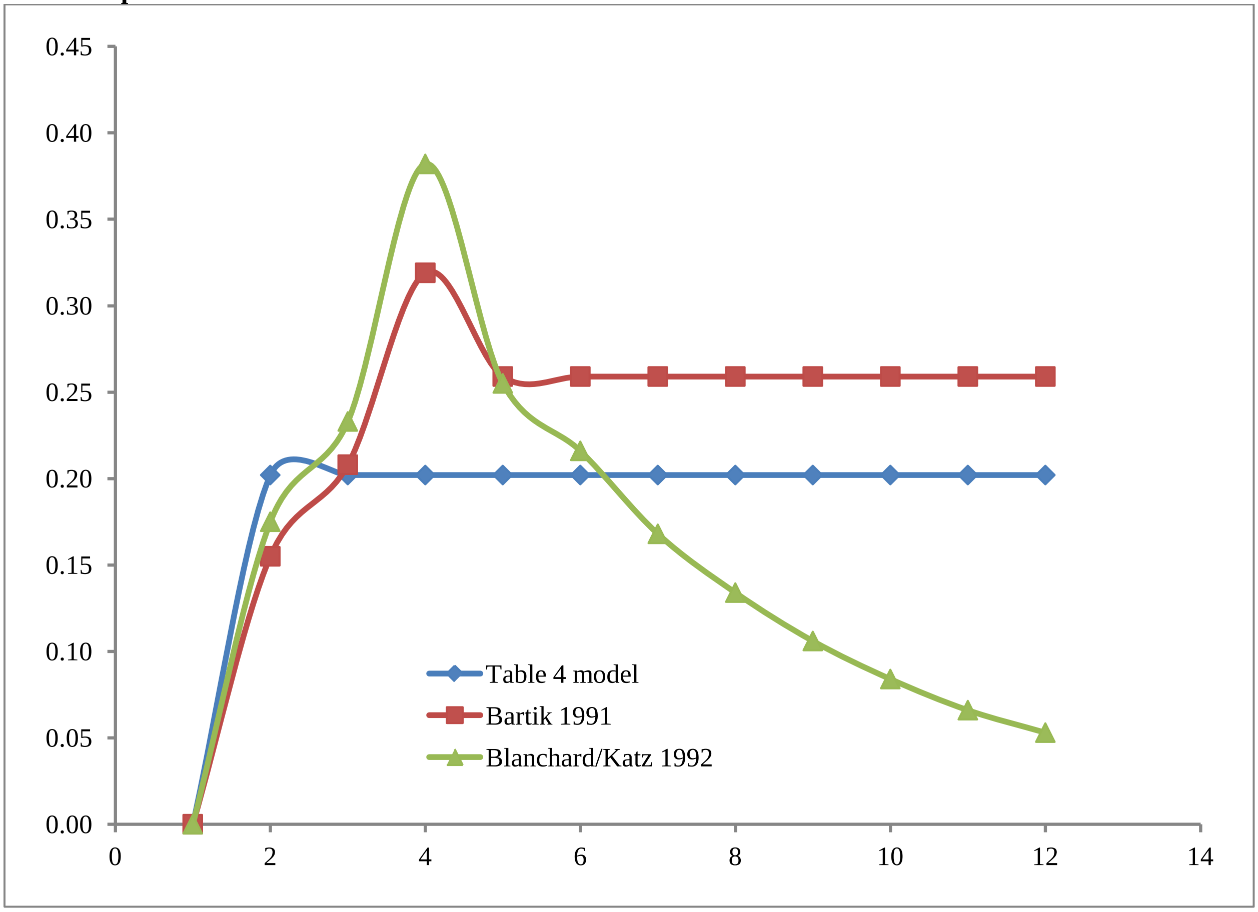
NOTE: Table reports results from 1,000 simulations of Blanchard-Katz model. Underlying model described in text. The effects reported are mean effects from 1,000 random draws from coefficient using estimated variance/covariance matrix. Pseudo-t is ratio of this mean effect to standard deviation across 1,000 simulations.
SOURCE: Author’s calculations.

Figure 1 Effects of Demand Shocks on Employment to labor Force Ratio, Current Specification vs. Older Specifications



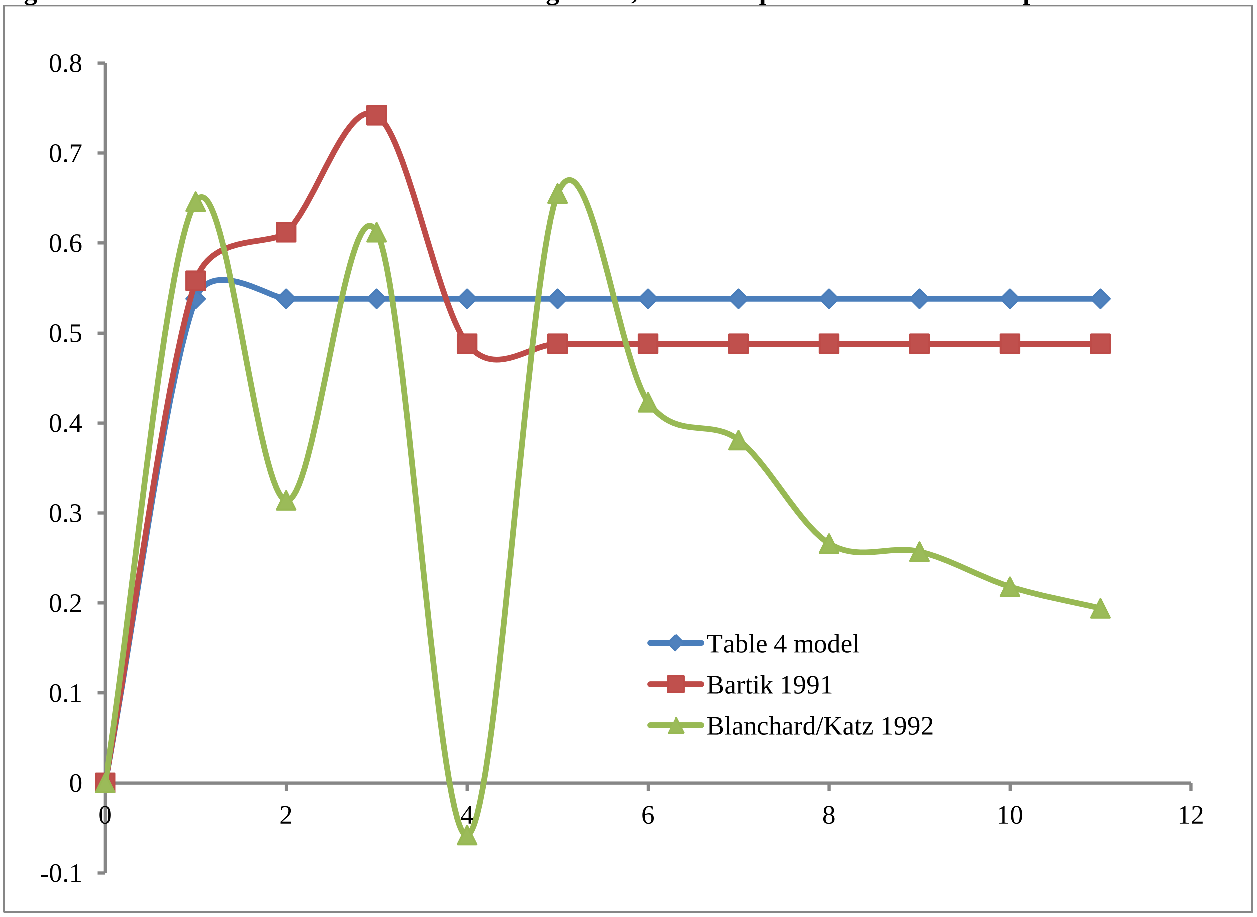
NOTE: This figure compares effects of local demand shock on employment to labor force ratio in current paper's Table 4 specification versus specifications more similar to those used in Bartik (1991) and Blanchard-Katz (1992). Units are for effects on ln(employment/labor force) of once-and-for-all permanent shock of 0.01 to ln(employment). Blanchard-Katz is specification with current and two lags in growth, and two lags in employment to labor force ratio and labor force participation rate. Blanchard-Katz estimated via 2SLS but only treating growth terms as endogenous. Bartik (1991) specification is 3-lag specification in employment growth, which is chosen as optimal based on considering all lag lengths up to 10. Specification is estimated via 2SLS. All 2SLS estimation uses predicted local growth based on local industry mix and national industry growth. All specifications include both year fixed effects and metro area fixed effects.
SOURCE: Author's calculations.

Figure 2 Effects of Demand Shocks on Labor Force Participation Rate, Current Specification vs. Older Specifications



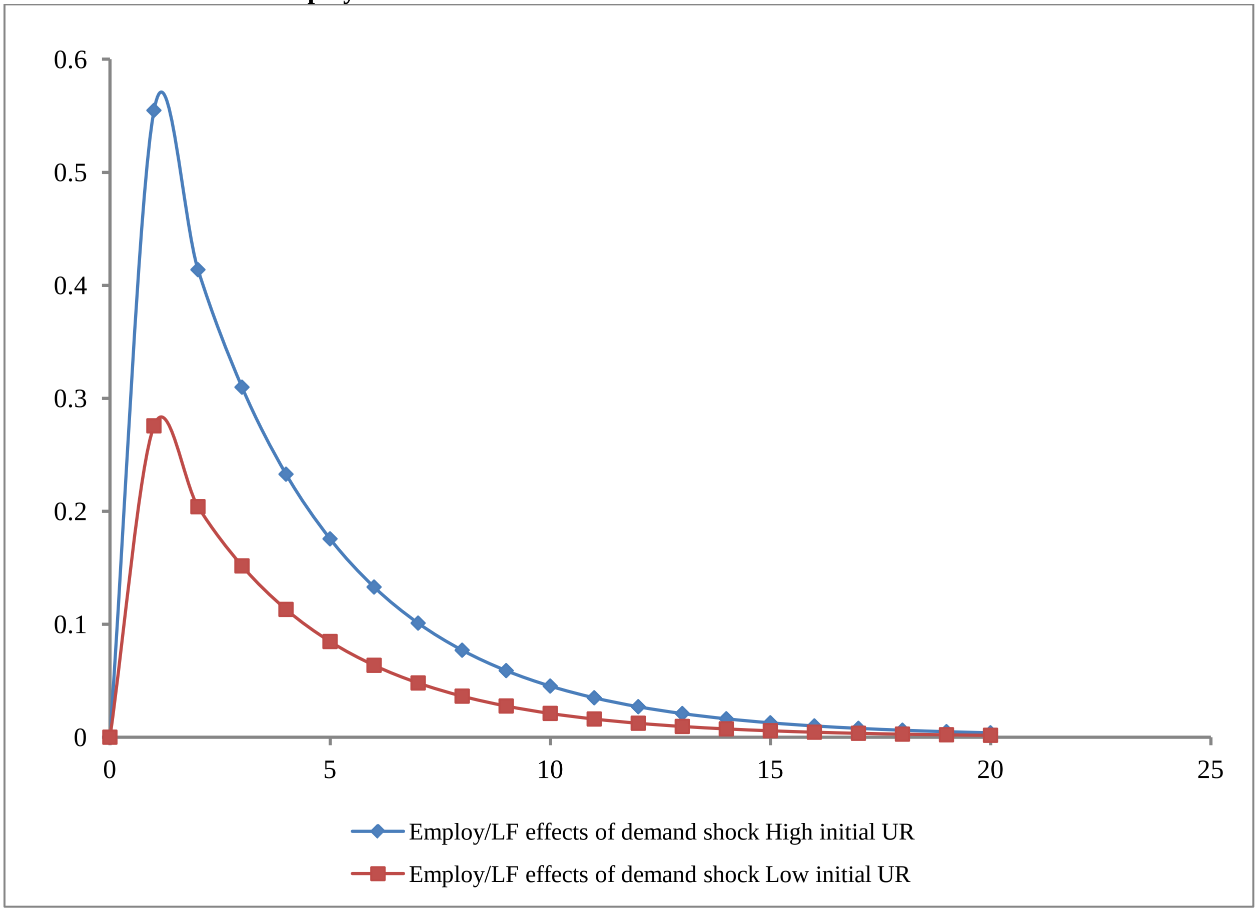
NOTE: This figure compares effects of local demand shock on labor force participation rate in current paper's Table 4 specification versus specifications more similar to those used in Bartik (1991) and Blanchard-Katz (1992). Units are for effects on ln(labor force participation rate) of once-and-for-all permanent shock of 0.01 to ln(employment). Blanchard-Katz is specification with current and two lags in growth, and two lags in employment to labor force ratio and labor force participation rate. Blanchard-Katz estimated via 2SLS but only treating growth terms as endogenous. Bartik (1991) specification is 3-lag specification in employment growth, which is chosen as optimal based on considering all lag lengths up to 10. Specification is estimated via 2SLS. All 2SLS estimation uses predicted local growth based on local industry mix and national industry growth. All specifications include both year fixed effects and metro area fixed effects.
SOURCE: Author's calculations.

Figure 3 Effects of Demand Shocks on Real Wage Rate, Current Specification vs. Older Specifications



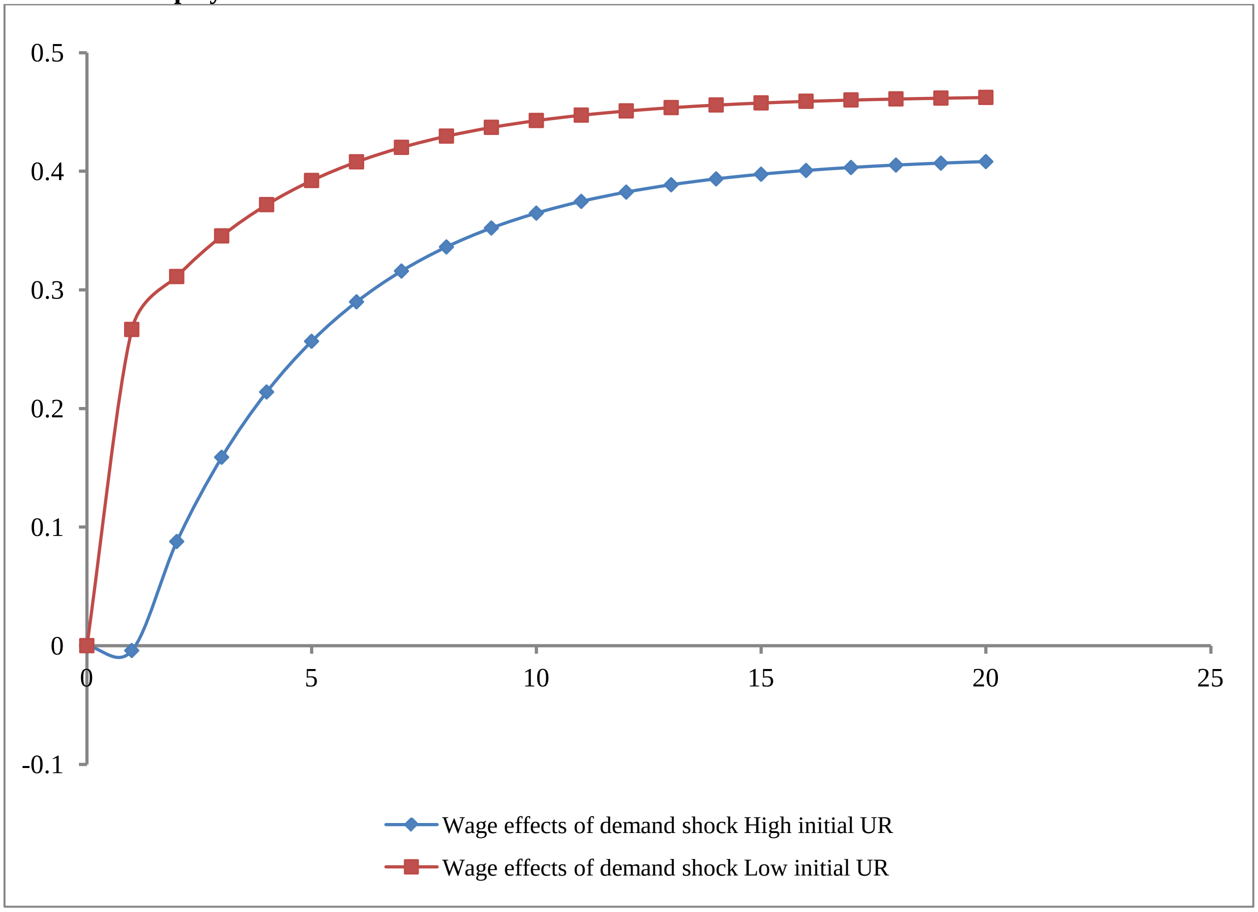
NOTE: This figure compares effects of local demand shock on real wage rates in current paper's Table 4 specification versus specifications more similar to those used in Bartik (1991) and Blanchard-Katz (1992). Units are for effects on ln(real wage rate) of once-and-for-all permanent shock of 0.01 to ln(employment). Blanchard-Katz is specification with current and four lags in growth, and four lags in real wage rate. Blanchard-Katz estimated via 2SLS but only treating growth terms as endogenous. Bartik (1991) specification is 3-lag specification in employment growth, which is chosen as optimal based on considering all lag lengths up to 10. Specification is estimated via 2SLS. All 2SLS estimation uses predicted local growth based on local industry mix and national industry growth. All specifications include both year fixed effects and metro area fixed effects.
SOURCE: Author's calculations.

Figure 4 Point Estimates of Effects of Local Demand Shock on Employment to Labor Force Ratio at High vs. Low Initial Unemployment Rates



NOTE: Figures 4 and 5 are based on simulations at high UR and low UR of model whose coefficient estimates are in Table 5. High UR and low UR, as in Tables 6 through 8, are 90th and 10th percentile of unemployment rate across 23 metro areas times 33 years in data. High UR is 10.0%, low UR is 4.2%.
SOURCE: Author’s calculations.

Figure 5 Point Estimates of Effects of Local Demand Shock on Real Wage Rates at High vs. Low Initial Unemployment Rates



NOTE: Figures 4 and 5 are based on simulations at high UR and low UR of model whose coefficient estimates are in Table 5. High UR and low UR, as in Tables 6 through 8, are 90th and 10th percentile of unemployment rate across 23 metro areas times 33 years in data. High UR is 10.0%, low UR is 4.2%.
SOURCE: Author's calculations.