Labor-Market Adjustment in Open Economies:

Evidence from U.S. States

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Abstract. In this paper we analyze whether regional economic integration across U.S. states conditions local labor-market adjustment. We examine the mechanisms through which states absorb changes in labor supplies and whether industry production techniques are similar across states. There are two main findings. First, states absorb changes in employment primarily through changes in production techniques that are common across all states and through changes in the output of traded goods, with the former mechanism playing the larger role. In contrast, state-specific changes in production techniques, which are one indication of state-specific changes in relative factor prices, account for relatively little factor absorption. Second, industry production techniques are very similar across states, especially for neighboring states and states with similar relative labor supplies. Both sets of results are consistent with productivity-adjusted FPE across either all states or groupings of related states.

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1 *Introduction*

Recent literature on U.S. labor markets identifies two important changes in national labor supplies. One is rising educational attainment of the labor force, among both new entrants and existing workers (Johnson, 1997). A second is rising immigration of individuals with low education levels relative to U.S. natives (Borjas, 1999). Both of these labor-supply shifts have varied across regions. For instance, immigration "gateway" states such as California have attracted a large share of new immigrants, and the increase in the relative supply of more-educated workers appears to have been strongest in the Northeast.

How do regions absorb differential changes in relative labor supplies? We delineate four adjustment mechanisms: changes in regional relative factor prices, interregional migration of labor and/or capital, changes in the regional output mix, and changes in underlying production technology. While the first mechanism may occur in either closed or open economies, the other three generally depend on regional openness to factor, trade, or technology flows. In this paper, we examine the mechanisms through which U.S. states absorb changes in relative labor supplies, with an emphasis on how economic openness conditions regional labor-market adjustment.

Literature on regional adjustment to labor-supply shocks focuses almost exclusively on wage adjustment in a closed-economy setting. An important strand of this literature assesses the impact of immigration on native wages in U.S. regions.[1] The standard approach is to regress the change in native wages on the change in the stock of immigrants across U.S. metropolitan areas. Most studies find that immigration has, at most, a small negative impact on local native wages. Adjustment mechanisms besides wage changes are generally ignored, except in a small literature

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[1] The literature on this subject is vast. Recent papers include Borjas, Freeman, and Katz (1997) and Card (1997). See Borjas (1994 and 1999) and Friedberg and Hunt (1995) for surveys.

on whether native migration responds to immigrant inflows. Evidence on this second adjustment mechanism is mixed. Filer (1992) and Borjas, Freeman, and Katz (1997) find that immigrant inflows to a region contribute to native outmigration, while Card (1997) finds that they do not.[2]

To our knowledge, no study has examined the role of the third adjustment mechanism, changes in regional output mix, in regional absorption of labor-supply changes. By the logic of the Rybczynski Theorem (1955), a core result of Heckscher-Ohlin (HO) trade theory, a region may absorb a factor-supply shock without factor-price changes by shifting production towards sectors that employ relatively intensively factors whose supplies are expanding. Openness to trade is essential for this mechanism to work, as it implies changes in regional outputs can be absorbed by changes in regional exports and imports.

There is a large literature on the fourth adjustment mechanism, technological change, but most of this research focuses on whether national shifts in production technology have been biased towards skilled workers and thus may have contributed to national increases in the relative demand for and wages of skilled labor (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman, Bound, and Griliches, 1994; Autor, Katz, and Krueger, 1998). We know of no work on the impact of such skill-biased technical change (SBTC) on regional labor markets. For a single region, national SBTC represents a change in *effective* labor supplies which, depending on other regional shocks, may either offset or exacerbate raw regional labor-supply changes.

To understand how U.S. states absorb differential labor-supply shocks, we perform two empirical exercises. Both use a new data set we construct on real state value added by industry and state labor employment by industry for four education categories: high-school dropouts,

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[2] In related work, Blanchard and Katz (1992) find that interregional employment shifts help alleviate regional variation in unemployment rates and promote regional wage convergence (see also Topel, 1986), and Topel (1994) finds that regional relative wages in the United States are correlated with changes in regional relative labor supplies.

high-school graduates, those with some college, and college graduates and beyond. The data cover 14 large U.S. states and 40 sectors, spanning all civilian industries, in 1980 and 1990.

The first exercise is a decomposition of changes in state employment by education category into four components: changes in output of nontraded goods, changes in output of traded goods, national changes in industry production techniques (i.e., unit factor requirements), and state-specific changes in industry production techniques. Changes in traded-goods output capture the contribution of output-mix changes to factor absorption; changes in national production techniques capture the contribution of national SBTC and other national shocks to factor absorption; and state-specific changes in production techniques capture the contribution of state-specific changes in relative factor prices to factor absorption. To preview our findings, state-specific changes in production techniques contribute little to factor absorption. This suggests that states adjust to labor-supply shocks more through open-economy mechanisms -- factor, trade, and technology flows -- than through state-specific changes in relative factor prices.

The second exercise is to compare industry production techniques across states. Equality of production techniques across states is consistent with regional factor-price equalization (FPE). To be more precise, since we allow for industry-neutral productivity differences across states, equality of production techniques is consistent with *productivity-adjusted* FPE. With FPE the related states experience common relative-wage responses to sufficiently-small factor-supply shocks in any one state (in the language of HO trade theory, the related states occupy the same cone of diversification). To preview our findings, production techniques are very similar across states, especially for neighboring states or states with similar relative labor supplies, which is consistent with FPE. This suggests that regional openness to flows of factors, goods, and technology is sufficient to ensure that state-specific factor-supply shocks tend to trigger common relative-wage responses across states.

This paper relates to two bodies of literature. The first, mentioned above, is that on regional wage impacts of immigration in the United States. It is commonly viewed as a puzzle why immigration has only small effects on native wages. Our findings suggest one resolution to this puzzle: regional FPE suppresses region-specific wage adjustment to region-specific labor-supply shocks. The second body of literature is that on empirical tests of HO trade theory. Harrigan (1995, 1997) and Bernstein and Weinstein (1998) examine whether national outputs vary systematically with national factor endowments, as predicted by the HO model. Davis, et al (1997) and Maskus and Webster (1999) test for FPE as a means of testing the HO model indirectly. Davis, et al, find evidence consistent with FPE across Japanese regions, but not across OECD countries. This methodology is also applied in Davis and Weinstein (1998), with more favorable results for the HO model. In this paper we extend this methodology to decompose how regions absorb factor-supply changes and to develop a sharper test of FPE.

The organization of the paper is as follows. In section 2, we motivate the empirical analysis based on the production side of the HO trade model. In section 3, we examine changes in state labor supplies from 1980 to 1990 and present the results for the decomposition of state employment changes. In section 4, we test for regional FPE by comparing industry production techniques across states. In section 5, we offer concluding remarks.

2 Heckscher-Ohlin Production Theory

In this section we present the production side of HO trade theory. This framework suggests two empirical exercises for examining labor-market adjustment in open economies such as U.S.

states. The first is a decomposition of state absorption of factor-supply changes into portions due to changes in traded and nontraded output and to national and state-specific changes in industry production techniques. The second is a test for equal industry production techniques across states, which would be consistent with regional FPE.

2a General-Equilibrium Relationships

Let there be N total industries and M primary factors of production in each state, where across states product markets are integrated. For each industry assume technology is constant returns to scale, free of externalities, and identical across all states. Suppressing state subscripts, in each state factor-market equilibrium implies

$$(1)\ \mathbf{V} = \mathbf{CX}\ ,$$

where **V** is an Mx1 vector of state primary factor supplies; **X** is an Nx1 vector of state real value-added output; and **C** is an MxN matrix of unit factor requirements (industry production techniques) in the state, such that element c_{mn} shows the units of factor m required to produce one unit of real value added in industry n. Equation (1) says that factor supply and factor demand are equal. A second equilibrium condition is that zero profits be earned in each sector:

$$(2)\ \mathbf{P} = \mathbf{C'W}\ ,$$

where **W** is an Mx1 vector of state factor prices and **P** is an Nx1 vector of world product prices assumed to be exogenous to the state. Equation (2) says that price equals average cost in each market, which are assumed to be perfectly competitive. For (2) to hold as an equality, as we assume, a given state must produce all N goods. Factor prices in (2) are not indexed by industry: within each state perfect intersectoral factor mobility ensures that each factor earns the same wage in all sectors. In the equilibrium described by equations (1) and (2), **W** is determined endogenously along with **X**, and the **C** matrix depends on production technology and **W**. [3,4]

Regional openness to flows of factors, technology, or goods can have an important impact on how states adjust to state-specific factor-supply shocks. FPE holds across a group of states if they face the same product prices, share common production technologies, and have sufficiently similar relative factor supplies that they produce the same set of goods.[5] If these flows are sufficient for there to be FPE across states, then states experience common factor-price responses to national factor-demand shocks and to factor-supply shocks specific to one or more states.

Factor flows across states are an obvious mechanism that contributes to FPE. Other than documenting how natives and immigrants contribute to state labor-supply changes, we leave such flows in the background of our analysis. We do so partly because there is abundant literature on this subject, and partly because it is difficult to separate the impacts of migration from those of native labor-force participation. Our analysis focuses on the contribution to factor-market adjustment of changes in production techniques and changes in state output mixes. Later we discuss how interregional factor flows may complement these mechanisms.

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[3] Industry production techniques are usually stated in terms of net output, not value added. Our data measure output as value added, not net output. To relate these two concepts, let **Y** be the Nx1 vector of net outputs; **X** be the Nx1 vector of value added; **Z** be the Nx1 vector of gross outputs; **B** be the MxN matrix of direct unit factor requirements, whose elements show the quantity of each primary factor that each industry uses directly to produce one real dollar worth of gross output; and **F** be the NxN matrix of intermediate input purchases by each industry from each industry. Using this notation, $\mathbf{Fdiag(Z)^{-1}}$ is the NxN input-output matrix, whose elements show the real dollar value of intermediate inputs each industry purchases from other industries to produce a dollar of gross output. By the definition of net output, $\mathbf{Y=(I-Fdiag(Z)^{-1})Z}$, and of value added, $\mathbf{X=(I-F'diag(Z)^{-1})Z}$. It follows from the full employment of factors that $\mathbf{D=B(I-Fdiag(Z)^{-1})^{-1}}$ is the MxN matrix of total (direct plus indirect) unit factor requirements, whose elements show the quantity of each primary factor each industry uses in total to produce one real dollar worth of net output, and $\mathbf{C=B(I-F'diag(Z)^{-1})^{-1}}$. This shows that **C** is a function of the same underlying elements as **D**.

[4] Without affecting the logic of the model, equation (2) could be relaxed to allow for constant price-cost markups or interindustry wage differentials. A more-fundamental departure from the HO assumption of zero profits in (2) would be to allow variable markups. This would break the tight linkage from product prices to factor prices that (2) represents.

[5] These are sufficient but not necessary conditions for FPE. See Blackorby, Schworm, and Venables (1983).

The flow of ideas across states helps equalize their production technology. Common technology plus FPE implies states share identical industry production techniques and experience common changes in production techniques in response to a wide variety of shocks. An additional point is that if technological change is biased towards specific factors, then the implied demand shifts can be thought of as a change in *effective* factor supplies (Davis, 1998). In the 1980s, the U.S. as a whole appears to have been subject to SBTC as well as a rise in the average education level of the labor force. National SBTC may have helped individual states absorb increases in the raw relative supply of more-educated workers by reducing this group's effective relative supply, thereby mitigating pressure for state-specific changes in factor prices.

Trade flows across regions are another mechanism that contributes to FPE. Openness to trade helps states adjust to factor-supply shocks by shifting production towards (away from) traded goods that employ intensively the factors whose supplies are expanding (declining). What does this output-mix adjustment imply for wages? In some cases there are no wage changes anywhere: neither in the state with the factor-supply change nor any other state. We refer to this outcome as *local factor-price insensitivity* (LFPI) to factor-supply changes (Leamer and Levinsohn, 1998). This is the logic of the Rybczynski Theorem (1955) in a generalized setting (Ethier, 1984). For LFPI to hold, it must jointly be the case that the supply shock is sufficiently small, that the region be sufficiently small that product prices remain fixed, and that N≥M.[6]

Alternatively, wages may change in the state with the labor-supply shock—particularly if the state is large enough to change product prices. But if that state shares FPE with other states, then

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[6] If the labor-supply shock is sufficiently small, then the region continues to make the same set of N products after the change as before, in which case the same sectors appear in the zero-profit conditions in equation (2). If the region is sufficiently small that its outputs do not affect world product prices, then **P** is unchanged and the same exogenous quantities—**P** and technology—appear in these same N equations in (2). And if N≥M, then the exogenous prices and technology values in (2) fully determine the M endogenous factor prices. This means that neither **W** nor **C** changes after the change in **V**.

its wage changes are shared across all states. Because both regions face the same price changes and produce the same products after the shock, by equation (2) both regions experience the same wage changes. LFPI is violated in the shock-receiving state, but thanks to product-market integration across the two regions there is no state-specific wage response to that shock.[7]

While the hypothesis of LFPI is interesting, it is difficult to evaluate in our data since state industry production techniques are changing over time, leaving open the possibility that state factor prices are also changing over time. To evaluate LFPI we would need labor-supply changes to be the only shock, but there is abundant evidence in our data of other shocks such as SBTC. Thus we focus our analysis on regional FPE.

2b Accounting Decompositions

We build on equation (1) to identify the mechanisms through which regional factor-supply changes are absorbed. Take first differences of (1) to obtain

$$(3)\ \ \Delta\mathbf{V} = \overline{\mathbf{C}}\Delta\mathbf{X} + \Delta\mathbf{C}\overline{\mathbf{X}}$$

where Δ is the time-difference operator and $\overline{\mathbf{Y}}$ represents the mean of $\mathbf{Y}$ across time. Equation (3) decomposes a state's change in factor supplies ($\Delta\mathbf{V}$) into two portions: that accounted for by output-mix changes (the first term on the right) and that accounted for by production-technique changes (the second term on the right).

To examine the role of regional trade and technology flows in factor absorption, (3) needs two modifications. First, we need to distinguish between output adjustment in traded and

[7] Both LFPI and FPE imply that state-specific endowment shocks do not trigger state-specific wage effects. But neither necessarily implies the other. LFPI is a statement about wage responses to labor-supply changes in a single region; FPE is a statement about wage (and perhaps production-technique) levels across two or more regions.

nontraded sectors. Second, we need to separate changes in production techniques attributable to national shocks (and thus common across regions) from those that are idiosyncratic to a state.

As a region grows, consumer preferences mandate changes in nontraded output which in turn mandate changes in factor demand (Helpman and Krugman, 1985). To assess the contribution of changes in traded output to factor absorption we must strip out of total factor-supply changes factor absorption due to nontraded goods (Davis and Weinstein, 1999). Define $\mathbf{I^{NT}}$ ($\mathbf{I^{T}}$) to be an NxN matrix with zero off-diagonal elements and diagonal elements equal to one if the row and column correspond to a nontraded (traded) sector and zero otherwise. Also, define $\mathbf{X^{NT}} \equiv \mathbf{I^{NT}X}$ and $\mathbf{X^{T}} \equiv \mathbf{I^{T}X}$. We then rewrite equation (3) as

$$(4)\ \ \Delta\mathbf{V} - (\overline{\mathbf{C}}\Delta\mathbf{X^{NT}} + \Delta\mathbf{C}\overline{\mathbf{X}}^{\mathbf{NT}}) = \overline{\mathbf{C}}\Delta\mathbf{X^{T}} + \Delta\mathbf{C}\overline{\mathbf{X}}^{\mathbf{T}}.$$

On the left of (4) we have the effective factor-supply change facing the traded sector. This may be absorbed through changes in either traded output or production techniques.

Next, consider national versus state-specific changes in industry production techniques. State production techniques, **C**, are a function of state relative factor prices and the underlying production technology. Changes in state production techniques may result from state-specific changes to factor prices or national shocks to technology and/or product prices. One obvious candidate for a national shock to industry production techniques is SBTC. If states begin with common industry production techniques, as would be consistent with FPE, and then are subject to common product-price and technology shocks, we would expect states to experience common adjustment in state production techniques.

To identify the possible role of such national shocks in state factor absorption, we distinguish changes in production techniques that are generalized across states, $\Delta\mathbf{C_G}$, from those that are idiosyncratic to a state, $\Delta\mathbf{C_I}$. We calculate $\Delta\mathbf{C_G}$ as the state **C** matrix in the initial year times the percentage change in production techniques (on a by-industry and by-factor basis) for all other U.S. states over the given time period. $\mathbf{\Delta C_I}$ is then the residual change:

$$\text{(5) } \mathbf{\Delta C_I = \Delta C - \Delta C_G}.$$

Substituting (5) into (4) we obtain the general accounting decomposition,

$$\text{(6) } \mathbf{\Delta V - (\overline{C}\Delta X^{NT} + \Delta C\overline{X}^{NT}) = \overline{C}\Delta X^{T} + \Delta C_G \Delta \overline{X}^{T} + \Delta C_I \overline{X}^{T}}.$$

Equation (6) identifies three ways in which states absorb factor-supply changes facing the traded sector: output mix changes in the traded sector (first term on the right), national changes in industry production techniques (second term on the right), and state-specific changes in production techniques (third term on the right). A small final term would suggest there is little role for state-specific changes in relative factor prices in absorbing state factor-supply changes.

In applying the decompositions in (3) and (6), it is important to recall that both hold as identities and thus cannot identify causal relationships among $\mathbf{\Delta V}$, $\mathbf{\Delta X}$, and $\mathbf{\Delta C}$. We implicitly allow for the possibility that part of the change in state factor supplies may be an endogenous response to changing relative economic conditions across states. The usefulness of (3) and (6) is they help uncover the mechanisms through which states adjust to factor-supply changes.

We make two additional points on implementing (3) and (6). First, $\mathbf{\Delta C}$ reflects changes in wages as well as technology, meaning it also reflects shocks to product prices and other determinants of wages. Without further information we cannot identify technology shocks alone. Nevertheless, we will show that $\mathbf{\Delta C}$ appears to be consistent with SBTC. Relatedly, the term $\mathbf{\Delta C_I \overline{X}^{T}}$ in (6) need not reflect state-specific wage changes: it could instead reflect state-specific technology changes which are consistent with FPE. We return to this point below.

Second, the decomposition in (3) is similar to the within- versus between-industry decompositions of employment changes that are commonly applied in labor economics (e.g., Katz and Murphy, 1992; Berman, Bound, and Griliches, 1994). The decomposition in (6) extends this approach in two ways: (i) we distinguish national from state-specific changes in production techniques, thus isolating the impact of national shocks on state factor-market adjustment; and (ii) we distinguish between adjustment in the traded and nontraded sectors, thus isolating the role of changes in traded-output mix on factor-market adjustment.

2c Testing for FPE

The decomposition in (6) can offer suggestive evidence of FPE across U.S. states by showing whether the term $\Delta \mathbf{C_I} \overline{\mathbf{X}}^{\mathbf{T}}$ makes a small contribution to factor absorption. Beyond this suggestive evidence, however, we can implement a more direct test for FPE across states. Again, FPE matters because if FPE holds across all states, then small state-specific factor-supply shocks do *not* lead to state-specific factor-price changes.

Suppose two states *i* and *j* have identical industry production techniques, or

$$(7)\ \mathbf{C^i} = \mathbf{C^j}\ .$$

As long as production technology is not Leontief, equality of industry production techniques implies FPE between states i and j, i.e., that $\mathbf{w^i}=\mathbf{w^j}$.[8] If (7) holds, then a wide range of shocks—state-specific factor-supply shocks, national or global shocks to product prices or technology—produce similar wage effects in both states.

Equation (7) suggests a simple way to test for FPE. We can compare industry production techniques across states to see if they are the same. If we find the same **C** matrices for a group of states, then we have evidence these states have common factor prices.

[8] This depends, of course, on the earlier assumptions that states possess identical production technology and that production is not subject to scale effects or externalities.

It is possible for two states to have equal factor prices yet not have equal production techniques thanks to scale effects, externalities, or differences in underlying production technology. We acknowledge our approach is subject to this interpretation issue, but also point out that this makes it *harder*, not easier, to find evidence of FPE using our approach. In testing for equal production techniques across states we are testing not just for equal factor prices but also for sufficiently similar production technologies. We think this additional information about production technologies is interesting in its own right, especially as technology flows are an important adjustment mechanism. Also, using production techniques follows closely existing tests of FPE. Later, we return to the issue of testing for FPE using direct wage data.[9]

There are a class of technology differences across states for which we can and do control. Following Trefler (1993), suppose there are differences in the productivity of factors across states which are neutral across industries. College graduates in California, for instance, could be uniformly more productive than college graduates in other states. Such differences could be due to differences in the average ability of workers across states, variation in state-specific characteristics (e.g., weather) which influence factor productivity, or even the presence of certain types of agglomeration economies. Given factor-specific but industry-neutral productivity differences across states, we can rewrite equation (4) as

$$(8)\ \mathbf{C^i = diag(\Pi^j)C^j}\ ,$$

where $\mathbf{\Pi^j}$ is an Mx1 vector which converts factor quantities in region j into productivity equivalent units for region i. Following (8), we test for FPE by testing for equality of industry production techniques across states while allowing for factor-specific, industry-neutral

[9] Another possibility is that if production technology permits minimal substitution between factors (as in the Leontief case), then two states could have equal **C** matrices but still have different factor prices. Though we cannot rule out this possibility, that we use relatively aggregate (two-digit SIC) industry data suggests it is unlikely to be a serious issue.

productivity differences. Under (8), FPE between state *i* and *j* implies not that nominal factor prices in the two states are equal but that *productivity-adjusted* factor prices are equal.

Our approach extends the methodology of Davis, et al (1997). Suppose factor-market equilibrium is given by equation (1) and FPE holds between two regions, *i* and *j*, as in (7). Then Davis, et al (1997) test for FPE by seeing if $\mathbf{V}^j=\mathbf{C}^i\mathbf{X}^j$, i.e., if factor supplies for region *j* can be predicted by combining output in region *j* with production techniques in region *i*. If the answer is yes, then the conclusion is that factor prices are equalized between *i* and *j*. One limitation of this approach is that if there are more goods than factors there is output indeterminacy: for a given **V** and **C**, there is not a unique **X** vector which satisfies equation (1) (Ethier, 1984; Bernstein and Weinstein, 1998). Following this logic, for a given **V** and **X**, there is not a unique **C** satisfying (1). Thus, $\mathbf{V}^j=\mathbf{C}^i\mathbf{X}^j$ can hold even if FPE does not. Our FPE test, because it requires states to have identical **C** matrices (up to productivity adjustments), is robust to output indeterminacy.[10]

To summarize this section, we have presented some basic aspects of the production side of HO trade theory linking factor markets with product markets. In doing this we have motivated two data exercises. First is the accounting decompositions in equations (3) and (6). This will indicate the mechanisms—state output mixes, state-specific production techniques, or national production-techniques—through which state factor-supply changes are absorbed. Our second data exercise is the test for productivity-adjusted FPE in equation (8).

3 Adjustments to State Changes in Labor Supplies

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[10] For completeness, we compared $\mathbf{V}^j$ and $\mathbf{C}^i\mathbf{X}^j$ for state pairs in our data and found that the two quantities are very similar.

In this section we first show that during the 1980s labor-supply changes varied across U.S. states, due partially to immigration. We then use the decompositions in (3) and (6) to show that the majority of state labor-supply changes were accounted for by mechanisms other than state-specific changes in production techniques.

To construct state labor supplies, we use data from the 1980 and 1990 5% Public Use Microsample (PUMS) of the *U.S. Census of Population and Housing*. An individual is included as part of the state labor supply if he or she is a member of the state labor force. Later in the analysis, we will require measures of industry employment and output by state. To construct the former, we combine PUMS data with industry employment data from the U.S. Bureau of Economic Analysis (BEA). Data on real industry value added at the state level also come from the BEA. To match industries from these two data sources we aggregate all civilian industries into 40 sectors, which are a mix of one-digit and two-digit industry classifications. We examine four education categories of labor: high-school dropouts, high-school graduates, those with some college, and college graduates. While it would be desirable to also examine non-labor factors, such as capital and land, there are no industry data on state employment of these factors over the sample period. The Data Appendix describes data sources and variable construction.[11]

3a Labor Supplies across U.S. States, 1980-1990

Tables 1a and 1b present data on labor supplies for 14 states plus the overall United States in 1980 and 1990. In addition to the six high-immigration or gateway states (California, Florida, Illinois, New Jersey, New York, Texas), we include data on eight other large states in the

[11] Value-added data are not available for finer geographic regions than states. Using four education categories is standard practice in the large empirical literature on immigration, in particular, and labor supply, in general (see note 1). These four

Northeast (Connecticut, Massachusetts), Midwest (Michigan, Ohio, Pennsylvania), South (Georgia, North Carolina), and West (Washington).[12] Each row of Table 1a reports the share of the total state (or national) labor force accounted for by each of the four labor categories; Table 1b reports changes in these shares.[13]

Table 1a shows that states differ widely in the distribution of the labor force across education categories. Relative to the United States as a whole, the labor force in the Northeast (CT, MA, NJ, NY) is skewed towards college graduates, the labor force in the Midwest (OH, IL, MI, PA) is relatively concentrated among high-school graduates, and the labor force in the South (FL, GA, NC, TX) is relatively concentrated among high-school dropouts. California is distinct in that by 1990 its labor force is concentrated in the extremes of the skill distribution, with relatively high shares for both high-school dropouts and college graduates.

Table 1b shows, consistent with previous findings, that during the 1980s there was a national increase in the relative supply of more-educated workers (Bound and Johnson, 1992; Juhn, Murphy, and Pierce, 1993; Katz and Murphy, 1992). Interestingly, this shift varied considerably across states. The increase in the share of college graduates was highest in the Northeast. Changes in Midwest shares generally mirrored those in the rest of the country, though the region did show a relatively large increase in the some-college share. In the South, there was a relatively large shift away from high-school dropouts in Georgia and North Carolina, but not in Florida. In

categories also accord with the preferences in Davis, et al (1997) for broadly defined “good” factors rather than narrowly defined “bad” factors (see their discussion on p. 427).

12 We select large states to guarantee sufficiently large sample sizes of workers by education category at the state and industry level in the PUMS data. To concord PUMS and BEA data, we must start with three-digit Census industries, which exceed 200 in number. Once we separate workers by education group and industry in the PUMS, cell sizes for small states are zero or near zero. For this reason, we exclude small states from the sample. The 14 sample states account for more that 65% of U.S. GDP.

13 Results using the working age population, instead of the total labor force, are similar to those reported in Tables 1 and 2.

the West, and particularly in California, there was a relatively small shift away from high-school dropouts and a relatively large shift away from high-school graduates.

Table 2 examines one source of state labor-supply changes, immigration. It shows the share of individuals in each labor category who are foreign born in 1980 and 1990. The gateway states for immigration are immediately apparent. New Jersey, New York, Florida, and, especially, California have relatively high immigrant shares in all education categories. Illinois and Texas (and also CT and MA) have high concentrations of immigrants among high-school dropouts only. Immigrant concentrations are much lower in the other states. In most states, over the 1980s immigrant shares rose markedly in every education category.

Comparing Tables 1 and 2 reveals an interesting pattern. Over the 1980s the gateway states have high and rising immigrant shares, particularly in the low-skilled categories. Yet all of these states except California still had a moderate to large decline in the relative supply of low-skilled workers. This suggests that in many states immigrant inflows were offset by a declining supply of low-skilled natives, via a combination of native outmigration, labor-force exits, or individual skill acquisition. This pattern is clear in the (unreported) change in labor-force shares of natives and immigrants by education category. In all states but California, declining supplies of low-skilled natives more than offset rising supplies of low-skilled immigrants.

3b Accounting Decompositions for U.S. States, 1980-1990

To provide context for our accounting decompositions, Table 3 shows three measures of industry factor intensity: the ratios of employment of high-school dropouts, high-school graduates, or those with some college to employment of college graduates. All measures use data for national industry employment in 1980 and 1990 (see appendix).

Factor intensities differ substantially across industries. In 1990, the ratio of high-school dropouts to college graduates ranges from 9.3 in household services to 0.05 in legal services. The ranking of industries by factor intensities is quite similar across the three intensity measures (rank correlations lie between 0.67 and 0.93). Relative factor intensities are also stable across time and states. Table 3 also shows the well-documented within-industry decline in low-skilled relative employment (Bound and Johnson, 1992; Katz and Murphy, 1992; Juhn, Murphy, and Pierce, 1993; Berman, Bound, and Griliches, 1994). Over the 1980s there is a large decrease in the employment of high-school dropouts and high-school graduates relative to college graduates and those with some college. Combined with the observed rise in the wage premium to skilled workers, these relative-employment shifts suggest SBTC.

To examine these mechanisms more systematically, we apply equation (3) to each state. Again, our goal is to see if state labor-supply changes are accounted for mainly by mechanisms other than state-specific changes in production techniques. Table 4 reports the decomposition in (3) for all four factors in each of the 14 states, grouped by broad geographic area. Each decomposition uses all 40 industries and spans 1980 to 1990. To ensure the decompositions conform with HO theory's full-employment conditions we measure $\mathbf{V}$ as total employment, not total labor force (as in Tables 1 and 2). To control for state business cycles we divide both sides of equation (1) by total state employment before calculating (3). This makes each element of $\Delta\mathbf{V}$ equal the change in the share of a given labor type in total state employment.

In Table 4 column (1) shows $\Delta\mathbf{V}$, the change in state factor employment; column (2) shows $\overline{\mathbf{C}}\Delta\mathbf{X}$, average production techniques times the change in state industry output (summed over all industries); and column (3) shows $\Delta\mathbf{C}\overline{\mathbf{X}}$, the change in state production techniques times mean industry output (summed over all industries). To provide context for later results the last two columns extend equation (3) by showing $\Delta\mathbf{C}_{\mathbf{G}}\overline{\mathbf{X}}$ and $\Delta\mathbf{C}_{\mathbf{I}}\overline{\mathbf{X}}$, which are generalized changes and idiosyncratic changes, respectively (described in equation (5)), in production techniques.

We identify three messages in Table 4. First, consistent with Tables 1 and 2 there are broad regional differences in employment changes. In the four Northeast states employment shifted uniformly up the skill rankings. In the West California looks the same, but for a much smaller shift away from high-school dropouts. In the four Midwest states employment grew most in the some-college category. The same was true in the four South states, but (except for Florida) they all showed much sharper drops in high-school-dropout shares.

Second, within each state qualitative changes in relative factor supplies are *not* matched by qualitative changes in output mix. In every state the $\Delta\mathbf{V}$ term is negative for the two less-educated categories, but in no state is the $\overline{\mathbf{C}}\Delta\mathbf{X}$ term negative for either category. Comparing elements of $\overline{\mathbf{C}}\Delta\mathbf{X}$ across factors within a state shows no clear pattern of larger changes for more-educated labor. So changes in factor-demand mandated by output changes across all sectors do not match changes in factor-supply. Consistent with Katz and Murphy (1992), column (3) shows that a key part of the story is $\Delta\mathbf{C}\overline{\mathbf{X}}$, within-industry changes in production techniques. Factor-demand changes mandated by production-technique changes generally match factor-supply changes: negative and large for the less-educated, small and positive for the more-educated.

Third, in almost all cases the large majority of a state's changes in production techniques are accounted for by generalized changes, not idiosyncratic (state-specific) changes. Exceptions to this are the Northeast and California, whose production techniques shifted less towards more educated workers than did the rest of the country. These states may have implemented new technologies favoring more-skilled workers earlier than other states did, in which case column (5) might reflect technological convergence across states. But these exceptions aside, the overall pattern suggests that observed state $\mathbf{\Delta C}$ are driven mostly by forces that are not state-specific.

To summarize, Table 4 indicates that changes in production techniques account for a large share of state employment changes, and that these changes in production techniques are relatively uniform common across states. This suggests that national shocks such as SBTC may be contributed substantially to state absorption of labor-supply shocks.

To build on Table 4 we now turn to the accounting decomposition in equation (6). Equation (6) shows that, net of absorption by the nontraded sector, a state may absorb employment changes through changes in traded output, generalized changes in production techniques, or idiosyncratic changes in production techniques. The results in Table 4 suggest that, if anything, output changes across all sectors worked against state labor-supply changes. With (6), we can now distinguish between output adjustment in traded and nontraded sectors. Table 4 also establishes the importance of generalized changes in production techniques. To abstract from these generalized changes and focus on the relative contributions to factor absorption of changes in traded output and idiosyncratic changes in traded production techniques, we rewrite (6) as

$$(6')\quad \mathbf{\Delta V} - (\overline{\mathbf{C}}\mathbf{\Delta X^{NT}} + \mathbf{\Delta C}\overline{\mathbf{X}}^{\mathbf{NT}}) - \mathbf{\Delta C_G}\mathbf{\Delta}\overline{\mathbf{X}}^{\mathbf{T}} = \overline{\mathbf{C}}\mathbf{\Delta X^T} + \mathbf{\Delta C_I}\overline{\mathbf{X}}^{\mathbf{T}}.$$

On the left of (6') we have $\mathbf{\Delta V^E}$, the "effective" change in factor supplies, net of nontraded absorption *and* generalized changes in production techniques, facing the traded sector. $\mathbf{\Delta V^E}$ can be absorbed either through changes in traded output or through state-specific technique changes.

Table 5 reports the decomposition in (6'). Column (1) shows $\mathbf{\Delta V^E}$; column (2) shows $\overline{\mathbf{C}}\mathbf{\Delta X^T}$, average production techniques times the change in state industry output for traded industries; column (3) shows $\mathbf{\Delta C_I}\overline{\mathbf{X}}^{\mathbf{T}}$, the idiosyncratic change in state production techniques times mean industry output for traded industries; and column (4) is the ratio of column (2) to column (1).

Table 5 reports results for a narrow definition of traded goods; in unreported results we find the same qualitative pattern for a broader definition.[14]

One important feature of Table 5 is that $\mathbf{\Delta V^E}$ is quite different from $\mathbf{\Delta V}$ in Table 4. Whereas total factor-supply changes ($\mathbf{\Delta V}$) generally reflect skill upgrading in every state, effective factor-supply changes ($\mathbf{\Delta V^E}$) are more varied. Similar to Table 4, the Northeast and Illinois show an increase in the relative effective supply of college graduates. But other states show a much different pattern. In California the increase in effective factor supplies is largest for high-school dropouts; in other Midwest states (MI, OH, PA) there is a relatively even increase in effective supplies for all factors; and in the South (GA, NC) the largest increase in effective factor supplies is for high-school graduates. Overall, differences between $\mathbf{\Delta V}$ and $\mathbf{\Delta V^E}$ suggest that raw changes in factor supplies may be a poor indicator of changes in traded output.

A second important feature of Table 5 is that for many states, changes in traded output account for a large fraction of how states absorb changes in effective factor supplies facing the traded sector. In contrast, state-specific changes in production techniques play a relative small role. This is a quite different picture than one gets from Table 4 (or from the within-between decompositions across industries in Katz and Murphy (1992) and Berman, Bound, and Griliches (1994)), and it confirms the just-made point about differences between $\mathbf{\Delta V}$ and $\mathbf{\Delta V^E}$. In each state, the qualitative changes in effective factor supply are matched by the qualitative changes in tradables output mix: within each state factors with large (small) changes in $\mathbf{\Delta V^E}$ are generally matched by large (small) changes in $\mathbf{\overline{C}\Delta X^T}$. Taking all state-factor observations together, $\mathbf{\Delta V^E}$ and $\mathbf{\overline{C}\Delta X^T}$ are the same sign for 53 of the 56 cases and the correlation between the two series is

[14] Our narrow definition of tradables includes agriculture, mining, manufacturing, investment finance, and business services. Our broader definition adds agricultural services, FIRE, and legal services.

0.63. Column (4), which shows the ratio of $\overline{\mathbf{C}}\Delta\mathbf{X}^{\mathbf{T}}$ to $\Delta\mathbf{V}^{\mathbf{E}}$, gives an indication of the importance of changes in the traded output mix. The mean value of this ratio is 1.33 (standard deviation of 2.00), but this is influenced by a few outliers. The median value of the ratio is 1.07.

Overall, Tables 4 and 5 indicate that state changes in employment are accommodated largely through generalized changes in production techniques (which are common across states) and, for the change in factor supplies facing tradables, through changes in the output mix of traded goods. State-specific changes in production techniques, in contrast, play a relatively small role in factor absorption. These findings are consistent with the hypothesis that state-specific factor-supply shocks do not trigger large state-specific wage effects. For more direct evidence on this question, we turn to our empirical tests for productivity-adjusted FPE across U.S. states.

4 Testing for Productivity-Adjusted FPE across U.S. States

4a Methodology

In this section we test for productivity-adjusted FPE across U.S. states in the 1980s. Following equation (8), we compare industry production techniques for each of the 91 unique state pairs in our sample. For each state-pair (*i*,*j*), we have data on unit factor requirements in 40 sectors (*n*) for four labor types (*m*) in two years (*t*), 1980 and 1990. Taking logs of each element of the matrices in equation (8) and pooling observations across industries, labor types, and years, we obtain the following equation for state pair *ij*:

$$(9)\quad \ln \mathbf{c}_{\mathbf{mnit}} = \alpha_{\mathbf{mijt}} + \beta \ln \mathbf{c}_{\mathbf{mnjt}} + \eta_{\mathbf{mnit}}$$

where $\alpha_{mijt}=log(\pi_{mijt})$ and η_{mnit} is a disturbance term resulting from measurement error and random productivity shocks. To allow for factor-specific productivity differences across state pairs in each year, we include fixed effects α_{mijt} for each state-pair, labor-type, and year combination, of which there are 728 (91x4x2) in the full sample. Testing whether these fixed-effect terms jointly equal zero is equivalent to testing the null hypothesis of no factor-specific, industry-neutral productivity differences across states. We pool observations across state pairs, yielding 28,392 (40x4x2x91) potential observations.[15] Under the null hypothesis of FPE, $\beta=1$: industry production techniques will be the same for all state pairs in all time periods.[16]

Theory does not dictate which state's production technique belong on the left of (9) and which on the right. We resolve this issue by ranking states by their average production techniques (across factors, industries, and years) and then for each observation having the high-productivity state's production technique be the regressand and the low-productivity state's production technique be the regressor. The results are robust to alternative data-organization methods such as randomly allocating regressand and regressor observation by observation.

4b Estimation Issues

There are several estimation issues to be addressed. One relates to efficient strategies for estimating β in (9). The disturbance term in (9) represents shocks to production techniques and, possibly, errors in measuring these techniques. Shocks to production techniques are likely to be correlated across labor types for a given industry, state, and year due, for example, to temporary product-market shocks that are specific to the industry, state, and year and which affect firms' jointly determined factor demands. In light of these shocks, OLS estimates of β in (9) will not be

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[15] Actual observations are somewhat less since we are missing observations on the tobacco industry for most states.

[16] To summarize the earlier discussion, the maintained hypotheses that are required to use state industry production techniques to test for FPE are that industry unit factor requirements across states are not subject to scale effects, externalities, or non-neutral differences in production technology.

efficient. Our solution is to allow the errors in (9) to be correlated across observations whose regressand has the same state, industry, and year.

A second estimation issue is the possibility of classical measurement error in the regressor, production techniques in partner states. Production techniques are calculated by combining BEA data on state value added, BEA data on state industry employment, and PUMS data on the share of workers in a given state-industry that belong to a given education group (see appendix). Each of these values may be measured with error. Measurement error may also arise if the average ability of workers by education group varies across states or if within each industry the mix of subindustries varies across states. If c_{mnjt} is measured with error, the OLS estimate of the coefficient β in (9) will be biased towards zero, leading us to reject FPE when it is true.

We lack obvious instruments for production techniques, so we address measurement error in two other ways. Since we have a single regressor, one option is to estimate the "reverse regression" (Klepper and Leamer, 1984) by making the $ln(c_{mnit})$ the independent variable and $ln(c_{mnjt})$ the dependent variable in equation (9). Asymptotically, the true value of β lies between the OLS estimate of β from (9) and the inverse of the OLS coefficient from the reverse regression. We estimate (9) and its reverse regression to determine whether the lower and upper bounds for β span the value of one. One limitation of this approach is that if measurement error is severe, the bounds on β may be so wide as to be uninformative.

Our second method for addressing measurement error is to use extraneous information on the variance of the measurement error to estimate equation (9) (Judge, et al, 1980). If we know the ratio of the variances of the true and observed values of $ln(c_{mnjt})$ then we can obtain a consistent estimate of β. We do not observe this ratio directly, so we approximate it using information on production techniques for the United States as a whole. If we assume both that U.S. production techniques are measured with zero error and that the variance of these U.S. techniques equals the variance of the true value of $ln(c_{mnjt})$, then we can use the ratio of the variance of U.S. production techniques to the variance of $ln(c_{mnjt})$ to measure the ratio of the variances for the true and observed values of $ln(c_{mnjt})$. In theory this variance ratio ranges from zero to one, and asymptotically $\beta_{EIV}=\beta_{OLS}$/Variance Ratio. A problem with EIV estimation is possible correlation in errors across groups: we do not have any information on cross-group correlations in measurement error, and so cannot obtain reliable standard errors for EIV coefficient estimates. Accordingly, we do not regard the reported standard errors for EIV coefficient estimates to be reliable (but we report them for completeness).

A third estimation issue is sample selection. Theory suggests that FPE should hold across all states for which the mechanisms generating this outcome operate sufficiently. One mechanism may be interstate factor mobility, which is likely to operate most strongly across neighboring states. Another mechanism may be product-market linkages, which requires that states have similar relative factor supplies such that they produce the same products and face the same zero-profit conditions. Our 14 states are diverse both geographically and, as demonstrated earlier, with respect to their relative factor supplies. We thus do not have a strong prior that productivity-adjusted FPE will hold across all states in the sample.

We examine this issue by estimating (9) on three different samples. The first is the full sample of all 91 state pairs. The second is a subsample of the 16 pairs of neighboring states. [17] Here the idea is that neighboring states are more likely to have interstate factor flows and thus productivity-adjusted FPE. The third is a subsample of 20 similarly endowed state pairs defined as

[17] The 16 pairs are as follows: MA with CT, NY, and NJ; CT with NY and NJ; NY with NJ; PA with OH, IL, and MI; OH with IL and MI; IL with MI; NC with GA and FL, GA with FL; and TX with CA.

the 20 state pairs in our overall data with the most-similar labor-supply vectors measured in terms of smallest Euclidean distance.[18] The idea is that similarly endowed states are more likely to have the same product mix and thus FPE thanks to product-market linkages.

4c Estimation Results

If the null hypothesis of productivity-adjusted FPE is true, this should be abundantly clear in the data: for every observation in equation (9), the two $ln(c_{mnkt})$ terms should be equal (up to a scalar constant equal across all industries for each state-pair/factor/year combination). Figures 1 through 4 plot log production techniques factor by factor for all state-pair/industry/year observations in the full sample of 14 states. The horizontal axis indicates production techniques for low-productivity states, and the vertical axis for high-productivity states. To show how the data line up, the 45-degree line passing through the origin is also shown.

Figures 1 through 4 give broad visual support for productivity-adjusted FPE. Under absolute FPE, in each figure all observations should lie exactly along the drawn 45-degree line. Under productivity-adjusted FPE, all observations for each state-pair/factor/year grouping should lie along *a* 45-degree line--but not necessarily the one through the origin. The overall impression is that the majority of observations are consistent with productivity-adjusted FPE.

Table 6 reports our estimation results. The table has three sections, each corresponding to one of the three samples of states described above. First, consider the full sample of states. The fixed effects for state-pair/factor/year groupings are jointly significantly different from zero, which is consistent with factor-specific, industry-neutral productivity differences across states. The

[18] For two states with employment of factor m of v^i_m and v^j_m (normalized by total state employment) we measure similarity as $[\Sigma_m(v^i_m - v^j_m)^2]^{1/2}$. We take the 20 state pairs with the most similar vectors (CT with MA, NJ, and NY; GA with FL, NC, and

forward fixed-effects coefficient estimate is 0.94, with a standard error of 0.015 and an R-squared of 0.89. This estimate, while close to one, is significantly different from one at standard confidence levels. This may suggest that productivity-adjusted FPE does not hold in this sample, or it may suggest that it does hold but is obscured by measurement error.

To examine the importance of measurement error we first estimate the reverse fixed-effects specification. This coefficient estimate is 0.943 (standard error 0.009, R-squared of 0.89), and again the fixed effects are jointly significantly different from zero (as they are in all regressions). The final column combines the information from the forward and reverse fixed-effects estimates: the true parameter value lies between the forward parameter estimate and the inverse of the reverse parameter estimate. This range is [0.94, 1.06], indicating the data are consistent with the hypothesis of productivity-adjusted FPE. Our second method of addressing measurement error is EIV regression. We report coefficient estimates from the forward and reverse EIV specifications, along with the implied parameter range. We reiterate our concern that the reported EIV standard errors are unreliable. In the EIV regressions the asymptotic range of the coefficient estimate narrows to [0.97, 1.03]. This provides additional support for productivity-adjusted FPE.

The middle and bottom portions of Table 6 report results for the subsamples of neighboring states and similarly endowed states. Again, we expect FPE to be more likely to hold within these subsamples thanks to greater factor flows and/or stronger product-market linkages. The results provide some confirmation of this prior. For the fixed-effect regressions it is again the case that we reject the null that the slope coefficient equals one. But relative to the full sample of states, the ranges of fixed-effect coefficient estimates for neighboring states, [0.96, 1.05], and similarly endowed states, [0.97, 1.06], are narrower. Similarly, in EIV regressions coefficient estimates are

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TX; NY with MA and NJ; IL with CT, FL, MA, MI, NJ, NY, and TX; MI with FL and OH; MA with NJ; PA with OH; FL with more tightly centered around one, with a range of [0.99, 1.02] for neighboring states and [0.99, 1.03] for similarly endowed states. That the forward and reverse estimates tightly bound one is consistent with productivity-adjusted FPE holding across these state groups.

In unreported results we examined the sensitivity of our findings to specification and estimation procedure. Instead of estimating (9) in levels, we estimated it in differences by taking the 1980-1990 time difference of all observations. Results are qualitatively the same as those in Table 6: coefficient estimates are generally less than one, but the forward-and-reverse intervals span one. The time-differenced coefficient estimates are less than levels estimates, consistent with time differencing aggravating measurement error (Griliches and Hausman, 1986).

We also tried addressing measurement error using instrumental variables (IV). Good instruments were not readily available, as there are few exogenous variables which are likely to be correlated with production techniques in the control region, but not with those in the state on which an observation is taken. Accordingly, we used the current and lagged ranks of $ln(c_{mnjt})$ as instruments for the variable. IV did not prove too helpful: the coefficient estimates are similar to their OLS counterparts in Table 6 while, consistent with weak instruments, standard errors generally increased. We also experimented with weighting all observations equally and with dropping industries like agriculture we thought most likely to have different product mixes across states. The results for these modifications are very similar to those that we report.

4d Discussion of Estimation Results

An important remaining issue is how one interprets our results in light of empirical evidence of persistent nominal regional wage differences in the United States (Coehlo and Ghali, 1971;

TX).

Johnson, 1983; Montgomery, 1992; Bernard and Jensen, 1999). Based on this literature, the prior of many researchers may be that we would easily reject FPE across U.S. states.

It is important to emphasize that *productivity-adjusted* FPE *is* consistent with nominal factor-price differences across states. For states i and j, equations (2) and (8) imply that $\mathbf{diag(\Pi^j)W^i=W^j}$, or that for labor type m, $w^j_m/w^i_m=\rho^j_m$. In other words, factor-specific, industry-neutral productivity differences across states allow nominal wage differences across states. The potential presence of such productivity differences accounts for why we look for evidence of FPE using data on state industry production techniques instead of direct data on state wages. An additional exercise would be to see whether estimated productivity differences across states could account for observed wage differences across states. This would involve combining our regional-integration perspective with standard regional hedonic wage regressions. This exercise could yield useful insights but is beyond the scope of this paper; we leave it for future work.

5 *Conclusion*

In this paper we analyze whether regional economic integration across U.S. states conditions local labor-market adjustment. We examine the mechanisms through which states absorb changes in labor supplies and whether industry production techniques are similar across states. There are two main findings. First, states absorb changes in employment primarily through changes in production techniques that are common across all states and through changes in the output of traded goods, with the former mechanism playing the larger role. In contrast, state-specific changes in production techniques, which are one indication of state-specific changes in relative factor prices, account for relatively little factor absorption. Second, industry production techniques are very similar across states, especially for neighboring states and states with similar relative labor supplies. Both sets of results are consistent with productivity-adjusted FPE across either all states or groupings of related states.

FPE implies that states experience similar relative-wage responses to factor-supply shocks specific to a single state, as long as the shock isn't so large as to move the state out of its cone of diversification. This could account for why existing studies find little impact of immigration on native wages across U.S. regions. The factor, trade, and technology flows across regions, which support FPE, may dampen region-specific wage adjustments.

In closing, we make three comments on areas for future research. First, our results are silent on the *national* implications of regional factor-supply shocks. We cannot use our approach to say whether immigration or other changes in state labor supplies may have altered wages in the United States as a whole. This clearly deserves greater attention. Second, in examining the mechanisms through which states absorb factor-supply changes we left in the background factor flows. Future work might try to estimate the relative contribution of interregional migration, trade, and technology flows to regional labor-market integration. Third, we have not analyzed regional variation in nominal wages or tried to account for the source of inter-state productivity differences. A natural extension of our work would be to compare interstate differences in industry production techniques with interstate differences in nominal wages.

Data Appendix

Output and Employment by Industry and State: We measure industry output at the state level as real value added in 1992 dollars. These data come from the United States Department of Commerce, Bureau of Economic Analysis (the raw data were obtained from http://www.bea.doc.gov/bea/regional/data.htm). We measure industry employment at the state level using total employment (all full and part-time workers) from the Regional Economic Information System of the Bureau of Economic Analysis (1969-1996 REIS CD ROM). For both output and employment, we use data for 1980 and 1990. The industries cover all civilian sectors of the economy. Data for 1980 were classified by the 1972 Standard Industrial Classification (SIC) code; data for 1990 were classified by the 1987 SIC code. We matched the 1990 data back to the 1972 SIC code, using the concordance from Wayne Gray which accompanies the National Bureau of Economic Research Manufacturing Productivity Data Base. The raw BEA data are available at the two-digit SIC level. In a few cases, concording data between years required us to aggregate several two-digit industry into a single sector (e.g., in our data the electrical machinery industry combines SIC industries 36 and 38). To concord BEA data to PUMS data (described below), we combined two-digit SIC industries into 40 sectors (listed in Table 3), which are a mix of one-digit and two-digit SIC industries, using the concordance given in, "The Relationship between the 1970 and 1980 Industry and Occupation Classification Systems," Technical Paper 59, Bureau of the Census, U.S. Department of Commerce.

State Labor Supplies by Education Category: We measure the total state labor force by four education categories: high-school dropouts, high-school graduates, those with some college, and college graduates. These data come from the 1980 and 1990 *5% Public Use Microsamples* (PUMS) of the *U.S. Census of Population and Housing*. An individual is counted as in the labor force if he or she is employed or unemployed but looking for work. We calculate state labor supplies by summing the population weights given in the 5% PUMS across all individuals that live in a given state, are part of the labor force, and belong to a given educational category.

Employment and Unit Labor Requirements by State, Industry, and Education Category: To calculate employment by state, industry, and education category, we combine data from the BEA and the PUMS. Beginning with the PUMS, we sum the earnings weights for all individuals who are employed (at work or with a job but not at work) in a given industry, work in a given state, and belong to a given educational category. We then use these totals to calculate the share of individuals in a given state and industry that belong to each education category. Multiplying these shares by total employment, as measured by the BEA, we obtain total employment by state, industry, and education category. To obtain unit labor requirements by state, industry, and education category, we simply take the ratio of employment by state, industry, and education category to value added by state and industry.

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Table 1a: U.S. State Labor Supplies, Levels in 1980 and 1990

State	Year	HSDO	HSG	SC	CG
United States	1980	25.0	34.8	22.5	17.7
	1990	18.1	29.9	29.6	22.4
Connecticut	1980	23.4	33.4	21.2	22.0
	1990	15.2	28.8	26.5	29.5
Massachusetts	1980	21.0	34.1	22.9	22.1
	1990	14.5	27.9	27.6	30.1
New Jersey	1980	24.0	35.6	19.5	20.9
	1990	16.6	30.6	24.8	28.0
New York	1980	23.6	33.1	22.0	21.2
	1990	17.3	28.4	27.3	27.0
Illinois	1980	25.1	34.4	22.5	18.0
	1990	16.9	29.0	30.4	23.8
Michigan	1980	23.4	37.7	23.3	15.6
	1990	15.9	31.4	33.3	19.5
Ohio	1980	24.2	41.0	19.5	15.2
	1990	16.6	36.5	27.7	19.2
Pennsylvania	1980	23.8	43.7	16.4	16.0
	1990	15.9	39.4	23.3	21.4
Florida	1980	25.9	34.1	24.0	16.1
	1990	20.3	29.3	30.6	19.8
Georgia	1980	33.1	32.3	18.9	15.7
	1990	21.8	31.5	26.0	20.7
North Carolina	1980	34.8	32.5	18.8	13.9
	1990	22.0	31.5	28.1	18.3
Texas	1980	29.4	29.2	23.6	17.8
	1990	21.8	26.0	30.5	21.7
California	1980	21.5	28.1	30.2	20.2
	1990	20.2	21.5	33.8	24.5
Washington	1980	17.9	34.4	28.2	19.6
	1990	13.1	26.4	36.3	24.2

Notes: Each cell reports the share of that state's total labor force (employed plus unemployed) accounted for by the factor in that cell. "HSDO" designates high-school dropouts; "HSG" designates high-school graduates; "SC" designates those with some college; and "CG" designates college graduates and beyond.

Table 1b: U.S. State Labor Supplies, Changes Over the 1980s

State	HSDO	HSG	SC	CG
United States	-6.9	-4.8	7.1	4.7
Connecticut	-8.2	-4.6	5.3	7.5
Massachusetts	-6.5	-6.2	4.7	8.0
New Jersey	-7.4	-5.0	5.4	7.0
New York	-6.4	-4.8	5.3	5.8
Illinois	-8.3	-5.5	7.9	5.8
Michigan	-7.6	-6.3	10.0	3.9
Ohio	-7.6	-4.5	8.2	4.0
Pennsylvania	-7.9	-4.3	7.0	5.3
Florida	-5.6	-4.8	6.7	3.8
Georgia	-11.3	-0.8	7.1	5.0
North Carolina	-12.8	-1.0	9.3	4.4
Texas	-7.6	-3.3	7.0	3.9
California	-1.3	-6.6	3.6	4.3
Washington	-4.8	-8.0	8.2	4.6

Notes: Each cell reports the level change from 1980 to 1990 in the share of that state's total labor force (employed plus unemployed) accounted for by the factor in that cell. "HSDO" designates high-school dropouts; "HSG" designates high-school graduates; "SC" designates those with some college; and "CG" designates college graduates and beyond.

Table 2: U.S. Immigrant Shares of Education Groups, 1980 and 1990

State	Period	HSDO	HSG	SC	CG
United States	1980	10.1	4.6	5.6	7.2
	1990	18.6	6.1	6.8	9.3
Connecticut	1980	15.3	7.0	6.3	7.1
	1990	18.2	8.2	7.8	8.0
Massachusetts	1980	17.5	6.2	4.8	6.3
	1990	23.1	8.2	7.1	8.6
New Jersey	1980	17.4	8.6	8.9	11.2
	1990	25.2	11.2	11.5	15.1
New York	1980	23.4	12.0	11.9	13.0
	1990	32.8	15.5	14.6	15.9
Illinois	1980	13.7	5.0	6.1	9.3
	1990	22.5	7.2	6.8	9.7
Michigan	1980	5.2	3.0	3.6	6.1
	1990	5.3	2.5	2.8	6.6
Ohio	1980	3.1	1.8	2.5	4.4
	1990	2.9	1.5	2.0	4.8
Pennsylvania	1980	4.0	1.9	2.7	4.6
	1990	4.5	2.0	5.6	5.0
Georgia	1980	1.1	1.7	2.6	3.1
	1990	3.8	2.3	3.1	5.2
North Carolina	1980	0.9	1.3	1.7	2.7
	1990	2.0	1.3	1.9	3.8
Florida	1980	15.4	9.3	10.9	11.4
	1990	25.4	11.9	12.4	13.4
Texas	1980	11.9	4.0	4.2	5.2
	1990	25.7	6.1	5.7	7.9
California	1980	33.0	11.4	11.0	14.0
	1990	54.5	19.3	16.0	19.4
Washington	1980	8.6	4.6	5.1	6.7
	1990	15.1	5.4	5.4	7.6

Notes: Each cell reports the share of that state's total labor force (employed plus unemployed) in that cell's education group accounted for by immigrants. "HSDO" designates high-school dropouts; "HSG" designates high-school graduates; "SC" designates those with some college; and "CG" designates college graduates and beyond.

Table 3: U.S. Industry Factor Intensity, 1980 and 1990

Industry Name	HSDO/CG 1980	HSDO/CG 1990	HSG/CG 1980	HSG/CG 1990	SC/CG 1980	SC/CG 1990
Agriculture	5.69	4.66	4.56	3.82	1.82	2.15
Agr. Services	2.11	1.90	1.41	1.49	1.20	1.58
Mining	1.62	0.91	2.21	1.76	1.25	1.31
Construction	3.86	2.47	4.68	3.68	2.29	2.52
Food Products	3.71	2.57	3.59	3.12	1.52	2.02
Tobacco	3.29	0.92	3.71	2.62	1.86	1.56
Textiles	9.49	6.41	7.20	8.05	1.76	3.41
Apparel	12.29	5.39	9.29	4.47	2.43	2.12
Lumber	8.69	4.79	8.06	6.28	2.84	3.49
Furniture	5.72	4.41	4.79	4.38	1.74	2.94
Paper	2.72	1.81	3.64	4.13	1.36	1.82
Printing	1.05	0.55	2.13	1.32	1.34	1.21
Chemicals	0.82	0.41	1.67	1.15	0.91	1.01
Petro. Refining	0.71	0.28	1.65	1.20	0.96	1.49
Rubber	2.59	2.73	4.05	4.40	1.28	2.85
Leather	14.25	4.04	14.25	5.93	2.63	2.03
Stone/Clay/Glass	4.81	1.75	6.74	3.17	2.63	1.94
Primary Metals	3.77	2.03	5.05	3.78	1.90	2.20
Metal Products	3.83	2.13	5.36	3.99	2.34	2.60
Machinery	1.76	0.80	3.43	1.74	1.78	1.63
Elec. Machinery	1.50	0.62	2.54	1.23	1.48	1.24
Tranport Equip.	1.71	0.73	3.14	1.70	1.60	1.61
Misc. Manuf.	3.12	1.58	3.91	2.02	1.80	1.68
Transport/Utilities	1.79	0.82	3.78	2.21	2.28	2.11
Wholesale Trade	1.47	0.65	2.57	1.49	1.73	1.45
Retail Trade	3.88	2.30	4.39	3.16	2.90	2.82
FIRE	0.41	0.22	1.71	1.02	1.37	1.37
Investment Finance	0.13	0.07	0.44	0.30	0.67	0.57
Lodging Services	4.67	2.30	4.18	3.07	2.61	2.74
Personal Services	5.70	1.70	8.02	3.30	4.32	2.69
Business Services	0.39	0.27	0.75	0.53	0.80	0.83
Auto Services	7.11	6.96	7.76	8.70	3.24	6.03
Repair Services	4.53	3.01	6.12	4.86	3.28	3.62
Entertainment	1.51	1.08	1.57	1.26	1.47	1.59
Health Services	0.69	0.33	1.18	0.77	1.20	1.22
Legal Services	0.04	0.05	0.37	0.24	0.43	0.43
Educ. Services	0.18	0.11	0.30	0.26	0.34	0.35
Social Services	0.53	0.37	0.74	0.65	0.77	0.82
Household Services	22.80	9.26	8.30	5.58	3.90	3.31
Government	0.55	0.23	1.49	0.96	1.18	1.37

Notes: Each cell reports the ratio of national employment of that cell's two factors for the industry and year of that cell. "HSDO" designates high-school dropouts; "HSG" designates high-school graduates; "SC" designates those with some college; and "CG" designates college graduates and beyond. Industry categories combine one- and two-digit SIC industries.

Table 4: Employment Decompositions

State	Factor	$\Delta \mathbf{V}$	$\overline{\mathbf{C}}\Delta \mathbf{X}$	$\Delta \mathbf{C}\overline{\mathbf{X}}$	$\Delta \mathbf{C}_G \overline{\mathbf{X}}$	$\Delta \mathbf{C}_I \overline{\mathbf{X}}$
		(1)	(2)	(3)	(4)	(5)
CT	HSDO	-8.27	4.38	-12.65	-9.76	-2.90
	HSG	-5.88	7.74	-13.62	-9.51	-4.10
	SC	5.25	6.71	-1.46	4.76	-6.22
	CG	8.90	6.89	2.01	3.13	-1.12
MA	HSDO	-6.90	3.32	-10.22	-8.31	-1.91
	HSG	-7.35	7.09	-14.43	-9.00	-5.43
	SC	4.78	6.76	-1.97	4.98	-6.95
	CG	9.46	7.62	1.84	3.36	-1.51
NJ	HSDO	-7.41	3.62	-11.03	-9.78	-1.24
	HSG	-5.95	6.98	-12.93	-9.82	-3.11
	SC	5.84	5.33	0.51	4.26	-3.75
	CG	7.51	5.81	1.70	2.08	-0.38
NY	HSDO	-6.01	3.11	-9.12	-8.51	-0.61
	HSG	-5.81	5.02	-10.83	-8.30	-2.53
	SC	5.72	4.36	1.37	4.84	-3.48
	CG	6.09	4.89	1.20	3.37	-2.16
IL	HSDO	-7.52	1.51	-9.03	-9.02	-0.01
	HSG	-6.40	2.14	-8.55	-8.80	0.26
	SC	8.05	2.06	6.00	4.39	1.61
	CG	5.88	2.28	3.60	2.48	1.12
MI	HSDO	-6.82	0.76	-7.58	-8.03	0.45
	HSG	-7.79	0.89	-8.68	-9.32	0.64
	SC	10.26	0.27	9.99	5.26	4.73
	CG	4.35	0.68	3.68	2.42	1.26
OH	HSDO	-7.15	1.78	-8.93	-8.87	-0.07
	HSG	-5.78	3.15	-8.93	-10.83	1.89
	SC	8.73	2.07	6.65	4.18	2.48
	CG	4.21	1.87	2.34	1.96	0.38
PA	HSDO	-7.66	1.93	-9.59	-8.82	-0.77
	HSG	-5.54	3.69	-9.22	-10.94	1.72
	SC	7.34	2.46	4.88	3.70	1.19
	CG	5.86	2.76	3.10	2.49	0.61

Table 4 (continued): Employment Decompositions

State	Factor	$\Delta\mathbf{V}$	$\overline{\mathbf{C}}\Delta\mathbf{X}$	$\Delta\mathbf{C}\overline{\mathbf{X}}$	$\Delta\mathbf{C}_G\overline{\mathbf{X}}$	$\Delta\mathbf{C}_I\overline{\mathbf{X}}$
		(1)	(2)	(3)	(4)	(5)
FL	HSDO	-5.18	2.47	-7.65	-9.13	1.48
	HSG	-5.74	3.44	-9.18	-7.24	-1.93
	SC	7.23	3.18	4.05	5.89	-1.84
	CG	3.68	2.06	1.62	2.93	-1.31
GA	HSDO	-11.11	4.13	-15.24	-13.41	-1.83
	HSG	-1.16	4.72	-5.89	-8.03	2.14
	SC	6.96	3.94	3.02	4.30	-1.27
	CG	5.32	3.25	2.06	2.25	-0.19
NC	HSDO	-12.82	4.46	-17.28	-14.75	-2.53
	HSG	-1.56	5.39	-6.95	-8.57	1.62
	SC	9.58	4.15	5.43	4.54	0.89
	CG	4.80	2.77	2.03	1.72	0.31
TX	HSDO	-8.39	1.32	-9.71	-11.40	1.70
	HSG	-3.55	1.59	-5.15	-7.37	2.22
	SC	7.64	2.06	5.59	4.15	1.43
	CG	4.30	2.29	2.00	1.61	0.39
CA	HSDO	-0.99	2.88	-3.88	-8.17	4.29
	HSG	-6.94	3.30	-10.24	-5.86	-4.38
	SC	3.30	4.29	-0.99	7.07	-8.06
	CG	4.63	3.37	1.26	3.40	-2.14
WA	HSDO	-4.30	0.85	-5.14	-6.31	1.17
	HSG	-8.59	0.91	-9.49	-7.44	-2.06
	SC	7.96	0.74	7.21	6.28	0.93
	CG	4.93	0.88	4.04	3.12	0.93

Notes: The decomposition for each state in this table follows equations (3) and (5) in the text. Column (1) shows the change in a given factor's share of total state employment; column (2) shows the contribution of changes in output to changes in factor employment; and column (3) shows the contribution of changes in production techniques to changes in factor employment. Columns (4) and (5) further decompose column (3) into the contributions of generalized changes in production techniques common across all states (column (4)) and changes in production techniques that are idiosyncratic to a given state (column (5)).

Table 5: Extended Employment Decompositions

State	Factor	ΔV^E	$\bar{C}\Delta X^T$	$\Delta C_I \bar{X}^T$	Ratio
		(1)	(2)	(3)	(4)
CT	HSDO	-0.08	0.60	-0.67	-7.50
	HSG	0.53	1.80	-1.27	3.40
	SC	0.24	2.12	-1.88	8.83
	CG	2.69	3.16	-0.47	1.17
MA	HSDO	-0.30	0.25	-0.56	-0.83
	HSG	0.55	1.88	-1.32	3.42
	SC	0.76	2.43	-1.67	3.20
	CG	3.32	4.03	-0.71	1.21
NJ	HSDO	0.17	0.38	-0.21	2.24
	HSG	1.24	1.66	-0.42	1.34
	SC	0.88	1.81	-0.93	2.06
	CG	3.01	3.32	-0.30	1.10
NY	HSDO	0.23	0.48	-0.26	2.09
	HSG	0.62	1.25	-0.63	2.02
	SC	0.45	1.38	-0.94	3.07
	CG	1.61	2.31	-0.70	1.43
IL	HSDO	0.54	0.35	0.19	0.65
	HSG	1.18	0.73	0.45	0.62
	SC	1.53	1.13	0.39	0.74
	CG	2.21	1.66	0.54	0.75
MI	HSDO	0.44	0.53	-0.10	1.20
	HSG	1.56	1.48	0.07	0.95
	SC	2.52	1.46	1.05	0.58
	CG	1.61	1.45	0.16	0.90
OH	HSDO	0.49	0.86	-0.37	1.76
	HSG	2.78	2.04	0.75	0.73
	SC	1.92	1.50	0.41	0.78
	CG	1.38	1.55	-0.18	1.12
PA	HSDO	-0.14	0.23	-0.37	-1.64
	HSG	1.47	0.70	0.76	0.48
	SC	1.29	0.94	0.36	0.73
	CG	1.71	1.45	0.26	0.85

Table 5 (continued): Employment Decompositions

State	Factor	$\Delta \mathbf{V}^E$	$\overline{\mathbf{C}}\Delta\mathbf{X}^T$	$\Delta\mathbf{C}_I\overline{\mathbf{X}}^T$	Ratio
		(1)	(2)	(3)	(4)
FL	HSDO	1.12	0.65	0.46	0.58
	HSG	1.36	1.08	0.28	0.79
	SC	1.23	1.21	0.02	0.98
	CG	0.87	1.08	-0.21	1.24
GA	HSDO	1.10	1.95	-0.85	1.77
	HSG	2.80	2.13	0.67	0.76
	SC	1.02	1.96	-0.94	1.92
	CG	1.89	2.01	-0.12	1.06
NC	HSDO	0.93	2.26	-1.33	2.43
	HSG	3.07	2.86	0.21	0.93
	SC	1.92	2.15	-0.23	1.12
	CG	1.70	1.83	-0.13	1.08
TX	HSDO	1.67	1.46	0.21	0.87
	HSG	1.95	1.72	0.22	0.88
	SC	1.53	1.92	-0.39	1.25
	CG	1.96	1.92	0.05	0.98
CA	HSDO	2.45	1.00	1.45	0.41
	HSG	0.40	1.41	-1.02	3.53
	SC	0.29	2.19	-1.91	7.55
	CG	1.83	2.31	-0.48	1.26
WA	HSDO	1.16	0.36	0.80	0.31
	HSG	0.85	1.15	-0.31	1.35
	SC	1.66	1.54	0.11	0.93
	CG	1.97	1.61	0.35	0.82

Notes: The decomposition for each state in this table follows equation (6') in the text. Column (1) shows the change in "effective" state employment of a given factor facing the traded sector (as defined in the text); column (2) shows the contribution of changes in traded output to changes in factor employment; and column (3) shows the contribution of state-specific changes in production techniques in the traded sector to changes in factor employment. Column (4) reports the ratio of column (2) to column (1): this is the share of changes in effective labor supply facing traded sectors accounted for by changes in output in traded sectors.

Table 6: Regressions Testing For Productivity-Adjusted FPE

State Groupings	Information Description	Forward Regression	Reverse Regression	Asymptotic Range
All	FE Coefficient Estimate	0.940	0.943	0.94-1.06
States	Standard Error	(0.015)	(0.009)	
	No. Obs.	28,134	28,134	
	R-squared	0.89	0.89	
	F Stat, Fixed Effects	32.38	32.10	
	EIV Coefficient Estimate	0.971	0.976	0.97-1.03
	Standard Error	(0.002)	(0.002)	
Neighboring	FE Coefficient Estimate	0.959	0.956	0.96-1.05
States	Standard Error	(0.013)	(0.011)	
	No. Obs.	4,938	4,938	
	R-squared	0.92	0.92	
	F Stat, Fixed Effects	20.34	24.22	
	EIV Coefficient Estimate	0.987	0.984	0.99-1.02
	Standard Error	(0.004)	(0.004)	
Similarly Endowed	FE Coefficient Estimate	0.972	0.945	0.97-1.06
States	Standard Error	(0.010)	(0.008)	
	No. Obs.	6,168	6,168	
	R-squared	0.92	0.92	
	F Stat, Fixed Effects	26.32	24.86	
	EIV Coefficient Estimate	0.996	0.969	0.99-1.03
	Standard Error	(0.003)	(0.003)	

Notes:

The table reports forward regressions of log production techniques for high-productivity states on log production techniques for low-productivity states. It also reports reverse regressions in which the dependent and independent variables are interchanged. Data are pooled across unique state pairs (91), industries (40), education categories (4), and years (2). The full sample includes all state pairs; the sample of neighboring states includes contiguous states; and the sample of similarly endowed states includes the 20 state pairs with the most-similar relative labor supplies.

All regressions include dummy variables for state pair, education category, and year combinations (of which there are 728 in the full sample) and are weighted by employment in the state industry. The reported standard errors are corrected for covariation in the errors across observations that have the same state, industry, and year. Errors-in-variables (EIV) coefficient estimates adjust OLS estimates by the ratio of the variance of the "true" regressor (i.e., measured without error) to the variance of the observed regressor, where this variance ratio is calculated using sample data and data on production techniques for the United States as a whole.

Figure 1

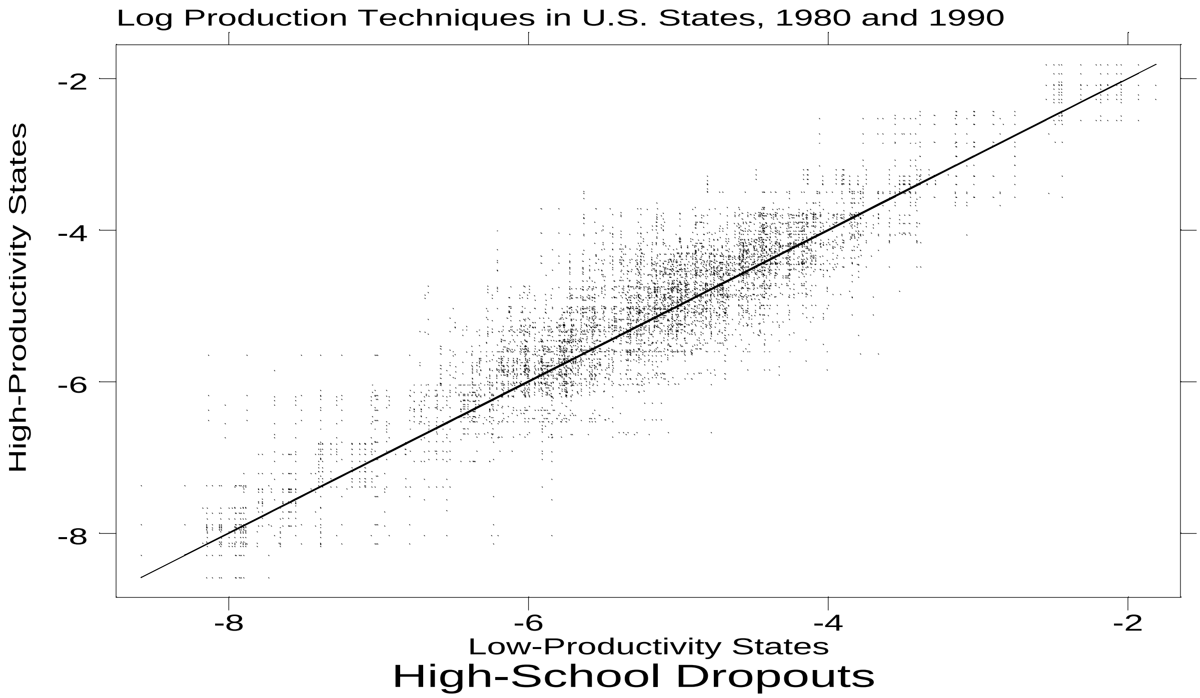
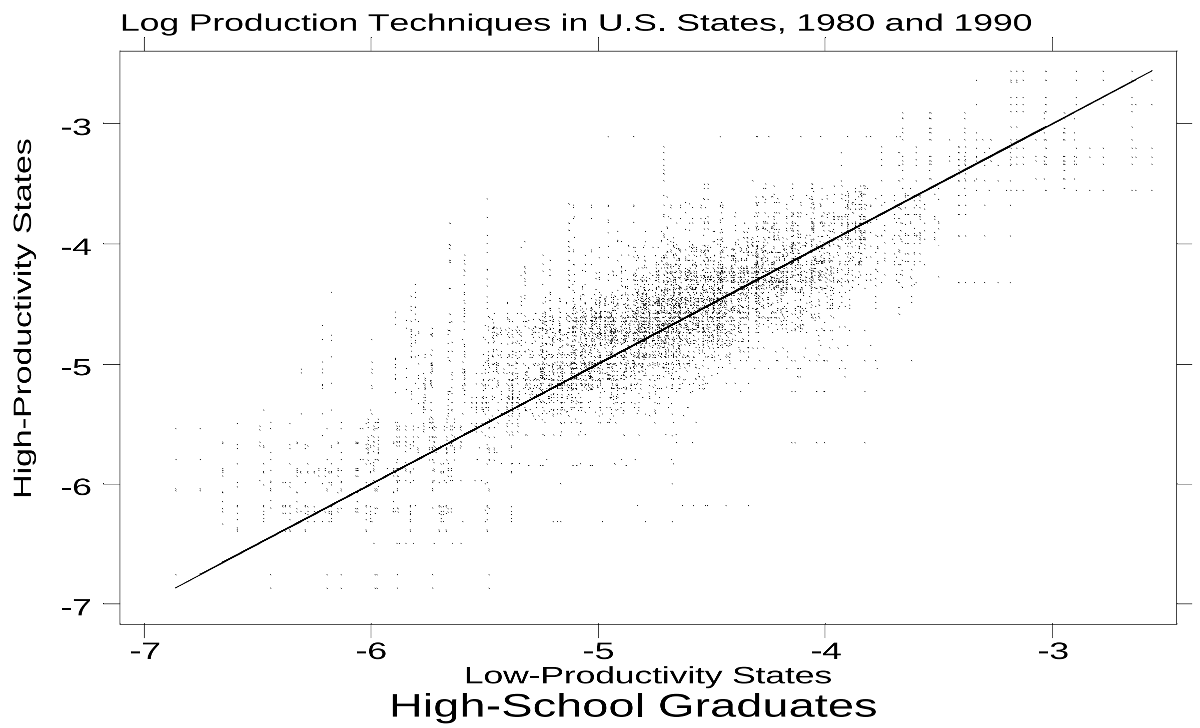


Figure 2



Notes: Each figure plots the industry production techniques for every observation in our full sample, where every observation contains two production techniques for a state pair in some industry and year. For each observation, production techniques for the high-productivity (low-productivity) state are on the horizontal (vertical) axis. In each figure the line is the 45-degree line passing through the origin.

Figure 3

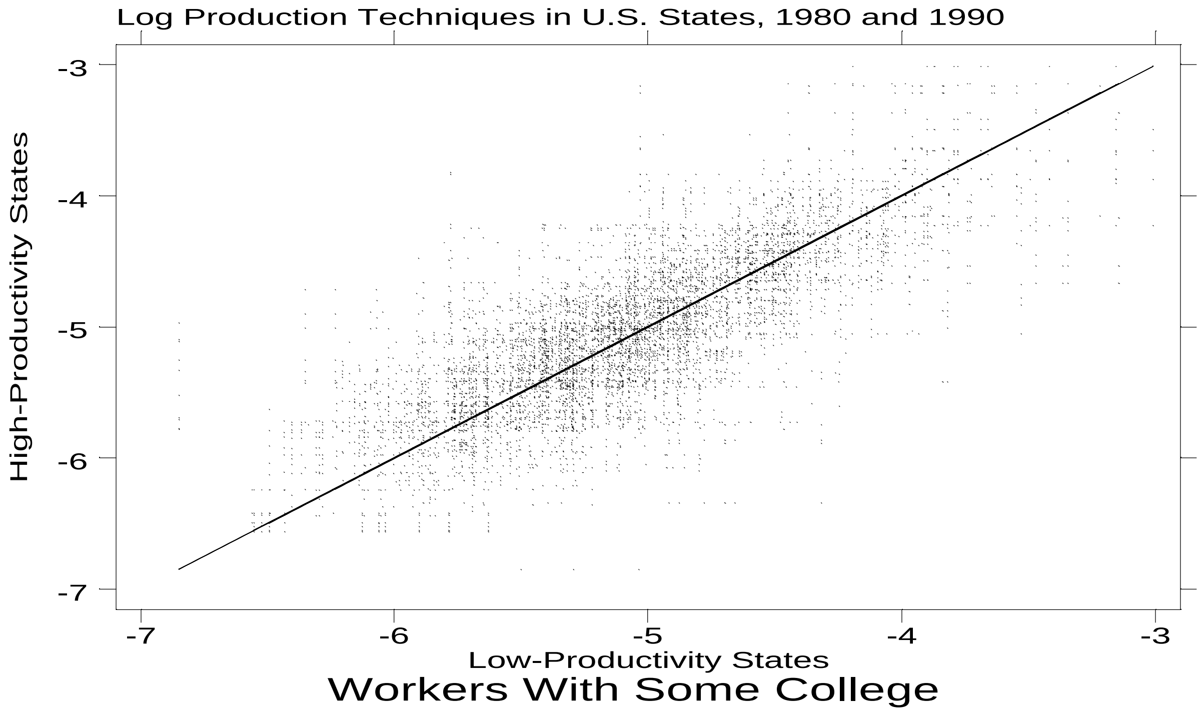
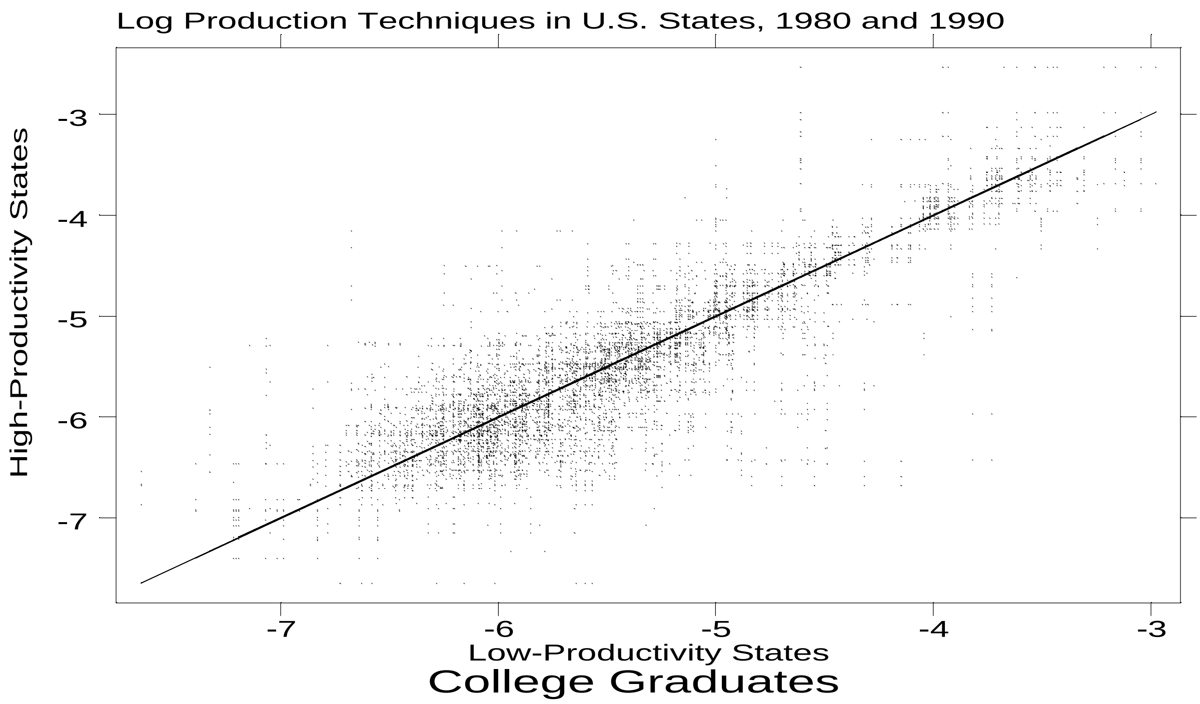


Figure 4



Notes: Each figure plots the industry production techniques for every observation in our full sample, where every observation contains two production techniques for a state pair in some industry and year. For each observation, production techniques for the high-productivity (low-productivity) state are on the horizontal (vertical) axis. In each figure the line is the 45-degree line passing through the origin.