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Econometric modeling of technical change

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ABSTRACT

The purpose of this paper is to present a new approach to econometric modeling of substitution and technical change. Substitution is determined by observable variables, such as prices of output and inputs and shares of inputs in the value of output. Our principal innovation is to represent the rate and biases of technical change by unobservable or latent variables. This representation is considerably more flexible than the constant time trends employed in the previous literature. An added advantage of the new representation is that the latent variables can be projected into the future, so that the rate and bias of technical change can be incorporated into econometric projections.

1. Introduction

The index number approach to productivity measurement has been the work horse of empirical research on the rate of technical change for half a century.[1] This salient concept has generated a vast literature on productivity measurement, recently surveyed by Jorgenson (2005). The key idea is to treat the level of technology as an unobservable or latent variable in a neo-classical production function. Under appropriate assumptions the rate of technical change is the residual between the growth rate of output and the growth rate of inputs. Using index numbers for these growth rates, the level of technology can be recovered without estimating the unknown parameters of the production function.

Recently, attention has shifted to the biases of technical change.[2] This shift is motivated by a wide range of applications, such as changes in the distribution of income, emphasized in the survey by Acemoglu (2002b), and determinants of energy conservation, highlighted in the survey by Jaffe et al. (2003). However, biases of technical change are not directly observable. In this paper we present a new econometric approach to measuring both the rate and the biases of technical change. Our key contribution is to represent the rate and biases by unobservable or latent variables.

The standard econometric approach to modeling the rate and biases of technical change was introduced by Binswanger (1974a,b) and described in the surveys by Binswanger and Ruttan (1978), Jorgenson (1986), and Ruttan (2001). Binswanger's approach is to represent price effects by the translog function of the input prices introduced by Christensen et al. (1973). He represents the rate and biases of technical change by constant time trends and fits the unknown parameters by econometric methods. This approach to modeling technical change is widely employed, for example, by Jorgenson and Fraumeni (1983), Jorgenson et al. (1987, Ch. 7), and, more recently, by Feng and Serletis (2008).

Binswanger's approach exploits the fact that price effects depend on observable variables, such as the prices of output and inputs and the shares of inputs in the value of output. The key to modeling these effects is to choose a flexible functional form that admits a variety of substitution patterns.[3] Our model of substitution, like Binswanger's, is based on the translog price function, giving the price of output as a function of the prices of inputs. The measures of substitution are unknown parameters that can be estimated from observable data on prices and value shares.

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1 For details see Diewert and Morrison (1986).

2 Acemoglu (2002a) presents models of biased technical change and reviews applications to macroeconomics, development economics, labor economics and international trade. Acemoglu (2007) surveys more recent developments in the literature and presents detailed results on relative and absolute biases of technical change.

3 Additional details are given by Jorgenson (1986). Barnett and Serletis (2008) provide a detailed survey of flexible functional forms used in modeling consumer demand, including parametric, semi-parametric, and non-parametric approaches.

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Our novel contribution is to replace the constant time trends that describe the rate and biases of technical change in Binswanger's model by latent or unobservable variables. An important advantage of the translog price function in this setting is that the resulting model is linear in the latent variables. We recover these variables by applying the Kalman (1960, 1963) filter, a standard statistical technique in macroeconomics and finance, as well as many areas of engineering.

An important feature of the Kalman filter is that latent variables representing the rate and biases of technical change can be recovered for the sample period. A second and decisive advantage of the Kalman filter is that the latent variables can be projected into the future, so that the rate and biases of technical change can be incorporated into econometric projections.[4] The rate of technical change captures trends in productivity, while biases of technical change describe changes in the structure of production.

We implement our new approach for modeling substitution and technical change for the post-war US economy, 1960–2005. This period includes substantial changes in the prices of fossil fuels and the wage rate. Energy crisis periods with dramatic increases in energy prices alternating with periods of energy price collapse are particularly valuable for our purposes. By modeling substitution and technical change econometrically, we are able to decompose changes in the price of output and the input value shares between price effects and the effects of technical change. Empirically, these two sets of effects are comparable in magnitude.

We also decompose the rate of technical change between an autonomous part, unaffected by price changes, and an induced part, responsive to price changes. The rate of induced technical change links the rate and biases of technical change through the correlation between the input prices and the latent variables representing biases. Efforts to economize on an input that has become more expensive or to increase the utilization of an input that has become cheaper will affect the rate of technical change. Although modest in size, rates of induced technical change are generally opposite in sign to rates of autonomous technical change.

In Section 2 we present our econometric model of substitution and technical change. We augment the translog price function by introducing latent variables that represent the rate and biases of technical change. In Section 3 we apply an extension of the Kalman filter to estimate the unknown parameters of the model and generate the latent variables. In Section 4 we extend the standard framework for the Kalman filter to include endogenous prices by introducing instrumental variables. We propose a two-step procedure based on two-step Maximum Likelihood Estimation and derive two diagnostic tests for the validity of the instruments.

In Section 5 we present our empirical results. We find that substitution and technical change are both important in representing changes in patterns of production. In particular, biases of technical change are quantitatively significant for all inputs. The rates of technical change decompose neatly between a negative rate of induced technical change and a positive rate of autonomous technical change, which generally predominates. This implies that biased technical change, a change in technology directed to a particular input, reduces the rate of technical change. Section 6 concludes.

[4] A detailed projection of US economic growth, incorporating projections of the rate and biases of technical change based on the Kalman filter, is presented by Jorgenson et al. (2008). The intertemporal general equilibrium model underlying these projections also incorporates the dynamics of capital accumulation and asset pricing, so that we do not include these dynamics in the specification of our models of production.

2. Econometric model

In our data set, production is disaggregated into 35 separate commodities produced by one or more of the 35 industries making up the US economy and listed in Table 1. The industries generally match two-digit sectors in the North American Industry Classification System (NAICS). Industries produce a primary product and may produce one or more secondary products. Each industry is modeled by a system of equations that represents possible substitutions among the inputs of capital, labor, energy and materials and the rate and biases of technical change.

Our focus on the US economy is motivated by the availability of a new data set constructed by Jorgenson et al. (2007a). On June 30, 2008, the European Union released similar data sets for the 25 member states prior to the enlargement to include Bulgaria and Romania on January 1, 2007.[5] The Research Institute for Economy, Trade and Industry in Japan has developed data sets of this type for mainland China, Japan, Korea, and Taiwan.[6] Our new methods for modeling substitution and technical change can be applied to these economies and others with similar data sets.

The production function expresses output as a function of capital, labor, m intermediate inputs, non-competing imports (X_N) and technology (t); for industry j:

$$Q_j = f(K_j, L_j, X_{1,j}, X_{2,j}, \ldots, X_{m,j}, X_{Nj}, t), \quad j = 1, 2, \ldots, 35. \tag{1}$$

At the first stage the value of each industry's output is allocated to four input groups—capital, labor, energy, and non-energy materials:

$$Q_j = f(K_j, L_j, E_j, M_j, t). \tag{2}$$

The second stage allocates the energy and non-energy material groups to the individual intermediate commodities. This stage is not discussed further in this paper.[7]

Assuming constant returns to scale and calculating the cost of capital as the residual that exhausts the value of output, the value of output is equal to the value of the four inputs:

$$P_{Qjt}Q_{jt} = P_{Kjt}K_{jt} + P_{Ljt}L_{jt} + P_{Ejt}E_{jt} + P_{Mjt}M_{jt}. \tag{3}$$

In representing substitution and technical change, it is more convenient to work with the dual price function instead of the production function in (2).[8]The price function expresses the unit output price as a function of all the input prices and technology, $P_{Qj} = p(P_{Kj}, P_{Lj}, P_{Ej}, P_{Mj}, t)$.

Dropping the industry subscript j for simplicity, we assume that the price function has the *translog* form:

$$\ln P_{Qt} = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln P_{it} + \frac{1}{2}\sum_{i,k} \beta_{ik} \ln P_{it} \ln P_{kt} + \sum_{i=1}^{n} \ln P_{it} f_{it} + f_{pt} \quad i, k = \{K, L, E, M\}. \tag{4}$$

We refer to the translog price function (4) as the *state-space model of producer behavior*. The parameters α_0, α_i and β_{ik} are estimated separately for each industry. The latent variables f_{it} and f_{pt} are also estimated separately for each industry, using the Kalman filter

[5] See van Ark et al. (2008).

[6] See Jorgenson et al. (2007b).

[7] In the data set constructed by Jorgenson et al. (2007a) the energy and non-energy aggregates in (2) are assumed to be homothetically separable within the production function (1). More details are given by Jorgenson et al. (2005).

[8] The dual price function is equivalent to the primal production function in that all the information expressed in one is recoverable from the other. Further details are given by Jorgenson (2000).

Table 1
List of sectors.

Sector number	Sector name
1	Agriculture
2	Metal mining
3	Coal mining
4	Petroleum and gas
5	Nonmetallic mining
6	Construction
7	Food products
8	Tobacco products
9	Textile mill products
10	Apparel and textiles
11	Lumber and wood
12	Furniture and fixtures
13	Paper products
14	Printing and publishing
15	Chemical products
16	Petroleum refining
17	Rubber and plastic
18	Leather products
19	Stone, clay, and glass
20	Primary metals
21	Fabricated metals
22	Industrial machinery and equipment
23	Electronic and electric equipment
24	Motor vehicles
25	Other transportation equipment
26	Instruments
27	Miscellaneous manufacturing
28	Transport and warehouse
29	Communications
30	Electric utilities
31	Gas utilities
32	Trade
33	Finance, insurance, and real estate
34	Services
35	Government enterprises

described in Section 3. Changes in the latent variables f_{it} represent biases of technical change and the latent variable f_{pt} represents the level of technology.

An important advantage of the translog price function in this application is that it generates input share equations that are linear in the latent variables representing the biases of technical change. Differentiation of the price function (4) with respect to the log of input prices yields the input share equations. For example, the demand for capital is derived from the capital share equation:

$$v_{Kt} = \frac{P_K K}{P_Q Q} = \alpha_K + \sum_k \beta_{Kk} \ln P_{kt} + f_{Kt}. \tag{5}$$

The share of capital is a linear function of the logarithms of the input prices and a latent variable corresponding to the bias of technical change.

The biases of technical change are the changes in the shares of inputs, holding the input prices constant, for example:

$$\Delta v_{Kt} = f_{Kt} - f_{K,t-1}. \tag{6}$$

The biases capture patterns of increasing or decreasing input use over time after accounting for price changes. If the latent variable f_{Kt} in Eq. (5) is increasing with time, the bias of technical change is "capital-using". For a given set of input prices, the share of capital is higher as a consequence of the change in technology. Alternatively, if f_{Kt} is decreasing, the bias of technical change is "capital-saving". It is important to emphasize that technical change may be capital-using at one point of time and capital-saving at another. This would be ruled out by the constant time trends used in Binswanger's approach. There is a separate bias for each of the productive inputs—capital, labor, energy, and materials.

The rate of technical change between t and $t-1$ is the negative of the rate of change in the price of output, holding the input prices constant:

$$\Delta T_t = -\sum_{i=1}^{n} \ln P_{it}(f_{it} - f_{i,t-1}) - (f_{pt} - f_{p,t-1}). \tag{7}$$

As technology progresses for a given set of input prices, the price of output falls. The first term in the rate of technical change (7) depends on the prices and the biases of technical change. We refer to this as the rate of *induced* technical change. If, for example, the price of capital input falls and the bias of technical change (6), corresponding to a change in the latent variable f_{Kt}, is capital-using, the rate of technical change in (7) will increase. However, if the bias of technical change is capital-saving, a decrease in the price for capital will retard the rate of productivity growth. The second term in (7) depends only on changes in the level of technology f_{pt}, so that we refer to this as the rate of *autonomous* technical change.

The rate of technical change (7) is the sum of induced and autonomous rates of technical change. Ordinarily, the autonomous rate of technical change would be positive, while the induced rate of technical change could be positive or negative. The rate of induced technical change is simply the negative of the covariance between the logarithms of the input prices and the biases of technical change. If lower input prices are correlated with higher biases of technical change, then the rate of induced technical change is positive.

The parameters β_{ik} capture the price responsiveness of demands for inputs for a given state of technology. These parameters are called *share elasticities* and represent the degree of substitutability among the inputs. For example, a lower price of capital leads to greater demand for capital input. This may lead to a higher or lower share of capital input, depending on the substitutability of other inputs for capital; this substitutability is captured by the share elasticity for capital input. Share elasticities may be positive or negative, so that the share of capital may increase or decrease with the price of capital input. When all share elasticities β_{ik} are zero, the cost function reduces to the Cobb–Douglas or linear logarithmic form and the shares are independent of input prices.

In estimating the unknown share elasticities, restrictions derived from production theory must be imposed on the translog price function (4). In more compact vector notation the price function and input share equations can be written as

$$\ln P_{Qt} = \alpha_0 + \boldsymbol{\alpha}' \ln \mathbf{p}_t + \frac{1}{2} \ln \mathbf{p}_t' \mathbf{B} \ln \mathbf{p}_t + \ln \mathbf{p}_t' \mathbf{f}_t + f_{pt} + \varepsilon_t^p \tag{4'}$$

$$\mathbf{v}_t = \boldsymbol{\alpha} + \mathbf{B} \ln \mathbf{p}_t + \mathbf{f}_t + \boldsymbol{\varepsilon}_t^v \tag{5'}$$

where $\mathbf{p} = (P_K, P_L, P_E, P_M)'$, $\mathbf{v} = (v_K, v_L, v_E, v_M)'$, $\mathbf{f}_t = (f_{Kt}, f_{Lt}, f_{Et}, f_{Mt})'$ and $\mathbf{B} = [\beta_{ik}]$. We have added disturbance terms ε_t^p and $\boldsymbol{\varepsilon}_t^v$, random variables with mean zero, to represent shocks to producer behavior for a given state of technology.

Homogeneity restrictions on the price function imply that doubling of all input prices doubles the output price, so that

$$\alpha_K + \alpha_L + \alpha_E + \alpha_M = 1. \qquad \sum_i \beta_{ik} = 0 \quad \text{for each } k. \tag{8}$$

In addition, the matrix of share elasticities must be symmetric, so that

$$\beta_{ik} = \beta_{ki}. \tag{9}$$

Finally, the price function must be "locally concave" when evaluated at the prices observed in the sample period; note that this does not imply that the cost function is "globally concave" at all possible prices. The concavity condition implies that

$$\mathbf{B} + \mathbf{v}_t \mathbf{v}_t' - \mathbf{V}_t, \tag{10}$$

must be non-positive definite at each t in the sample period,[9] where B is the matrix of parameters in (4′) and $\mathbf{V}_t$ is a diagonal matrix with the shares along the diagonal. These restrictions on the parameter estimates are easily implemented by means of standard optimization code.[10]

Since the shares for all four inputs sum to unity, the latent variables representing biases of technical change f_{it} must sum to zero. Similarly, the shocks to producer behavior for a given state of technology $\boldsymbol{\varepsilon}_t^v$ sum to zero. We solve out these constraints on the shocks, as well as the homogeneity constraints (8), by expressing the model (4′) and (5′) in terms of relative prices and dropping one of the Eq. (5′) for the shares and one of the latent variables representing biases of technical change.

We assume that the latent variables corresponding to biases of technical change f_{it} are stationary since the value shares $\mathbf{v}_t$ are non-negative and sum to unity. We assume, further, that the level of technology is non-stationary but the first difference, $\Delta f_{pt} = f_{pt} - f_{pt-1}$, is stationary, so that technology evolves in accord with a stochastic trend or unit root. To implement a model of production based on the price function (4), we express the technology state variables as a vector auto-regression (VAR).

Let $\mathbf{F}_t = (1, f_{kt}, f_{lt}, f_{et}, \Delta f_{pt})'$ denote the vector of stationary state variables. The *transition equation* is

$$\mathbf{F}_t = \boldsymbol{\Phi}\mathbf{F}_t + u_t, \tag{11}$$

where u_t is a random vector with mean zero representing technology shocks and $\boldsymbol{\Phi}$ is a matrix of unknown parameters of a first-order VAR. The transition Eq. (11) determines a vector of latent variables, including the biases as well as the determinants of the rate of technical change. This equation is employed in projecting the vector of latent technology variables, given the values of these variables during the sample period and estimates of the unknown parameters of the coefficient matrix $\boldsymbol{\Phi}$.

3. Application of the Kalman filter

The econometric technique for identifying the rate and biases of technical change is a straightforward application of the Kalman filter, introduced by Kalman (1960, 1963) and presented in detail by Hamilton (1994, Chapter 13) and others. In the empirical research described in the following section, the Kalman filter is used to model production in each of the 35 sectors of our data set. The latent variables in the state-space specification of the price function (4) determine current and future patterns of production along with relative prices, which are the covariates of the Kalman filter.

The model underlying the Kalman filter is as follows:

$$\underset{(r\times 1)}{\xi_t} = \underset{(r\times r)}{F}\ \underset{(r\times 1)}{\xi_{t-1}} + \underset{(r\times 1)}{v_t}, \tag{12}$$

$$\underset{(n\times 1)}{y_t} = \underset{(n\times k)}{A'}\ \underset{(k\times 1)}{x_t} + \underset{(n\times r)}{H'}\ \underset{(r\times 1)}{\xi_t} + \underset{(n\times 1)}{w_t}, \tag{13}$$

where ξ_t, $t = 0, 1, 2, \ldots, T$, is the vector of unobserved latent variables and y_t, $t = 1, 2, \ldots, T$ is the vector of observations on the dependent variables. The vector y_t is determined by ξ_t and x_t, the vector of observations on the explanatory variables. The subscript t denotes time and indexes the observations.

In the model underlying the Kalman filter the *state equation* is (12) and the *observation equation* is (13), where x_t is exogenous, that is, uncorrelated with the disturbance w_t. The shocks v_t and w_t are assumed uncorrelated at all lags and

$$E(v_t v_\tau') = \begin{cases} \underset{(r\times r)}{Q} & t = \tau \\ 0 & \text{otherwise} \end{cases}$$

$$E(w_t w_\tau') = \begin{cases} \underset{(n\times n)}{R} & t = \tau \\ 0 & \text{otherwise} \end{cases}$$

where Q and R are the covariance matrices for the disturbances. The matrices A, H, F, R, Q include unknown parameters, but some of their elements may be known. For simplicity, we denote the unknown components of these matrices by the parameter vector θ.

Computation of the standard Kalman filter involves two procedures, *filtering* and *smoothing*. In filtering we use the maximum likelihood estimator (MLE) to estimate the unknown parameter vector θ. The log-likelihood function, based on the normal distribution, is computed by the forward recursion described by Hamilton (1994):

$$\max_{\theta} l(\theta|Y_T) = \max_{\theta} \sum_{t=1}^{T} \log N(y_t|\hat{y}_{t|t-1}, V_{t|t-1}),$$

where the matrix,

$$Y_t = (y_t', y_{t-1}', \ldots y_1', x_t', x_{t-1}', \ldots x_1')',$$

consists of the observations up to time t and the mean and variance are

$$\hat{y}_{t|t-1} = E(y_t|Y_{t-1});\ V_{t|t-1} = E[(y_t - \hat{y}_{t|t-1})(y_t - \hat{y}_{t|t-1})'].$$

Both are functions of θ and the data, calculated in the forward recursion. We use numerical methods to calculate the covariance matrix of the maximum likelihood estimator $\hat{\theta}$. In smoothing, we estimate the latent vector ξ_t, given the maximum likelihood estimator, using the backward recursion described by Hamilton (1994).

The econometric model we have presented in Section 2 can be expressed in the form required by the Kalman filter with the following definitions:

$$y_t = \begin{bmatrix} v_{Kt} \\ v_{Lt} \\ v_{Et} \\ \ln \dfrac{P_{Qt}}{P_{Mt}} \end{bmatrix}, \qquad x_t = \begin{bmatrix} 1 \\ \ln \dfrac{P_{Kt}}{P_{Mt}} \\ \ln \dfrac{P_{Lt}}{P_{Mt}} \\ \ln \dfrac{P_{Et}}{P_{Mt}} \\ \dfrac{1}{2}\left(\ln \dfrac{P_{Kt}}{P_{Mt}}\right)^2 \\ \dfrac{1}{2}\left(\ln \dfrac{P_{Lt}}{P_{Mt}}\right)^2 \\ \dfrac{1}{2}\left(\ln \dfrac{P_{Et}}{P_{Mt}}\right)^2 \\ \ln \dfrac{P_{Kt}}{P_{Mt}} \ln \dfrac{P_{Lt}}{P_{Mt}} \\ \ln \dfrac{P_{Kt}}{P_{Mt}} \ln \dfrac{P_{Et}}{P_{Mt}} \\ \ln \dfrac{P_{Lt}}{P_{Mt}} \ln \dfrac{P_{Et}}{P_{Mt}} \end{bmatrix},$$

$$A' = \begin{bmatrix} \alpha_K & \beta_{KK} & \beta_{KL} & \beta_{KE} & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_L & \beta_{KL} & \beta_{LL} & \beta_{LE} & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_E & \beta_{KE} & \beta_{LE} & \beta_{EE} & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_0 & \alpha_K & \alpha_L & \alpha_E & \beta_{KK} & \beta_{LL} & \beta_{EE} & \beta_{KL} & \beta_{KE} & \beta_{LE} \end{bmatrix},$$

9 More detail on the implications of imposing concavity at all data points in the sample is provided by Gallant and Golub (1984).

10 For additional details see Gallant and Golub (1984).

$$\xi_t = \begin{bmatrix} 1 \\ f_{Kt} \\ f_{Lt} \\ f_{Et} \\ f_{pt} \\ f_{pt-1} \end{bmatrix},$$

$$H' = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \ln\dfrac{P_{Kt}}{P_{Mt}} & \ln\dfrac{P_{Lt}}{P_{Mt}} & \ln\dfrac{P_{Et}}{P_{Mt}} & 1 & 0 \end{bmatrix}, \qquad w_t = \begin{bmatrix} \varepsilon_{Kt} \\ \varepsilon_{Lt} \\ \varepsilon_{Et} \\ \varepsilon_{pt} \end{bmatrix},$$

$$v_t = \begin{bmatrix} 0 \\ u_{Kt} \\ u_{Lt} \\ u_{Et} \\ u_{dpt} \\ 0 \end{bmatrix} \qquad F' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \chi_K & \delta_{KK} & \delta_{KL} & \delta_{KE} & \delta_{Kp} & -\delta_{Kp} \\ \chi_L & \delta_{LK} & \delta_{LL} & \delta_{LE} & \delta_{Lp} & -\delta_{Lp} \\ \chi_E & \delta_{EK} & \delta_{EL} & \delta_{EE} & \delta_{Ep} & -\delta_{Ep} \\ \chi_p & \delta_{pK} & \delta_{pL} & \delta_{pE} & \delta_{pp}+1 & -\delta_{pp} \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}.$$

4. Instrumental variables

We require two modifications of the standard Kalman filter. First, we impose the concavity constraints (10) at each data point in the sample period by simply adding these constraints to the computation of the MLE, converting this from an unconstrained to a constrained optimization. Second, the explanatory variables are prices determined by the balance of demand and supply, so that they may be endogenous. We introduce exogenous instrumental variables, say z_t, to deal with the potential endogeneity of the prices.[11] We assume that the vector z_t includes the observations on these variables at time t and satisfies the equation:

$$\underset{(k\times 1)}{x_t} = \underset{(k\times m)}{\Pi}\ \underset{(m\times 1)}{z_t} + \underset{(k\times 1)}{\eta_t}, \tag{14}$$

where z_t is uncorrelated with $\boldsymbol{\eta}_t$ and w_t, and $\boldsymbol{\eta}_t$ is correlated with w_t but uncorrelated with v_t.

Combining Eq. (14) with the observation equation and the state equation:

$$\underset{(n\times 1)}{y_t} = \underset{(n\times k)}{A'}\ \underset{(k\times 1)}{x_t} + \underset{(n\times r)}{H'}\ \underset{(r\times 1)}{\xi_t} + \underset{(n\times 1)}{w_t},$$
$$\underset{(r\times 1)}{\xi_t} = \underset{(r\times r)}{F}\ \underset{(r\times 1)}{\xi_{t-1}} + \underset{(r\times 1)}{v_t},$$

we can construct a new observation equation;

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} A'\Pi \\ \Pi \end{bmatrix} z_t + \begin{bmatrix} H' \\ O \end{bmatrix} \xi_t + \begin{bmatrix} A'\eta_t + w_t \\ \eta_t \end{bmatrix},$$

or:

$$\underset{[(n+k)\times 1]}{\tilde{y}_t} = \underset{[(n+k)\times m]}{\tilde{A}'}\ \underset{(m\times 1)}{\tilde{x}_t} + \underset{[(n+k)\times r]}{\tilde{H}'}\ \underset{(r\times 1)}{\xi_t} + \underset{[(n+k)\times 1]}{\tilde{w}_t},$$

leaving the state equation unchanged. The new model satisfies the exogeneity requirement of the Kalman filter. This would be a promising approach if the size of Π were small; however, in our application, this matrix involves 120 unknown parameters.

A more tractable approach is the two-step Kalman filter, obtained by a direct application of the two-step MLE (Wooldridge, 2002, Ch. 13). If the parameter Π were known, we could replace x_t with $\Pi z_t + \eta_t$ and formulate a new observation equation, $y_t = A'\Pi z_t + H'\xi_t + (A'\eta_t + w_t)$, where z_t is the exogenous explanatory variable. Motivated by this idea, we proceed in two steps:

[11] Input and output prices for each of the 35 sectors are determined within an intertemporal general equilibrium model like those presented by Jorgenson (1998) and employed by Jorgenson et al. (2008).

Step One: Estimate $\hat{\Pi} = XZ'(ZZ')^{-1}$ using OLS to obtain a consistent estimator of Π, where X and Z represent the matrices of observations on x_t and z_t, $t = 1, 2, \ldots, T$.

Step Two: Replace X in the standard Kalman filter with $\hat{X} = \hat{\Pi}Z$, that is, replace x_t with the fitted value $\hat{x}_t$ at time t, and use the standard filtering procedure to obtain the two-step MLE of the unknown parameters in the matrices A, H, F, R, Q.[12]

Wooldridge (2002, Chapter 13) shows that $\hat{\theta}$ is a consistent estimator of the parameter θ. In addition, it is asymptotically normal with

$$\begin{aligned}
\sqrt{N}(\hat{\theta}-\theta) &= \frac{A_0^{-1}}{\sqrt{N}}\sum_{i=1}^{N}[-g_i(\theta;\Pi)] + O_p(1) \\
&= -\frac{A_0^{-1}}{\sqrt{N}}\left\{\frac{\partial l(Y,X,Z,\theta,\Pi)}{\partial\theta} + \left[\frac{1}{N}\frac{\partial l(Y,X,Z,\theta,\Pi)}{\partial\theta\partial\Pi}\right]\right. \\
&\quad \left.\times\left[N(Z'Z)^{-1}Z'\eta\right]\right\} + O_p(1) \\
&\approx -\frac{A_0^{-1}}{\sqrt{N}}\left\{\frac{\partial l(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta}\right. \\
&\quad \left. + \frac{\partial l(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta\partial\Pi}(Z'Z)^{-1}Z'\hat{\eta}\right\} + O_p(1)
\end{aligned}$$

where

$$A_0 = \frac{1}{N}\frac{\partial l^2(Y,X,Z,\theta,\Pi)}{\partial\theta\partial\theta'} \approx \frac{1}{N}\frac{\partial l^2(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta\partial\theta'}.$$

Therefore,

$$\begin{aligned}
\mathrm{Var}(\hat{\theta}-\theta) &\to \frac{A_0^{-1}}{N}\sum_{i=1}^{N}[-g_i(\theta;\gamma)]\sum_{i=1}^{N}[-g_i(\theta;\gamma)]'\frac{A_0^{-1}}{N} \\
&= \frac{N}{N}\left[\frac{\partial l^2(Y,X,Z,\theta,\Pi)}{\partial\theta\partial\theta'}\right]^{-1}\left[\frac{\partial l(Y,X,Z,\theta,\Pi)}{\partial\theta}\right. \\
&\quad \left. + \frac{\partial l(Y,X,Z,\theta,\Pi)}{\partial\theta\partial\Pi}(Z'Z)^{-1}Z'\eta\right]\left[\frac{\partial l(Y,X,Z,\theta,\Pi)}{\partial\theta}\right. \\
&\quad \left. + \frac{\partial l(Y,X,Z,\theta,\Pi)}{\partial\theta\partial\Pi}(Z'Z)^{-1}Z'\eta\right]'\frac{N}{N}\left[\frac{\partial l^2(Y,X,Z,\theta,\Pi)}{\partial\theta\partial\theta'}\right]^{-1} \\
&\approx \left[\frac{\partial l^2(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta\partial\theta'}\right]^{-1}\left[\frac{\partial l(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta}\right. \\
&\quad \left. + \frac{\partial l(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta\partial\Pi}(Z'Z)^{-1}Z'\hat{\eta}\right]\left[\frac{\partial l(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta}\right. \\
&\quad \left. + \frac{\partial l(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta\partial\Pi}(Z'Z)^{-1}Z'\hat{\eta}\right]'\left[\frac{\partial l^2(Y,X,Z,\hat{\theta},\hat{\Pi})}{\partial\theta\partial\theta'}\right]^{-1}.
\end{aligned}$$

We estimate this covariance matrix numerically after calculating the two-step MLE.

Table A.1 of the Appendix provides a list of the instrumental variables and Fig. A.1 displays the instruments graphically. These are treated as exogenous variables in the intertemporal general equilibrium model employed by Jorgenson et al. (2008). We employ two tests to check the validity of our instrumental

[12] Estimates of the unknown parameters of our state-space model are presented in Table S1 and S2 of the Supplement to this paper. This can be downloaded from www.economics.harvard.edu/faculty/jorgenson/. A similar approach for estimation of models with time-varying parameters has been introduced by Kim (2006) and Kim and Nelson (2006).

variables. Fortunately, we have more instrumental variables than endogenous explanatory variables; in fact, there are eleven non-constant instruments in z_t and nine endogenous explanatory variables in x_t. This enables us to conduct a test of over-identifying restrictions to confirm the exogeneity of the instruments.

We carry out the test of over-identifying restrictions as follows: first, we select any two non-constant instrumental variables out of the 11 $z_t^{(m-k)}$, where $m-k = 12-10 = 2$. Second, in the second-stage Kalman filter, we include $z_t^{(m-k)}$ as an exogenous variable in the observation equation and keep the state equation the same as before:

$$\underset{(n\times 1)}{y_t} = \underset{(n\times k)}{A'}\underset{(k\times 1)}{\hat{x}_t} + \underset{[n\times(m-k)]}{C'}\underset{[(m-k)\times 1]}{z_t^{(m-k)}} + \underset{(n\times r)}{H'}\underset{(r\times 1)}{\xi_t} + \underset{(n\times 1)}{w_t^{(m-k)}}$$

$$\underset{(r\times 1)}{\xi_t} = \underset{(r\times r)}{F}\underset{(r\times 1)}{\xi_{t-1}} + \underset{(r\times 1)}{v_t}.$$

Note that $\hat{X}$, the observation matrix of $\hat{x}_t$, $t = 1, 2, \ldots, T$, satisfies $\hat{X} = \hat{\Pi}Z = XZ'(ZZ')^{-1}Z$ with rank $k = 10$; therefore, selection of any two non-constant instrumental variables yields the same test statistic. Moreover, if our null hypothesis that z_t is uncorrelated with w_t is true, the addition of $z_t^{(m-k)}$ to the observation equation will not affect the original Kalman filter. We perform a Likelihood Ratio Test of the hypothesis that C is zero by comparing l and l_g, the log-likelihood values before and after the introduction of $z_t^{(m-k)}$. Under the null hypothesis of exogeneity the difference is asymptotically chi squared:

$$2(l_g - l) \overset{a}{\sim} \chi^2_{n\times(m-k)}.$$

The results presented in Table A.2 of the Appendix show that the instrumental variables are exogenous.

Second, we apply a Likelihood Ratio Test to the hypothesis of zero correlation between endogenous explanatory variables and instrumental variables. Let $\hat{\Sigma}$ represent the empirical covariance matrix of $\dot{x}_t$, the nine non-constant elements of x_t, and $\tilde{\Sigma}$ represent the corresponding empirical covariance matrix of $\dot{x}_t - \dot{\Pi}z_t$, the residuals from the fitted values of the $\dot{x}_t$'s in the linear regression, where $\dot{\Pi}$ represents the corresponding sub-matrix of Π. The log-likelihood for the later is

$$\begin{aligned}\ln\tilde{L} &= -\frac{(k-1)T}{2}\ln|2\pi| - \frac{T}{2}\ln|\tilde{\Sigma}| \\ &\quad - \frac{1}{2}\sum_{t=1}^{T}(\dot{x}_t - \dot{\Pi}z_t)'\tilde{\Sigma}^{-1}(\dot{x}_t - \dot{\Pi}z_t) \\ &= -\frac{(k-1)T}{2}\ln|2\pi| - \frac{T}{2}\ln|\tilde{\Sigma}| + \frac{(k-1)T}{2}.\end{aligned}$$

The quadratic term is replaced by a constant due to the ML process of the linear regression. For $\hat{\Sigma}$, we can derive a similar log-likelihood:

$$\ln\hat{L} = -\frac{(k-1)T}{2}\ln|2\pi| - \frac{T}{2}\ln|\hat{\Sigma}| + \frac{(k-1)T}{2}.$$

This is a linear regression, where the parameters before the constant term in z_t are unconstrained and all other parameters in $\dot{\Pi}$ are fixed at zero.

The Likelihood Ratio Test statistic is

$$LR = -2(\ln\hat{L} - \ln\tilde{L}) = T(\ln|\tilde{\Sigma}| - \ln|\hat{\Sigma}|).$$

This statistic is asymptotically chi-squared, where the number of degrees of freedom is equal to the number of parameters that are constrained, $(m-1)*(k-1) = 11*9 = 99$ in our model. The results presented in Table A.3 of the Appendix show that the instrumental variables are highly correlated with the endogenous variables. We conclude that both diagnostic tests confirm the validity of our instruments.

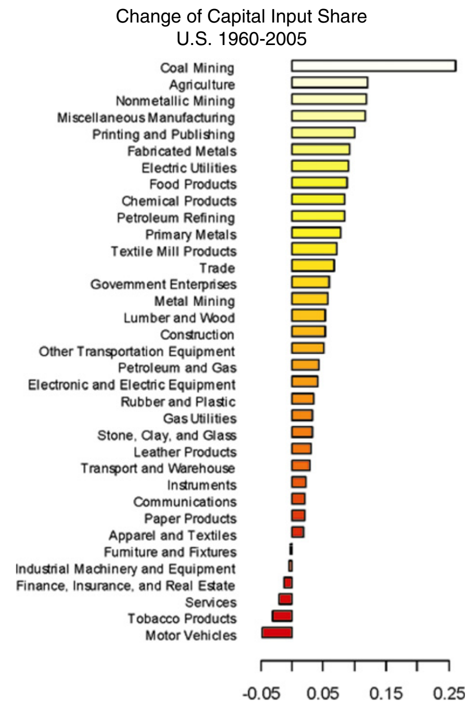

Fig. 1. $v_{KT} - v_{K1}$. Note: Year 1 = 1960, Year T = 2005.

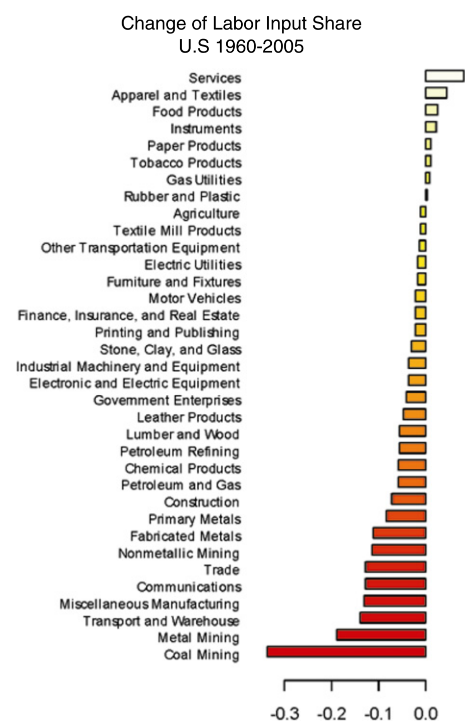

Fig. 2. $v_{LT} - v_{L1}$.

5. Empirical results

In this section we present the rate and biases of technical change for the state-space model of producer behavior (4) for each of the 35 sectors of the US economy listed in Table 1. In Figs. 1–4 we give the changes in input shares of the four inputs—capital, labor, energy, and materials—over the period 1960–2005. These are the dependent variables for the value share of capital input in Eq. (5) and the remaining value shares. The industries are ordered by the magnitude of the changes. In general, the capital input shares have

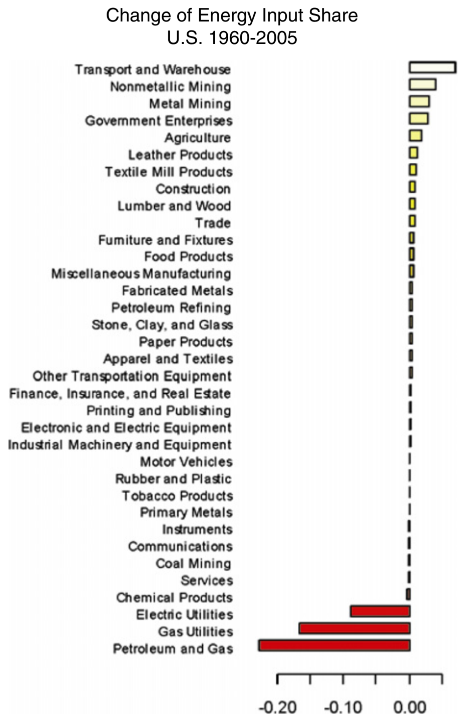

Fig. 3. $v_{ET} - v_{E1}$.

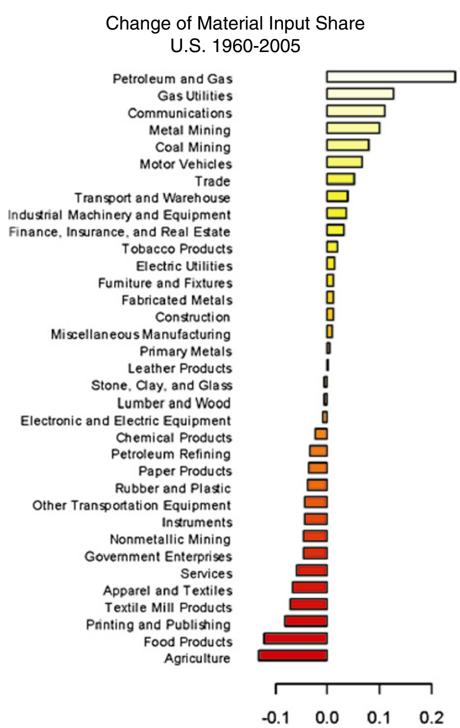

Fig. 4. $v_{MT} - v_{M1}$.

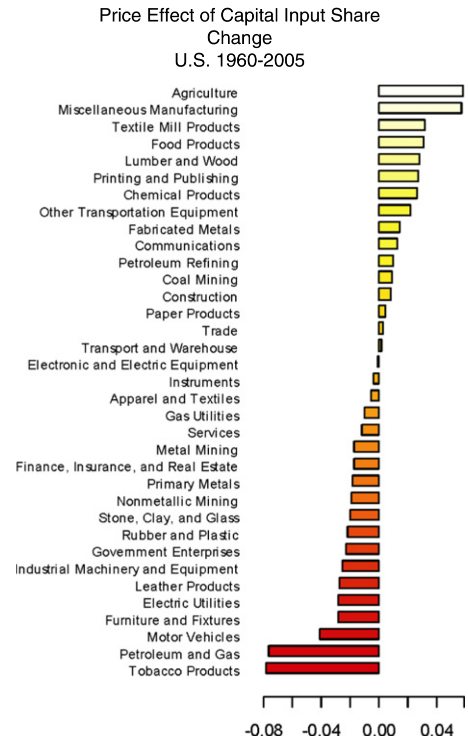

Fig. 5. $\left(\beta_{KK}\ln\frac{P_{KT}}{P_{MT}}+\beta_{KL}\ln\frac{P_{LT}}{P_{MT}}+\beta_{KE}\ln\frac{P_{ET}}{P_{MT}}\right)-\left(\beta_{KK}\ln\frac{P_{K1}}{P_{M1}}+\beta_{KL}\ln\frac{P_{L1}}{P_{M1}}+\beta_{KE}\ln\frac{P_{E1}}{P_{M1}}\right)=(\beta_{KK}\ln P_{KT}+\beta_{KL}\ln P_{LT}+\beta_{KE}\ln P_{ET}+\beta_{KM}\ln P_{MT})-(\beta_{KK}\ln P_{K1}+\beta_{KL}\ln P_{L1}+\beta_{KE}\ln P_{E1}+\beta_{KM}\ln P_{M1})$.

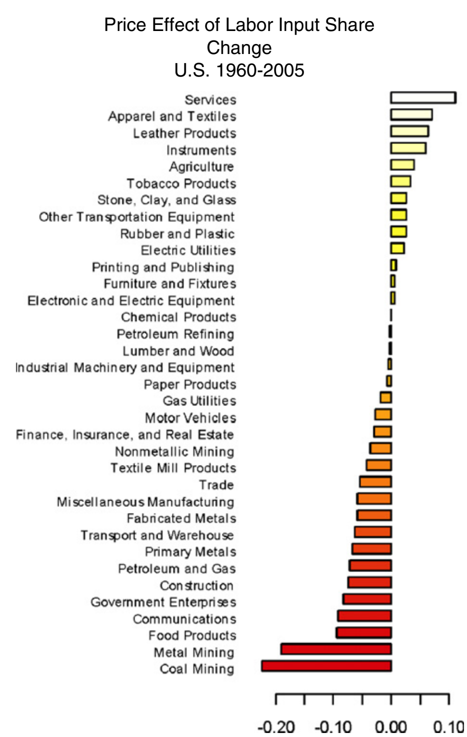

Fig. 6. $(\beta_{KL}\ln\frac{P_{KT}}{P_{MT}}+\beta_{LL}\ln\frac{P_{LT}}{P_{MT}}+\beta_{LE}\ln\frac{P_{ET}}{P_{MT}})-(\beta_{KL}\ln\frac{P_{K1}}{P_{M1}}+\beta_{LL}\ln\frac{P_{L1}}{P_{M1}}+\beta_{LE}\ln\frac{P_{E1}}{P_{M1}})=(\beta_{KL}\ln P_{KT}+\beta_{LL}\ln P_{LT}+\beta_{LE}\ln P_{ET}+\beta_{LM}\ln P_{MT})-(\beta_{KL}\ln P_{K1}+\beta_{LL}\ln P_{L1}+\beta_{LE}\ln P_{E1}+\beta_{LM}\ln P_{M1})$.

increased, some of them very substantially. With some notable exceptions the labor shares have decreased and the energy shares have increased slightly. The materials shares are almost evenly divided between increases and decreases.

We next allocate changes in the input shares between a price effect, corresponding to the second term in Eq. (5), and the bias of technical change (6), corresponding to the third term in (5). The price effects presented in Figs. 5–8 represent the responses of production patterns to price changes through substitution among inputs. These responses are substantial, but appear to be evenly balanced between negative and positive effects for capital and energy. The labor price effects are predominantly negative,

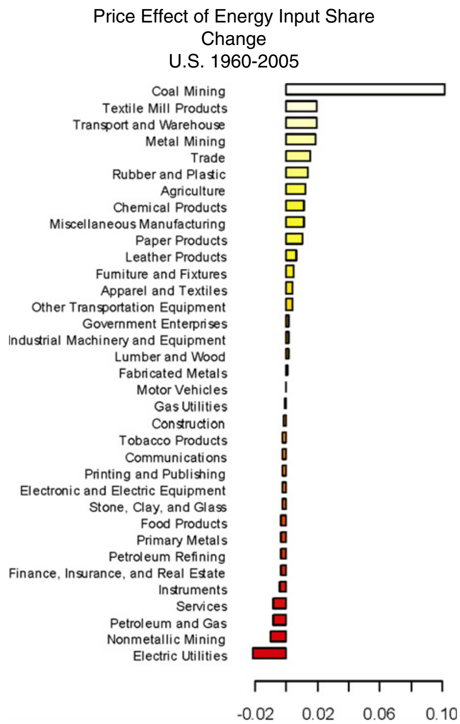

Fig. 7. $(\beta_{KE}\ln\frac{P_{KT}}{P_{MT}} + \beta_{LE}\ln\frac{P_{LT}}{P_{MT}} + \beta_{EE}\ln\frac{P_{ET}}{P_{MT}}) - (\beta_{KE}\ln\frac{P_{K1}}{P_{M1}} + \beta_{LE}\ln\frac{P_{L1}}{P_{M1}} + \beta_{EE}\ln\frac{P_{E1}}{P_{M1}}) = (\beta_{KE}\ln P_{KT} + \beta_{LE}\ln P_{LT} + \beta_{EE}\ln P_{ET} + \beta_{EM}\ln P_{MT}) - (\beta_{KE}\ln P_{K1} + \beta_{LE}\ln P_{L1} + \beta_{EE}\ln P_{E1} + \beta_{EM}\ln P_{M1})$.

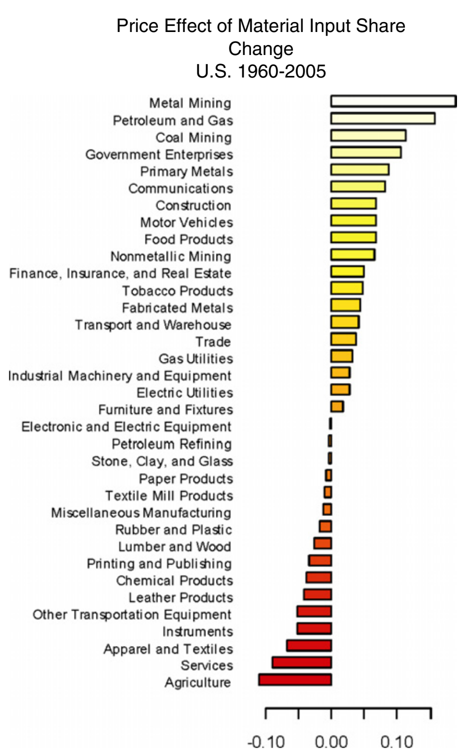

Fig. 8. $(\beta_{KM}\ln P_{KT}+\beta_{LM}\ln P_{LT}+\beta_{EM}\ln P_{ET}+\beta_{MM}\ln P_{MT})-(\beta_{KM}\ln P_{K1}+\beta_{LM}\ln P_{L1}+\beta_{EM}\ln P_{E1} + \beta_{MM}\ln P_{M1})$.

reflecting increases in wages relative to prices, while the materials price effects are predominantly positive. These price effects rule out a Cobb–Douglas or linear logarithmic specification for the price function (4).

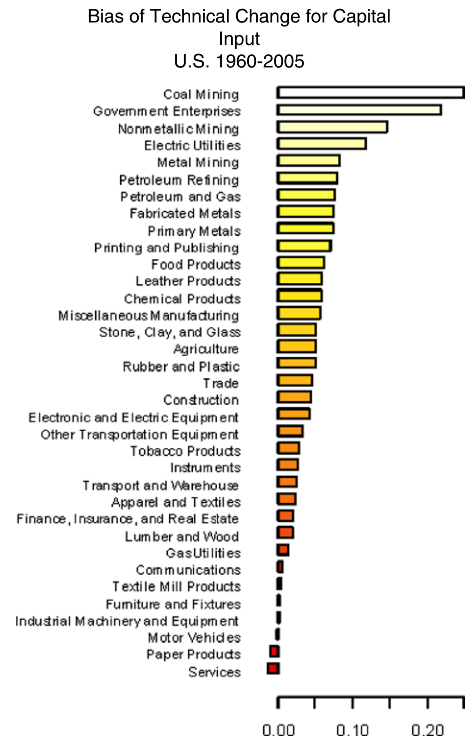

Fig. 9. $f_{KT} - f_{K1}$.

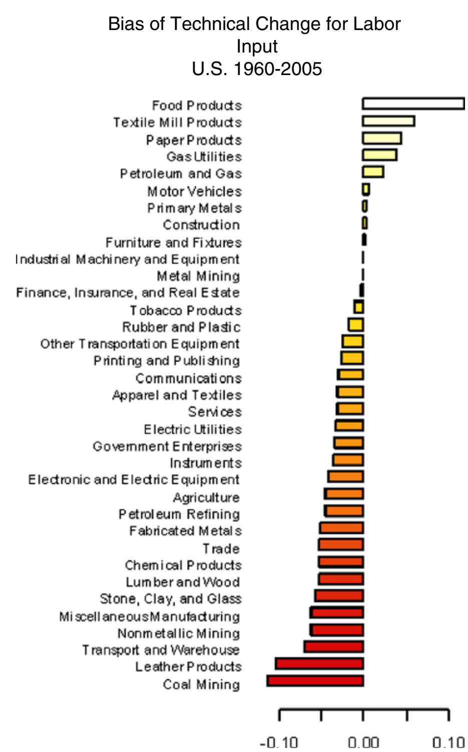

Fig. 10. $f_{LT} - f_{L1}$.

We present the biases of technical change (6) in Figs. 9–12.[13] The biases of technical change for capital input are predominantly capital-using and substantial in magnitude, especially for Coal Mining and Government Enterprises. The biases are capital-saving

13 Biases in Figs. 9–12 and projections in Figs. 19–22 can be downloaded in time series format as Figs. S.1–4 of the Supplement to this paper.

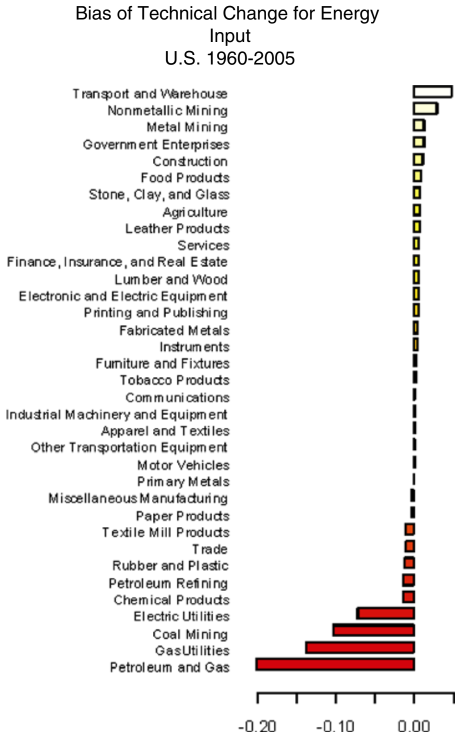

Fig. 11. $f_{ET} - f_{E1}$.

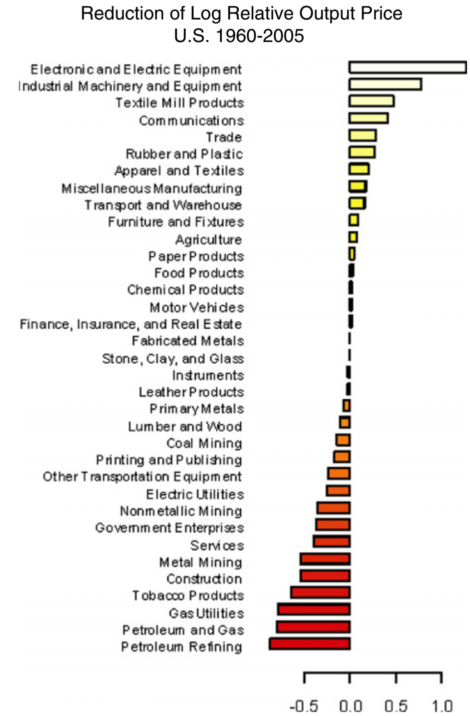

Fig. 13. $-\left(\ln \frac{P_{QT}}{P_{MT}} - \ln \frac{P_{Q1}}{P_{M1}}\right)$.

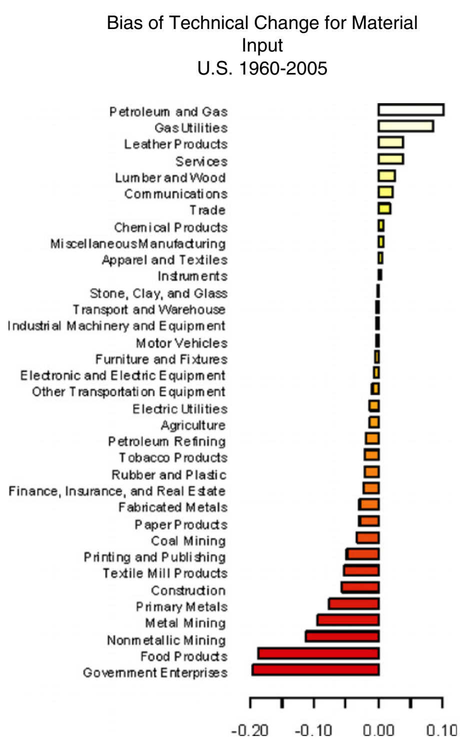

Fig. 12. $f_{MT} - f_{M1}$.

but relatively small for Paper Products and Services. The biases of technical change for labor input are divided between labor-saving technical change for industries like Leather Products and Coal Mining and labor-using change for industries such as Food Products and Textile Mill Products.

The biases of technical change for energy are relatively small in magnitude, reflecting the small size of the energy shares for most industries. The bias for energy is energy-using for Transportation and Warehousing and energy-saving for Electric and Gas Utilities, Coal Mining, and Petroleum and Gas Mining. Finally, the biases of technical change for materials are predominantly materials-saving and substantial in size, especially for Government Enterprises and Food Products. However, the biases are materials-using for Petroleum and Gas Mining and Gas Utilities.

We conclude that the biases of technical change are comparable in magnitude to the price effects. Substitution among inputs and biased technical change are both important determinants of changes in the input shares. However, the biases also play a significant role in our state-space model of producer behavior as determinants of the rate of induced technical change. We turn next to changes in the price of output and its decomposition into a price effect, corresponding to the second and third terms in Eq. (4), and the rates of induced and autonomous technical change in Eq. (6).

Fig. 13 presents reductions in the logarithms of prices of the outputs of the 35 industries, relative to the prices of materials inputs in each sector. Not surprisingly, these price changes are almost evenly divided between positive and negative values with the large reductions for Electronic and Electrical Equipment and Industrial Machinery and Equipment as the outstanding exceptions. The Electronic and Electrical Equipment industry produces semiconductor components for computers and other electronic equipment, while Industrial Machinery and Equipment includes computers. Technical change has resulted in a very dramatic fall in the prices of outputs for these industries, relative to the materials they consume.

The price effects presented in Fig. 14 are differences between the price reductions in Fig. 13 and the rates of technical change in Eq. (7). These price effects result from substitution among inputs and are dominated by increases in wage rates, relative to prices of materials inputs. Using estimates of the biases of technical change, we can divide the rate of technical change between the rate of induced technical change, corresponding to the first term in Eq. (7), and the rate of autonomous technical change, corresponding to the second term in this equation.

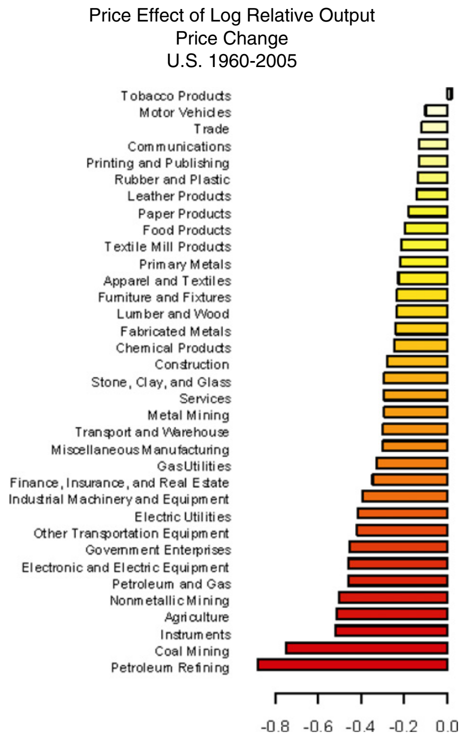

Fig. 14.

$$
-\left\{
\begin{array}{l}
\left[\alpha_K \quad \alpha_L \quad \alpha_E \quad \beta_{KK} \quad \beta_{LL} \quad \beta_{EE} \quad \beta_{KL} \quad \beta_{KE} \quad \beta_{LE}\right]
\left(
\begin{bmatrix}
\ln \frac{P_{KT}}{P_{MT}} \\
\ln \frac{P_{LT}}{P_{MT}} \\
\ln \frac{P_{ET}}{P_{MT}} \\
\frac{1}{2}\left(\ln \frac{P_{KT}}{P_{MT}}\right)^2 \\
\frac{1}{2}\left(\ln \frac{P_{LT}}{P_{MT}}\right)^2 \\
\frac{1}{2}\left(\ln \frac{P_{ET}}{P_{MT}}\right)^2 \\
\ln \frac{P_{KT}}{P_{MT}} \ln \frac{P_{LT}}{P_{MT}} \\
\ln \frac{P_{KT}}{P_{MT}} \ln \frac{P_{ET}}{P_{MT}} \\
\ln \frac{P_{LT}}{P_{MT}} \ln \frac{P_{ET}}{P_{MT}}
\end{bmatrix}
-
\begin{bmatrix}
\ln \frac{P_{K1}}{P_{M1}} \\
\ln \frac{P_{L1}}{P_{M1}} \\
\ln \frac{P_{E1}}{P_{M1}} \\
\frac{1}{2}\left(\ln \frac{P_{K1}}{P_{M1}}\right)^2 \\
\frac{1}{2}\left(\ln \frac{P_{L1}}{P_{M1}}\right)^2 \\
\frac{1}{2}\left(\ln \frac{P_{E1}}{P_{M1}}\right)^2 \\
\ln \frac{P_{K1}}{P_{M1}} \ln \frac{P_{L1}}{P_{M1}} \\
\ln \frac{P_{K1}}{P_{M1}} \ln \frac{P_{E1}}{P_{M1}} \\
\ln \frac{P_{L1}}{P_{M1}} \ln \frac{P_{E1}}{P_{M1}}
\end{bmatrix}
\right) \\
+\sum_{t=2}^{T} f_{Kt}\left(\ln \frac{P_{Kt}}{P_{Mt}} - \ln \frac{P_{Kt-1}}{P_{Mt-1}}\right) + f_{Lt}\left(\ln \frac{P_{Lt}}{P_{Mt}} - \ln \frac{P_{Lt-1}}{P_{Mt-1}}\right) + f_{Kt}\left(\ln \frac{P_{Et}}{P_{Mt}} - \ln \frac{P_{Et-1}}{P_{Mt-1}}\right)
\end{array}
\right\}.
$$

The rates of autonomous technical change given in Fig. 16 are predominantly positive and substantial in magnitude. Electronic and Electric Equipment leads all other industries with a rate of autonomous technical change that exceeds even the very dramatic rate of decline of the relative price of the industry's output. Industrial Machinery and Equipment, the industry that includes computers, has the second largest rate of autonomous technical change. The Tobacco Products industry and Petroleum and Gas Mining have sizable negative rates of autonomous technical change.

The rates of induced technical change in Fig. 15, corresponding to the first term in Eq. (7), depend on the correlations between prices of inputs and biases of technical change. If this correlation is negative, input-using technical change corresponds to low input prices and input-saving change to high input prices, so that the rate of induced technical change is positive. The rates of induced technical change presented in Fig. 15 are predominantly negative, so that input-using technical change is correlated with high input prices and input-saving technical change with low input prices.[14]

Our overall conclusion from the empirical results presented in Figs. 13–16 is that rates of autonomous and induced technical change are substantial in magnitude and opposite in sign. However, autonomous technical change predominates, so that rates of technical change are positive for most industries. Rates of technical change are large relative to the price effects associated with substitution among inputs. The price effects exert upward pressure on output prices while induced technical change exerts pressure in the same direction, but both are offset by positive rates of autonomous technical change.

In order to explore changes in the direction and magnitude of biases in technical change in greater detail, we sub-divide the

[14] Rates of induced and autonomous technical change in Figs. 15 and 16 and projections in Figs. 23 and 24 can be downloaded in time series format as Fig S.5 of the Supplement to this paper.

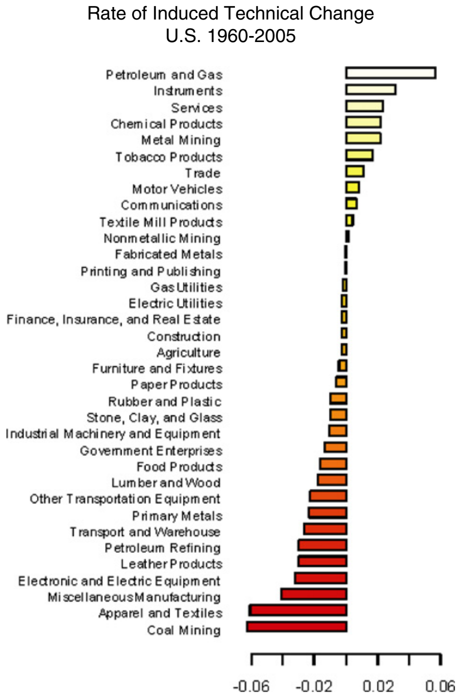

Fig. 15. $-\left[\sum_{t=2}^{T}\ln\frac{P_{Kt}}{P_{Mt}}(f_{Kt}-f_{Kt-1})+\ln\frac{P_{Lt}}{P_{Mt}}(f_{Lt}-f_{Lt-1})+\ln\frac{P_{Et}}{P_{Mt}}(f_{Et}-f_{Et-1})\right] = -\left[\sum_{t=2}^{T}\ln P_{Kt}(f_{Kt}-f_{Kt-1})+\ln P_{Lt}(f_{Lt}-f_{Lt-1})+\ln P_{Et}(f_{Et}-f_{Et-1})+\ln P_{Mt}(f_{Mt}-f_{Mt-1})\right]$.

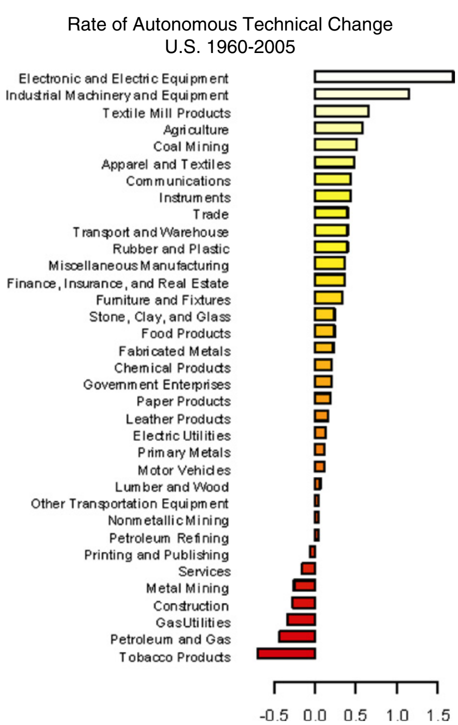

Fig. 16. $-(f_{pT}-f_{p1})$.

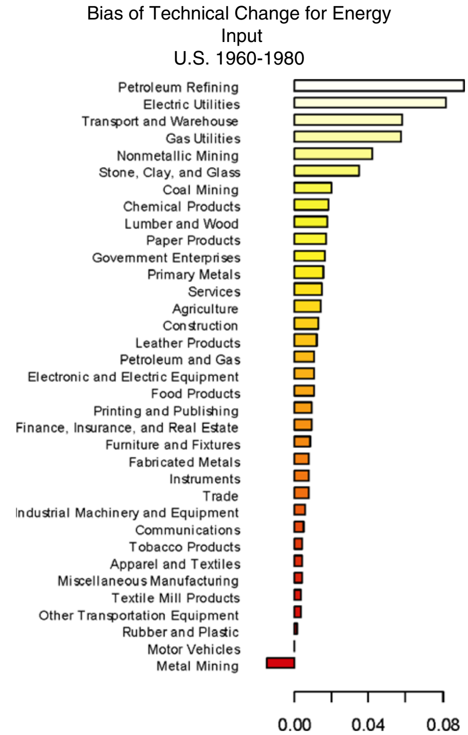

Fig. 17. $f_{E1980}-f_{E1}$.

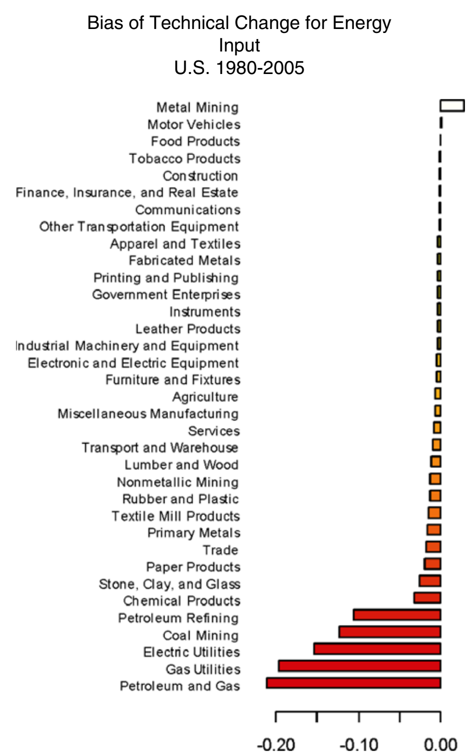

Fig. 18. $f_{ET}-f_{E1980}$.

biases for energy input into two sub-periods, 1960–1980 and 1980–2005. Recall that the biases of technical change are first differences of the latent variables, as in Eq. (6). In Figs. 17 and 18 the biases are both energy-saving and energy-using for the seven most intensive energy-using sectors during the sample period—petroleum refining, electric and gas utilities, transportation and warehousing, coal mining, chemical products, and stone, clay, and glass. This pattern would have been concealed by constant time trends.

There is a common pattern of energy-using change from 1960–1980 and energy-saving change from 1980–2005, except for metal mining. The turning point was the Second Oil Crisis, when energy prices reached their postwar peaks in real terms. We conclude that high energy prices after 1980 are correlated with

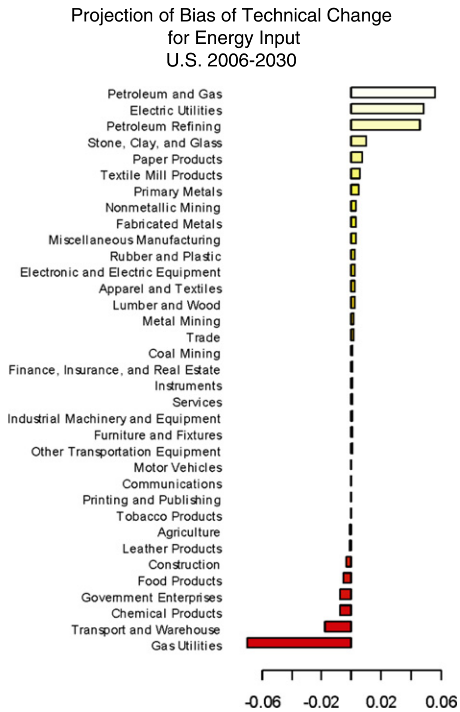

Fig. 19. $f_{E2030} - f_{ET}$.

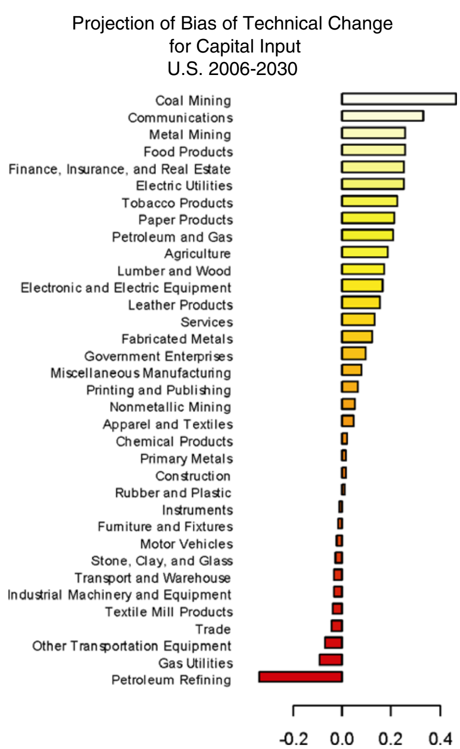

Fig. 20. $f_{K2030} - f_{KT}$.

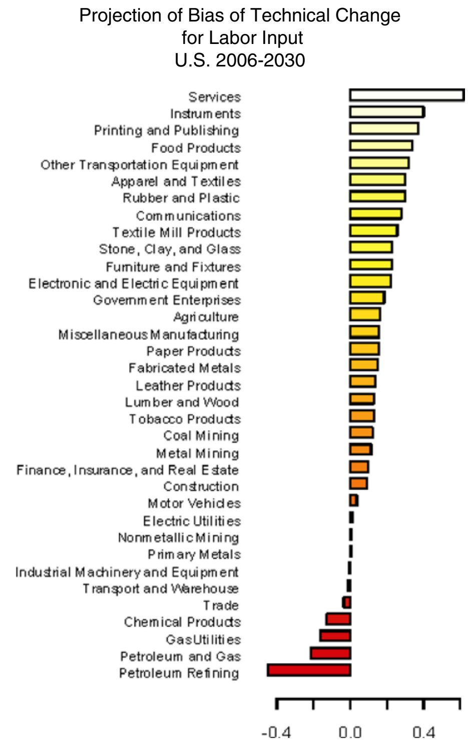

Fig. 21. $f_{L2030} - f_{LT}$.

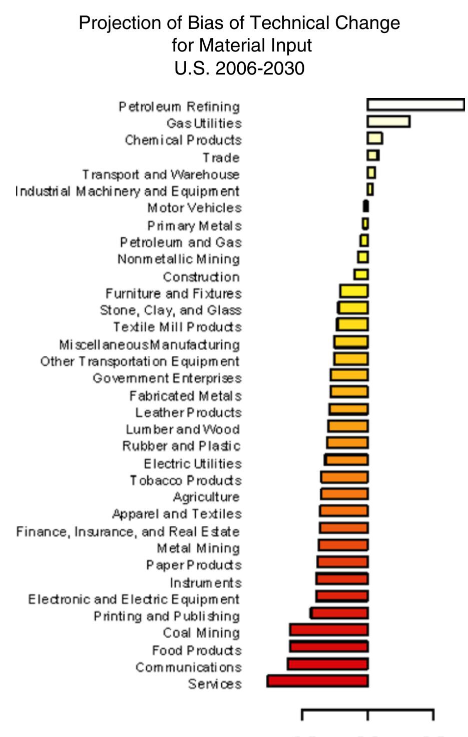

Fig. 22. $f_{M2030} - f_{MT}$.

energy-saving change, while low energy prices before 1980 are correlated with energy-using change. This pattern would also have been concealed by constant time trends.

The latent variables f_{it} converge to constants, so that biases of technical change corresponding to changes in these variables converge to zero. In Fig. 19 we present projections of the biases of technical change for energy for the period 2006–2030. Note that the projected biases for the seven most energy-intensive industries are not simple extrapolations of the trends toward energy conservation we have identified after 1980. Projected biases are energy-saving for gas utilities, transportation and warehousing, and chemical products. However, projected biases are energy-using for electric utilities, petroleum refining, stone, clay, and glass, and coal mining. As before, these projections are inconsistent with the constant time trends in Binswanger's approach.

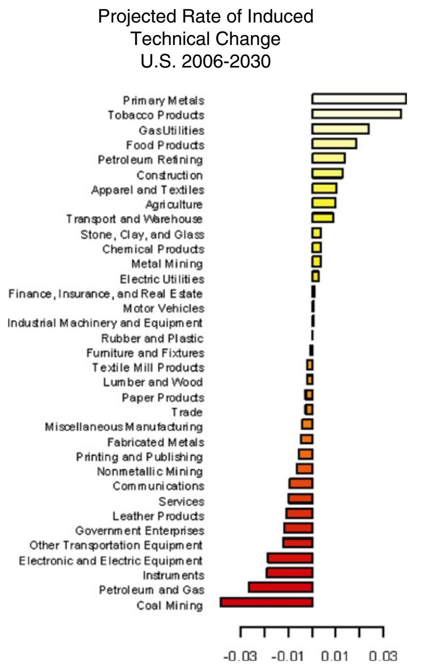

Fig. 23. $-\left[\ln \frac{P_{KT}}{P_{MT}}(f_{K2030}-f_{KT})+\ln \frac{P_{LT}}{P_{MT}}(f_{L2030}-f_{LT})+\ln \frac{P_{ET}}{P_{MT}}(f_{E2030}-f_{ET})\right]$.

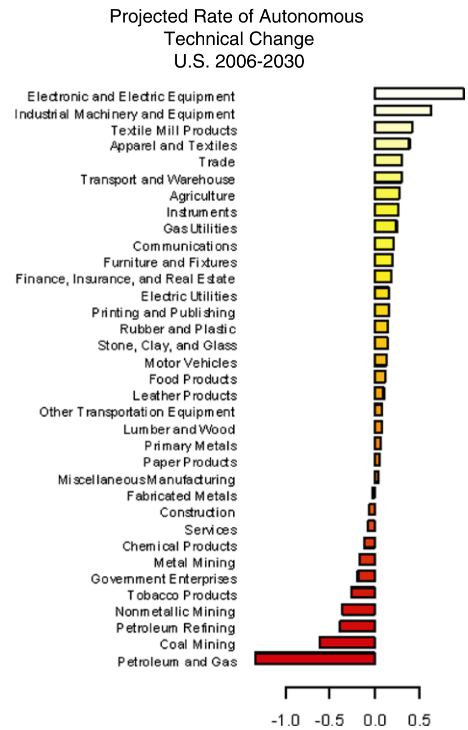

Fig. 24. $-(f_{p2030}-f_{pT})$.

Table A.1
Instrumental variables.

1	Constant
2	Average marginal tax rate on personal labor income
3	Effective Corporate Income tax rate
4	Average Marginal Tax Rate on Dividends
5	Rate of Taxation on Consumption Goods
6	Time endowment in 2000 dollars/Lagged private wealth including claims on government and the ROW
7	Lagged price of personal Consumptions Expenditure/Lagged price index of private domestic labor input
8	Lagged price of leisure and unemployment/Lagged price index of private domestic labor input
9	Lagged price of capital services for household/Lagged price index of private domestic labor input
10	Lagged real full consumption/Lagged private wealth including claims on government and the ROW
11	US population/Lagged private wealth including claims on government and the ROW
12	Government Demand/Lagged private wealth including claims on government and the ROW

In Figs. 20–22 we give projections of biases of technical change for capital, labor, and materials for the period 2006–2030. These projections are not simple extrapolations of biases during the sample period and many alternate between input-using and input-saving bias. This variation is particularly pronounced in the case of energy input and characterizes biases of technical change during the sample period, 1960–2005, and the projection period, 2006–2030. We conclude that the latent variables representing biases of technical change must be sufficiently flexible to capture variations between input-using and input-saving technical change.

The levels of technology f_{pt} converge to linear trends, corresponding to constant rates of autonomous technical change. Recalling that we employ the dual representation of technology (4), falling trends correspond to positive rates of technical change, while rising trends represent negative rates. In Figs. 23 and 24 we give projections of the rates of induced and autonomous technical change. Rates of induced technical change are relatively small in magnitude and are evenly divided between positive and negative values. Rates of autonomous technical change are predominantly positive in sign and substantial in magnitude. The projections for electronic and electric equipment, including semiconductors, have very rapid rates of technical change. Projected rates of technical change for industrial machinery and equipment, including computers, are the next most rapid, also extrapolating trends during the sample period. Negative rates of autonomous technical change are substantial in magnitude for coal mining and petroleum and gas mining.

6. Conclusion

Our principal innovation is to generate empirical measures of the rate and biases of technical change as latent or unobservable variables, while retaining flexibility in modeling substitution in terms of observable variables such as prices and value shares. We find that biases of technical change are substantial in magnitude, comparable to responses to price changes. Biases of technical change are generally capital-using and materials-saving and biases for energy alternate between energy-using before 1980 and energy-using afterward. Projections of the biases of technical change are not consistent with the constant time trends employed in Binswanger's approach.

The rate of induced technical change captures the correlation between the biases of technical change and the prices of inputs. Perhaps surprisingly, this correlation is positive, so that rates of induced technical change are predominantly negative. Technical change directed toward increasing or decreasing the utilization of a particular input generally reduces the rate of technical change. However, rates of autonomous technical change are predominantly positive and much greater in magnitude. Projections of rates of technical change are positive and substantial, suggesting a relatively optimistic outlook for future US economic growth.

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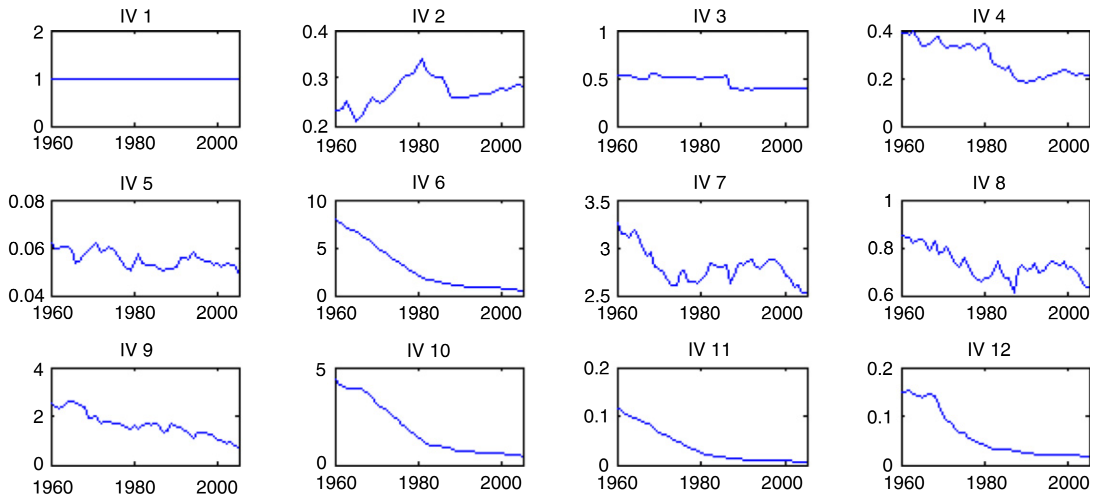

Fig. A.1. Instrumental variables.

Table A.2
Tests for overidentification.

Sector	l_g	l	$2(l_g - l)$	p-value	p-value*35
1	563.48	562.65	1.67	0.990	34.63
2	454.21	447.07	14.28	0.075	2.62
3	481.81	478.00	7.61	0.473	16.55
4	509.39	508.64	1.50	0.993	34.74
5	550.44	547.61	5.66	0.685	23.97
6	714.71	712.61	4.19	0.839	29.38
7	730.60	727.74	5.72	0.679	23.75
8	604.98	604.94	0.07	1.000	35.00
9	704.31	702.58	3.47	0.902	31.56
10	709.93	708.88	2.11	0.978	34.21
11	638.50	637.66	1.68	0.989	34.62
12	691.26	688.36	5.82	0.668	23.37
13	630.64	627.61	6.07	0.640	22.40
14	722.78	719.49	6.59	0.581	20.33
15	620.06	618.78	2.55	0.959	33.57
16	531.17	526.66	9.01	0.342	11.96
17	702.20	699.77	4.86	0.772	27.03
18	597.88	596.47	2.82	0.945	33.08
19	660.17	658.94	2.47	0.963	33.71
20	647.79	641.26	13.07	0.109	3.83
21	702.88	700.86	4.03	0.854	29.90
22	701.61	697.96	7.30	0.505	17.67
23	648.23	648.00	0.47	1.000	35.00
24	674.59	670.90	7.38	0.496	17.36
25	648.00	642.70	10.61	0.225	7.87
26	700.77	695.14	11.26	0.187	6.56
27	673.38	669.86	7.06	0.530	18.56
28	607.55	602.54	10.01	0.264	9.26
29	781.95	776.59	10.72	0.218	7.64
30	595.61	594.48	2.25	0.972	34.03
31	560.82	552.14	17.35	0.027	0.93
32	703.84	699.63	8.43	0.392	13.73
33	765.86	760.74	10.24	0.248	8.69
34	726.58	721.86	9.43	0.307	10.76
35	572.33	564.66	15.34	0.053	1.85

Notes: (1) The number of degrees of freedom for the LR test for each sector is 8. (2) The null hypothesis is that the instrumental variables are exogenous. (3) High p-values indicate that we cannot reject the null hypothesis of exogeneity. (4) The last column presents p-values adjusted for simultaneous inference.

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Table A.3
Tests of validity of the instrumental variables.

Sector	LR	p-value
1	677.89	<0.001
2	580.45	<0.001
3	679.11	<0.001
4	762.29	<0.001
5	717.90	<0.001
6	646.73	<0.001
7	672.32	<0.001
8	646.00	<0.001
9	782.78	<0.001
10	643.17	<0.001
11	541.68	<0.001
12	600.82	<0.001
13	668.19	<0.001
14	743.66	<0.001
15	732.65	<0.001
16	692.95	<0.001
17	734.26	<0.001
18	625.93	<0.001
19	829.69	<0.001
20	626.03	<0.001
21	726.69	<0.001
22	696.75	<0.001
23	791.19	<0.001
24	601.69	<0.001
25	596.51	<0.001
26	777.20	<0.001
27	588.84	<0.001
28	568.53	<0.001
29	762.82	<0.001
30	657.10	<0.001
31	748.91	<0.001
32	856.78	<0.001
33	755.03	<0.001
34	715.89	<0.001
35	764.75	<0.001

Notes: (1) Number of degrees of freedom for the LR test for each sector is 99. (2) The null hypothesis is that instrumental variables are uncorrelated with the endogenous independent variables. (3) Low p-values indicate that we can reject the null hypothesis of no correlation.

Appendix A

See Tables A.1–A.3.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, doi:10.1016/j.jeconom.2009.12.002.

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