Dark Matter: Measuring Unobserved Productivity Growth due to Computers through its Impact on Observables

Alwyn Young, London School of Economics, January 2026

"You can see the computer age everywhere
but in the productivity statistics." (Solow 1987)

Abstract

I find systematic deviations in the relationship between measured industry total factor productivity growth and price & downstream demand growth associated with the use of computer and electronics intermediate inputs in production. The effects are robustly negative, indicating an overstatement of quality adjusted output and productivity growth in using industries of between .003 and .006 per percentage expenditure share on computer & electronic intermediates. These estimates are confirmed by regressions of measured productivity growth on own and upstream computer input use. After adjustment for mismeasurement, there is no association between computer intermediates use and total factor productivity growth.

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I. Introduction

Unobserved objects can be quantified and measured by observed systematic discrepancies in the causal relationships between observables. Linearly and trivially, if $y = x\beta$, y_o & x_o are observed and β is known, then unobserved x is given by $x_{uo} = y_o/\beta - x_o$. Econometrically, in a world in which x is not the sole determinant of y and β is unknown, if an observable indicator z_o exists such that $x_{uo} = \gamma z_o + \eta$, then both β and γ can be consistently estimated by running the non-linear regression $y_o = (x_o + \gamma z_o)\beta + \varepsilon$. As this is equivalent to running $y_o = x_o\beta_x + z_o\beta_z + \varepsilon$ and estimating $\gamma = \beta_z/\beta_x$, one sees that consistency requires the standard OLS assumption that the plim of the product of the regressors and errors is zero, as well as $\beta_z = \gamma\beta_x$, i.e. that z_o affects y_o only through its influence (γ) on x_{uo}, which has the same effect on y_o as x_o. The last can be relaxed to allow x_{uo} to have an impact $f(\beta)$, where the function f() is known. This naturally arises in cases where the linear relationship is on an unobservable $y_{uo} = (x_o + x_{uo})\beta + \varepsilon$, and there is an additional known discrepancy between y_o and y_{uo} driven by x_{uo}, as is the case below.

This paper applies this idea to a topic that has troubled economists and statisticians for some decades, the question of whether we are properly measuring the quality-adjusted gains from the use of computer technology. The lefthand side observables are measured quality-adjusted prices and demand growth (y_o), the righthand side observables are measured total factor productivity growth (x_o) and computer factor income shares (z_o) and the unobservable of interest is mismeasurement of total factor productivity growth associated with the use of computer related inputs ($x_{uo} = \gamma z_o$). The key identifying assumptions are that: (1) total factor productivity growth and computer factor income shares are exogenous to price and quantity shocks (the OLS consistency requirement); (2) the movements of true quality adjusted prices and quantities demanded (y_{uo}) are the same function of true total factor productivity growth (x_o+x_{uo}), regardless of its origin (the common β requirement); and (3) the use of computer inputs has no impact on price and quantities demanded other than through its impact on true productivity growth (the exclusion restriction). (1) is addressed econometrically using controls and instruments, (2) by excluding components of demand (e.g. own-industry intermediate use) that might depend upon the form of productivity growth, and (3) by following standard measurement precepts of defining price and quantity in quality adjusted units. The tested null hypothesis is that of no systematic mismeasurement associated with computer related inputs, $\gamma = 0$.

The linear relation, $x_{uo} = \gamma z_o$, is motivated by Solow's comment quoted above, which suggests that we fail to measure what we do with computers. This can be operationalized as mismeasurement of average rates of computer-factor augmenting technical change in computer using industries, so that the degree of mismeasurement is proportional to the expenditure share on computer inputs. Mismeasurement of the output of one sector translates into mismeasurement of total factor productivity growth in the opposite direction in downstream industries that use its output. Thus, the mismeasurement hypothesis actually implies mismeasurement in users and in users of users, with effects going in opposite directions. While linkages of mismeasurement through the input-output table have long been understood (e.g. Griliches and Lichtenberg 1984), their implications for empirical effects of opposite sign do not appear to have been explored.

I find evidence of mismeasurement in what we do with computer and electronic intermediates. The point estimates are all decidedly negative, implying that we systematically overstate the factor augmenting gains associated with the use of these inputs. These results are robust to the use of different samples based upon different disaggregations of demand into national income accounting components. They are found using various forms of short or long run variation, i.e. in panel data, with and without industry and year fixed effects, and in long run industry means data. They are not driven by endogeneity of factor shares, as they remain when these are instrumented with pre-growth shares and lagged values of dependent variables are added to eliminate serial correlation in residuals. They are not driven by endogeneity of total factor productivity to price and demand shocks, as they are robust to adjustments for business cycle variation and capital utilization, the use of long run industry means data and, even, a wide grid search over all possible imposed values of the relationship between price and quantity and the productivity growth regressor.

Put simply, the relationship between price and demand growth and total factor productivity growth differs systematically and robustly from that implied by elasticities of demand and supply in a manner correlated with both within and between industry variation in the quantity of computer intermediate inputs. Similarly statistically significant and robust deviations are not found for any other input. I interpret this deviation in terms of a model of overstatement of factor augmenting technical change, i.e. what we do with computer inputs. Excluding outlier results in both directions, point estimates indicate an overstatement of industry output and total factor productivity growth of between .003 and .006 percent per annum per percentage share of computer and electronics inputs in total factor payments.

The paper whose observations are closest in spirit to this one is Acemoglu et al (2014). While documenting the correlation of higher industry labour productivity growth with some measures of computer technology use, they note that it is peculiarly negatively associated with real output growth, i.e. inconsistent with expected changes in demand following a reduction in price brought on by total factor productivity growth. The present paper expands this emphasis on using confirmatory observables into a methodology that quantifies mismeasurement using estimated relationships between left and righthand side observables, finding, similarly, that there are virtually no supply and demand elasticities that can eliminate the discrepancy between price, quantity and total factor productivity growth associated with computer and electronics intermediates use. Unless, of course, one allows for the possibility that the gains from such use are overestimated.

The association of higher labour productivity growth with some measures of computer use in pre- and early millennial data has been documented by Stiroh (2002) and Acemoglu et al (2014). In that spirit, this paper also runs a simple linear regression of total factor productivity growth on the expenditure share on domestically produced computer and electronics intermediate inputs, documenting a similar positive relation in post-millennial data. However, it also finds a substantial negative impact of the use of computer and electronic intermediates in upstream industries. This positive own effect and negative supplier effect is consistent with overstatement of the output gains from intermediate input use, which would overstate productivity growth in users while understating it in users of users. The point estimates from these regressions are very similar to those found using the "dark matter" methodology that concentrates on the relationship between observable price, quantity and total factor productivity growth.

Consequently, once adjustment for estimated mismeasurement is made, there is basically no relation between industry productivity growth and computer intermediate input use. This echoes the pushback to Solow's comment given by Gordon (2000) and Oliner & Sichel (2000): while the growth of computer capital has contributed greatly, in a standard growth accounting framework, to growth outside that sector and there has also been rapid total factor productivity growth in computing industries, it is less obvious that there should be an additional productivity contribution from the use of those inputs. The computer productivity revolution most obviously lies in Moore's Law and the extraordinary fall in the price of computational power, and less obviously in what we accomplish with that power.[1]

The new millennium has witnessed a US productivity slowdown with, for example, the Bureau of Economic Analysis' data described below showing private sector total factor productivity growth of .012 per annum between 1997 and 2000 falling to .007 in 2000-2023. Opinion pieces in the popular press express the view that this is due to a failure to properly measure the gains from computer technology (e.g. Aeppel 2015, Alloway 2015), but in considered academic analyses Byrne, Fernald & Reinsdorf (2016) and Syverson (2017) persuasively argue that such unmeasured gains cannot explain the productivity slowdown. This paper argues that insofar as this mismeasurement is attached to the sale of particular products, it should show up as discrepancies in the relation between price, quantity and total factor productivity growth and, hence, is actually measurable. It finds evidence of mismeasurement,

[1]In this regard, it is sobering to reflect on the fact that the Apollo 11 command and lunar module guidance computers each had only 2KB of RAM, which would be insufficient for almost any phone app today.

but unexpectedly in the opposite direction. At the aggregate level, this translates into at least ⅛ of measured US private sector GDP growth between 1997 and 2023, and ½ of private sector total factor productivity growth during that period as well. The estimated overstatement of growth is falling rapidly over time as the role of computer intermediates in the economy falls. Ironically, the productivity "slowdown" can largely be resolved, but by recognizing the overstatement, rather than understatement, of the gains from the use of computers.

The Boskin commission (1996) famously concluded that the Consumer Price Index (CPI) was biased upwards by 1.1 percent per year, of which about half could be attributed to a failure to measure quality improvements. This, along with other well-known studies finding unmeasured gains to quality improvement and variety (e.g. Gordon 1990, Bils and Klenow 2001, Bils 2009), might lead readers to conclude that growth is unambiguously underestimated. A number of studies, however, point in the opposite direction. For example, Gordon (2009) and Gordon and VanGoethem (2007) find downward biases in the CPI of 3 percent per annum for women's apparel and 1 percent per annum in rental shelter over many decades, while Aizcorbe and Ripperger-Suhler (2024) estimate a negative chain drift in hedonic price indices in 2011-2020 of 6 and 8 percent per annum for desktop and notebook computers, respectively. On the theoretical level, Feenstra (1995) finds that in a discrete choice framework with pricing above marginal cost log-linear hedonic regressions, such as those used in the analysis of computer prices, would overstate price declines, Hobijn (2002) shows that if price per unit quality rises with quality both hedonic and matched-model price indices will overstate price declines, Harper (2007) notes that durable goods obsolescence leads to an overstatement of quality change, and Aizcorbe and Copeland (2007) argue that with intermittent purchases price indices will tend to understate true movements in the cost of living index as consumers do not gain from price declines above their reservation value. While this paper is not about the methodology of price indices, to aid in the interpretation of its results I summarize some of these insights in a short explanation of how obsolescence and lifecycle differences in the reservation values of buyers can lead both hedonic and matched-model price indices to overstate price declines and output growth in durable goods industries upgrading quality through the use of computer and electronics intermediates.

The paper proceeds as follows: Section II presents a model of systematic mismeasurement of factor augmenting technical change and discusses how data on price and demand can be used to identify the rate of mismeasurement. Special emphasis is given to explaining the sources of identification, the steps taken to avoid endogeneity bias, and the methods used to demonstrate it is not determining the results. Section III introduces the BEA industry level total factor productivity and input output data. Monte Carlos are used to guide the methods used and emphasis placed in later results, highlighting relatively accurate inference using heteroskedasticity robust standard errors and differences in efficiency and power between estimation using disaggregated versus aggregated demand.

Section IV presents the main results using the dark matter methodology, emphasizing the robustness of results to sample and specification changes, as well as controls and instruments used to address possible endogeneity of total factor productivity growth and factor shares. The finding of overstated productivity growth in computer using industries is shown to remain when elasticities of demand and supply are taken as known and given almost any value the reader may like, emphasizing robustness to any possible bias in the estimation of these elasticities. As confirmatory evidence, Section V regresses total factor productivity growth on computer factor shares. While such regressions might be interpreted as demonstrating the positive effects of computer use, in the light of the dark matter results the finding of a positive association with own computer intermediates use and negative association with upstream use suggests a different interpretation, i.e. that of mismeasurement. Section VI evaluates the implications for growth in the aggregate economy, while Section VII concludes with a summary of results and short discussion of potential sources of downward bias in hedonic and matched-model durable goods price indices.

II. Estimating Mismeasurement Using Observables

(a) A Model of Systematic Mismeasurement in an Input-Output Framework

We assume throughout that national income accountants accurately measure nominal values but have difficulty disentangling these into price and quantity components. Let true and measured gross output and price in perfectly competitive industry *i* in period *t* be given by

$$(1a)\quad Q_{it}^{T} = F_i(f_{1it}^{T}M_{1it}^{T},\ldots,\ f_{Jit}^{T}M_{Jit}^{T})\quad P_{it}^{T} = C_i(W_{1t}^{T}/f_{1it}^{T},\ldots,\ W_{Jt}^{T}/f_{Jit}^{T})$$

$$(1b)\quad Q_{it}^{M} = F_i(f_{1it}^{M}M_{1i}^{T},\ldots,\ f_{Jit}^{M}M_{Jit}^{T})\quad P_{it}^{M} = C_i(W_{1t}^{T}/f_{1it}^{M},\ldots,\ W_{Jt}^{T}/f_{Jit}^{M})$$

where superscripted T and M denote true and measured values, F_i production functions which are constant returns to scale in J inputs $M_1 \ldots M_J$, C_i cost functions which are constant returns to scale in J input prices $W_1 \ldots W_J$, and f_{jit} factor augmenting productivity parameters. (1a) are standard production and cost functions. (1b) is a formalization of *what* national income accountants implicitly measure, not *how* they actually measure output quantities and prices as, with rare exceptions,[2] these are not measured by examining input quantities and prices, let alone productivity parameters. For this reason, the factor quantity and price arguments in the functions on the righthand side of (1b) are true values, even though these might not be measured accurately. The failure to properly appreciate and quantify the degree to which technical change is allowing industries to use inputs in novel and more productive ways (f_{jit}) appears as implicit

[2]Most notably government, which is not included as an industry in the analysis below.

unobserved (UO) discrepancies between true and measured factor augmenting productivity, $f_{jit}^{UO} = f_{jit}^{T}/f_{jit}^{M}$.

Differentiating (1) and (2) with respect to time and using the equivalence between elasticities and expenditure shares implied by perfect competition, the difference between measured and true output quantity and price growth is seen to be

$$(2a) \quad \hat{Q}_{it}^{M} = \hat{Q}_{it}^{T} - \sum_{j=1}^{J} \theta_{jit}\hat{f}_{jit}^{UO} \qquad (2b) \quad \hat{P}_{it}^{M} = \hat{P}_{it}^{T} + \sum_{j=1}^{J} \theta_{jit}\hat{f}_{jit}^{UO},$$

where θ_{jit} is the expenditure share of input j and ^ denotes a proportional growth rate. Since nominal output is measured correctly, i.e. $P_{it}^{T}Q_{it}^{T} = P_{it}^{M}Q_{it}^{M}$, offsetting errors in prices and quantities arise equally whether national income accountants derive real quantity indices by deflating nominal values using constructed price deflators or price indices by dividing nominal values by constructed quantity measures. Furthermore, as the output of each sector is used as an input in others, the same errors in disentangling price and quantity are propagated through the input-output table. Thus, when industry n is used as an input in sector i, we have:

$$(3) \quad \hat{M}_{nit}^{M} - \hat{M}_{nit}^{T} = \hat{Q}_{nt}^{M} - \hat{Q}_{nt}^{T} \ \& \ \hat{W}_{nt}^{M} - \hat{W}_{nt}^{T} = \hat{P}_{nt}^{M} - \hat{P}_{nt}^{T}.$$

We order inputs so that the first N correspond to the industry indices i, with the remaining J - N consisting of primary factors.

While the mismeasurement of what we do with computer inputs translates naturally into the mismeasurement of the intermediate inputs of downstream sectors, for the purposes of our analysis here we assume that primary factor inputs are measured accurately. As this assumption may be of concern to readers, the on-line appendix estimates mismeasurement of primary factor inputs using a similar methodology. Although point estimates consistently find that the growth of computer capital is overstated, the results are not statistically significant at the .01 level. While one might think that the mismeasurement of domestic output found below would result in mismeasurement of the growth of computer capital input, this is not the case, as computer related fixed capital investment is predominantly and increasingly based upon imports.[3] The analysis below of mismeasurement of what industries do with computer inputs is based upon the prices of and demand for private sector domestically produced output.

While true total factor productivity growth in industry i, i.e. the true growth of output minus the factor income share weighted growth of true factor inputs, is

$$(4) \quad \hat{A}_{it}^{T} = \hat{Q}_{it}^{T} - \sum_{j=1}^{J} \theta_{jit}\hat{M}_{jit}^{T} = \sum_{j=1}^{J} \theta_{jit}\hat{f}_{jit}^{T},$$

[3]According to the input-output tables, the import share of non-residential fixed investment in equipment of computer & electronics industry origin rose from 27% in 1997-1999 to 61% in 2021-2023.

measured total factor productivity growth, equal to measured output growth minus the factor income share weighted measured growth of inputs, is given by

$$(5)\quad \hat{A}_{it}^{M} = \hat{Q}_{it}^{M} - \sum_{j=1}^{J} \theta_{jit}\widehat{M}_{jit}^{M} = \hat{A}_{it}^{T} + \hat{Q}_{it}^{M} - \hat{Q}_{it}^{T} - \sum_{j=1}^{J} \theta_{jit}(\widehat{M}_{jit}^{M} - \widehat{M}_{jit}^{T})$$

$$\Rightarrow\ \hat{A}_{it}^{M} = \hat{A}_{it}^{T} - \sum_{j=1}^{J} \theta_{jit}\hat{f}_{jit}^{UO} + \sum_{j=1}^{N} \theta_{jit} \sum_{k=1}^{J} \theta_{kjt}\hat{f}_{kjt}^{UO}.$$

Mismeasurement of what is done with inputs impacts own industry TFP estimates directly in one direction and the TFP estimates of downstream industries indirectly in the opposite direction.

(b) Estimation framework

We aim to identify the above by looking at the market for industry output, where the moving supply and demand curves follow

$$(6a)\ \hat{Q}_{it}^{S} = \rho\hat{P}_{it}^{T} + \rho\hat{A}_{it}^{T} + \eta_{i}^{S} + \eta_{t}^{S} + \epsilon_{it}^{S},$$

$$(6b)\ \hat{Q}_{it}^{D} = \sum_{D=C,X\ldots} \phi_{Dit}\,\widehat{D}_{it}^{T},\ \text{where}\ \phi_{Dit} = \frac{D_{it}^{T}}{\sum_{D} D_{it}^{T}}\ \ \&\ \ \widehat{D}_{it}^{T} = -\sigma_{D}\hat{P}_{it}^{T} + \eta_{i}^{D} + \eta_{t}^{D} + \epsilon_{it}^{D},$$

$$(6c)\ \hat{Q}_{it}^{S} = \hat{Q}_{it}^{D}.$$

In (6b) D denotes the different national income components of demand, i.e. consumption (C), exports (X), etc. The growth of total real demand is the sum of the growth of these components weighted by their shares of total industry sales (ϕ_{Dit}). We model each component as deriving from the maximization of a CES utility or production aggregator with elasticity of substitution σ_{D}, as in

$$(7)\ U_{Dt} = \left(\sum_{i} \alpha_{it}^{D}(D_{it}^{T})^{\frac{\sigma_{D}-1}{\sigma_{D}}}\right)^{\frac{\sigma_{D}}{\sigma_{D}-1}},\ \ \text{so that}\ \ \widehat{D}_{it}^{T} = -\sigma_{D}\hat{P}_{it}^{T} + \sigma_{D}\hat{\alpha}_{it}^{D} + \hat{E}_{t}^{D} - \hat{P}_{t}^{D},$$

$$\text{where}\ E_{t}^{D} = \sum_{i} D_{it}^{T}P_{it}^{T}\ \text{and}\ P_{t}^{D} = \sum_{i}(P_{it}^{T})^{1-\sigma_{D}}(\alpha_{it}^{D})^{\sigma_{D}}.$$

The η_{t}^{D} year fixed effects in (6b) capture the effect of $\hat{E}_{t}^{D} - \hat{P}_{t}^{D}$, the growth of nominal D-type expenditure divided by its CES aggregator price index, which will include elements such as imports not included in our demand system. The η_{i}^{D} industry fixed effects capture long run values of $\sigma_{D}\hat{\alpha}_{it}^{D}$, as there might be trends in α_{it}^{D} brought about by, say, unmodelled non-homotheticity in demand (i.e. a dependence of α_{it}^{D} on E_{t}^{D}/P_{t}^{D}).

Industry marginal cost evolves according to

$$(8)\ \sum_{j} \theta_{jit}\widehat{W}_{jt} - \sum_{j} \theta_{jit}\hat{f}_{jit}^{T} = \sum_{j} \theta_{jit}\widehat{W}_{jt} - \hat{A}_{it}^{T},$$

where the θ_{jit}, W_{jt} and f_{jit}^{T} are the factor j input expenditure shares, prices and augmenting productivity described earlier above. Consequently, in (6a) the η_i^S industry fixed effects reflect the impact of long run trends in relative factor prices on relative industry costs brought about by differences in factor proportions, while the η_t^S year fixed effects capture inflation in all factor prices. Differences in industry factor proportions and general equilibrium determination of factor prices, not to mention unmodelled short term adjustment costs, determine the industry elasticity of supply ρ in (6a). As each percent of total factor productivity growth lowers industry costs and supply curves by an equivalent amount, the $\rho\hat{A}_{it}^T$ term comes from the assumption of perfect competition or, more generally, constant markups. As discussed below, this assumption is not central to the analysis.

Setting the growth of supply equal to demand allows us to solve for the growth of equilibrium prices and quantities:

$$(9)\quad \hat{P}_{it}^T = \frac{-\eta_i^S - \eta_t^S - \epsilon_{it}^S - \rho\hat{A}_{it}^T + \sum_D \phi_{Dit}(\eta_i^D + \eta_t^D + \epsilon_{it}^D)}{\rho + \sum_D \phi_{Dit}\sigma_D}$$

$$\hat{D}_{it}^T = \frac{\sigma_D[\eta_i^S + \eta_t^S + \epsilon_{it}^S + \rho\hat{A}_{it}^T - \sum_D \phi_{Dit}(\eta_i^D + \eta_t^D + \epsilon_{it}^D)]}{\rho + \sum_D \phi_{Dit}\sigma_D} + \eta_i^D + \eta_t^D + \epsilon_{it}^D.$$

(9) can be described as a system of linear equations with heterogeneous coefficients and error disturbances determined by the demand shares ϕ_{Dit}

$$(10)\quad \mathbf{y}_{it}^T = \boldsymbol{\beta}_{it}(\phi_{Dit})\mathbf{x}_{it}^T + \boldsymbol{\epsilon}_{it}(\phi_{Dit}),$$

where $\mathbf{y}_{it}^T$ is the vector of true price and demand growth, $\mathbf{x}_{it}^T$ the vector formed by true total factor productivity growth and industry and time dummy variables, and we use () to emphasize that both the matrix of coefficients $\boldsymbol{\beta}_{it}$ and covariance structure of the residuals $\boldsymbol{\epsilon}_{it}$ are determined by unknown parameters[4] and the empirical demand shares ϕ_{Dit}. I refer to (9) and (10) below as the "structural" model, which can be estimated using maximum likelihood techniques and the assumption of multivariate normally distributed disturbances ϵ_{it}^S and ϵ_{it}^D.

If demand shares are all identical, $\phi_{Dit} = \phi_D$, then (9) can be simplified to:

$$(11)\quad \hat{P}_{it}^T = \beta_P\hat{A}_{it}^T + \mu_i^P + \mu_t^P + \varepsilon_{it}^P \text{ and } \hat{D}_{it}^T = \beta_D\hat{A}_{it}^T + \mu_i^D + \mu_t^D + \varepsilon_{it}^D \ (D = C, X, \ldots),$$

$$\text{where for } k = i,t\text{: } \mu_k^P = \frac{-\eta_k^S + \sum_D \phi_D\eta_k^D}{\rho + \sum_D \phi_D\sigma_D} \text{ and } \mu_k^D = \sigma_D\frac{\eta_k^S - \sum_D \phi_D\eta_k^D}{\rho + \sum_D \phi_D\sigma_D} + \eta_k^D,$$

$$\varepsilon_{it}^P = \frac{-\epsilon_{it}^S + \sum_D \phi_D\epsilon_{it}^D}{\rho + \sum_D \phi_D\sigma_D},\quad \varepsilon_{it}^D = \sigma_D\frac{\epsilon_{it}^S - \sum_D \phi_D\epsilon_{it}^D}{\rho + \sum_D \phi_D\sigma_D} + \epsilon_{it}^D,$$

$$\beta_P = \frac{-\rho}{\rho + \sum_D \phi_D\sigma_D} \text{ and } \beta_D = \frac{\sigma_D\rho}{\rho + \sum_D \phi_D\sigma_D}.$$

(11) can be re-expressed as a seemingly unrelated system of linear equations

[4]The elasticities ρ and σ_D, the fixed effects η_i and η_t, and the covariance structure of the shocks ϵ^S and ϵ^D.

$$(12)\quad \mathbf{y}_{it}^T = \mathbf{\Pi}\mathbf{x}_{it}^T + \boldsymbol{\varepsilon}_{it},$$

with $\mathbf{y}_{it}^T$ and $\mathbf{x}_{it}^T$ as defined following (10) above. With common regressors for each dependent variable, the seemingly unrelated coefficient estimates $\mathbf{\Pi}$ are simply the row-by-row OLS estimates, as is also the case when (12) is estimated using maximum likelihood with a multivariate normal error distribution. I refer to (11) and (12) below as the "seemingly unrelated regression" (SUR) model.

The reader will naturally object that demand shares are not identical, and hence the regression coefficients are intrinsically heterogeneous. The latter, however, is true of most empirical work, where the effects of the dependent variables are likely to be heterogeneous. While it is usually the case that $y_i = \boldsymbol{x}_i{}'\boldsymbol{\beta}_i + \epsilon_i$, applied econometricians nevertheless run the regression $y_i = \boldsymbol{x}_i{}'\boldsymbol{\beta} + \varepsilon_i$, with $\varepsilon_i = \boldsymbol{x}_i'(\boldsymbol{\beta}_i - \boldsymbol{\beta}) + \epsilon_i$. As long as the expectation $E(\boldsymbol{x}_i\varepsilon_i) = \mathbf{0}$, which is satisfied if the heterogeneity is independent of the regressors, with fixed regressors the expectation of the coefficient estimate of $\boldsymbol{\beta}$ is the expectation of $\boldsymbol{\beta}_i$, with an analogous consistency result with stochastic regressors if plim $\sum_i \boldsymbol{x}_i\varepsilon_i/N = \mathbf{0}$. In our case, the effects of dummy variables are mechanically accounted for by subtracting industry and time means, so if the structural model is literally true unbiasedness of the SUR OLS estimates β_P and β_D requires that the variation of ϕ_{Dit} net of industry and time means is independent of the same for true total factor productivity growth. In the empirical sample, the correlations of these are all but zero, as reported below. Heteroskedasticity robust standard errors are used throughout, in both SUR and structural estimation, to account for unmodelled intrinsic heteroskedasticity of the error terms.

Econometric theory tells us that if the structural model is strictly true, it yields more efficient estimates, as it explicitly accounts for variation across observations in $\boldsymbol{\beta}_{it}(\phi_{Dit})$ and the covariance structure of the errors. Conversely, the advantage of the SUR model is that it is not dependent upon a particular theoretical framework and hence valid under more general least squares conditions regarding the expectation or plim of products of regressors and errors. In baseline specifications using the actual data I find results given by the two approaches to be practically identical. I then rely on the flexibility of the SUR framework to explore larger specification changes, such as the inclusion of lags of the dependent variables and other additional regressors, without taking a formal stand on their implications for observational level heterogeneity in coefficients and the covariance structure of errors.

In the supply and demand system described above all prices and quantities are true values, as emphasized by the superscripted Ts. If mismeasurement applies, say, only to the use of one input j, (2) & (5) earlier can be simplified to

$$(13)\quad \hat{P}_{it}^T = \hat{P}_{it}^M - \theta_{jit}\hat{f}_{jit}^{UO},\quad \hat{Q}_{it}^T = \hat{Q}_{it}^M + \theta_{jit}\hat{f}_{jit}^{UO}$$

$$\&\quad \hat{A}_{it}^T = \hat{A}_{it}^M + \left(\theta_{jit} - \Omega_{jit}\right)\hat{f}_{jit}^{UO},\ \text{where } \Omega_{jit} = \textstyle\sum_{n=1}^{N}\theta_{nit}\theta_{jnt}.$$

As we deflate industry demand nominal values using the industry price index, we have $\widehat{D}_{it}^{T} - \widehat{D}_{it}^{M} = \widehat{Q}_{it}^{T} - \widehat{Q}_{it}^{M} = \theta_{jit}\hat{f}_{jit}^{UO}$ for all components of demand D as well. If we let γ_j denote the economy-wide average rate of mismeasurement of factor augmenting productivity growth in the use of input j, we can then substitute and rewrite the SUR system in terms of measured values as:

$$(14)\quad \widehat{P}_{it}^{M} = \theta_{jit}\gamma_j + \beta_P[\hat{A}_{it}^{M} + (\theta_{jit} - \Omega_{jit})\gamma_j] + \mu_i^P + \mu_t^P + \varepsilon_{it}^P$$

$$\widehat{D}_{it}^{M} = -\theta_{jit}\gamma_j + \beta_D[\hat{A}_{it}^{M} + (\theta_{jit} - \Omega_{jit})\gamma_j] + \mu_i^D + \mu_t^D + \varepsilon_{it}^D \quad (\text{for } D = C, X \ldots),$$

which is a non-linear SUR system. As happens for other parameters, variation in $\hat{f}_{jit}^{UO}$ across i and t is incorporated in the error term and unmodelled. The structural system can similarly be estimated by substituting (13) into (9) and either assuming $\hat{f}_{jit}^{UO} = \gamma_j$ for all i and t or formally modelling variation as a random effect, $\nu_{it} = \hat{f}_{jit}^{UO} - \gamma_j$. As estimating the latter is computationally costly and I find has minimal effect on headline results, structural estimates reported below assume the former.

In linear SUR with identical regressors, the generalized least squares (GLS) solution, weighting by the estimate of the covariance matrix of errors, is simply the equation-by-equation OLS solution. In the non-linear SUR system (14), with cross-equation restrictions on coefficients and local regressors (equal to derivatives with respect to parameters) that are not identical, the solution depends upon the covariance structure. If iterated until the estimated covariance matrix of residuals converges, this GLS solution is identical to maximization of the SUR system using maximum likelihood with normally distributed errors. I use this iteration below, so that both the SUR and structural results are maximum likelihood estimates. However, the SUR point estimates do not actually depend upon the assumption of normal errors and are valid under more general GLS conditions regarding plims and moments of regressors.

(c) Discussion of Identification

As noted in the Introduction, the conditions for identification above are simply those of standard linear or non-linear least squares, namely that the expectation or plim of the product of total factor productivity growth and factor share regressors with the error term is zero, i.e. exogeneity of the regressors, coupled with an interpretation of ratios of coefficients that requires that expenditure shares have no impact on price and quantity growth other than through their effects on true total factor productivity growth, an exclusion restriction, and that the impact of true total factor productivity growth on true price and quantity growth is the same regardless of its factor augmenting origin, i.e. a common β.

Total factor productivity growth impacts many observables within an industry, such as the relative use of factors, but these observables are likely to be heavily influenced by the factor augmenting form total factor productivity growth takes. It is plausible, however, that the form total factor productivity growth takes within an industry is not relevant to the downward shift in the supply curve or the equilibrium demand of users. In keeping with this argument, I remove own-industry-use intermediate input demand from the SUR specifications below to show that it does not determine results. Here one of the advantages of the SUR specification presents itself. The structural system cannot drop a segment of demand, because it relies upon calculating the weighted sum of demand changes ($\sum_D \phi_{Dit}\sigma_D$). However, if total factor productivity growth is correlated with the errors for one component of demand, i.e. endogenous to it, that component can be dropped from the SUR system and the remaining coefficients on total factor productivity growth estimated without prejudice. It is only that, with the reduced dimension of the system, it is no longer possible to map back from the β_P and β_D to the underlying elasticities ρ and σ_D using the equivalences given in (11) above.

For computer expenditure shares not to influence price and quantity other than through total factor productivity growth, it is necessary that our conception of price, quantity and productivity include quality improvements. (9), (11) and (14) allow for this, as they describe factor-augmenting-technical-change adjusted price and quantity as functions of true factor-augmenting-adjusted productivity. Here we follow standard national income accounting principles, re-expressing quality improvements as changes in quality adjusted prices per unit of quality adjusted quantity.

The identification of the slopes of supply and demand curves is a standard econometric problem, but of less importance here than the preceding exposition might suggest. In (6) above total factor productivity growth shifts the supply curve, allowing the identification of the demand elasticities σ_D in (9) and (11). The additional assumption in (6) that productivity growth shifts the supply curve one for one identifies the supply elasticity, but is not actually needed. To see this, note that if total factor productivity growth shifts the supply function by an unknown amount τ , then in moving from (6) to (11) in the SUR model we have

$$(15)\ \beta_P = \frac{-\tau\rho}{\rho + \sum_D \phi_D\sigma_D} \text{ and } \beta_D = \frac{\sigma_D\tau\rho}{\rho + \sum_D \phi_D\sigma_D}$$

and it is still the case that the ratio $-\beta_D/\beta_P$ identifies σ_D. The separate identification of the supply elasticity ρ from these coefficients, however, requires that τ be known, as can be seen by noting that otherwise we have $N_D + 1$ equations in $N_D + 2$ unknowns, where N_D denotes the number of components of demand. However, as can be seen in (11), knowledge of neither ρ, σ or τ is needed to estimate the value of γ_j, which depends only on β_P and β_D and not their decomposition. The non-structural SUR model highlights the fact that we are identifying mismeasurement from the way in which productivity growth affects price and quantities, without having to take a definitive structural stand on why that relation exists. In particular, since τ need not be 1, deviations from perfect competition in the form of variation of markups with productivity growth is not ruled out.

There is also the conventional issue of the endogeneity of regressors, i.e. their correlation with the error terms in (9) and (11). With regards to the factor shares θ_{jit} and Ω_{jit}, we are regressing the *growth* of prices and quantities on the *levels* of these regressors, so endogeneity would have to derive from correlated shocks. To this end, in the analysis below I include lagged values of the dependent variables as regressors to "whiten" the residuals and, to avoid distortions brought about by pre-testing, present results with different lag structures side-by-side.

An additional potential correlation stems from the use of discrete time growth measures. As the BEA's total factor productivity measures use standard Tornqvist indices based on the average value of factor shares, I use these average shares as regressors in baseline specifications below. The motivation for this is straightforward. If one takes a second order approximation of the production function in (1) with respect to ln inputs, one gets the translog production function

$$(16)\ \ln Q_{it}^T = \alpha_0 + \sum_{j=1}^J \alpha_j \ln f_{jit}^T M_{jit}^T + \sum_{j=1}^J \sum_{k=1}^J \frac{\beta_{jk}}{2} \ln f_{jit}^T M_{jit}^T \ln f_{kit}^T M_{kit}^T.$$

As under perfect competition the factor income share equals the derivative of the ln of output with respect to the ln of input, with some manipulation one finds that

$$(17)\ \ln \frac{Q_{it}^T}{Q_{it-1}^T} - \sum_{j=1}^J \bar{\theta}_{jit} \ln \frac{M_{jit}^T}{M_{jit}^T} = \sum_{j=1}^J \bar{\theta}_{jit} \ln \frac{f_{jit}^T}{f_{jit-1}^T}, \text{where } \bar{\theta}_{jit} = \frac{\theta_{jit}+\theta_{jit-1}}{2},$$

so that a productivity index based upon average factor shares is exact for changes across discrete time. However, through factor prices or adjustment costs that vary by factor, period t factor shares may be endogenous to t-1 to t price and demand growth shocks.

To address the possible endogeneity of average factor shares, I instrument these using initial t-1 factor shares, which are predetermined with respect to t-1 to t growth (especially once lagged dependent variables are added). Given the non-linear specifications, this is most easily addressed by full information maximum likelihood (FIML), wherein we append the first stage equations to the SUR price and demand system:

$$\begin{aligned}
(18)\quad \hat{P}_{it}^M &= \bar{\theta}_{jit}\gamma_j + \beta_P[\hat{A}_{it}^M + (\bar{\theta}_{jit} - \bar{\Omega}_{jit})\gamma_j] + \mu_i^P + \mu_t^P + \varepsilon_{it}^P \\
\hat{D}_{it}^M &= -\bar{\theta}_{jit}\gamma_j + \beta_D[\hat{A}_{it}^M + (\bar{\theta}_{jit} - \bar{\Omega}_{jit})\gamma_j] + \mu_i^D + \mu_t^D + \varepsilon_{it}^D \\
\bar{\theta}_{jit} &= \alpha_{\theta\theta}\theta_{jit-1} + \alpha_{\theta\Omega}\Omega_{jit-1} + \alpha_{\theta A}\hat{A}_{it}^M + \mu_i^\theta + \mu_t^\theta + \varepsilon_{it}^\theta \\
\bar{\Omega}_{jit} &= \alpha_{\Omega\theta}\theta_{jit-1} + \alpha_{\Omega\Omega}\Omega_{jit-1} + \alpha_{\Omega A}\hat{A}_{it}^M + \mu_i^\Omega + \mu_t^\Omega + \varepsilon_{it}^\Omega.
\end{aligned}$$

Lagged values of $\hat{P}_{it}^M$ and $\hat{D}_{it}^M$, as well as business cycle controls, are added as exogenous variables in some specifications. When instrumented below, the estimated values of γ_j for headline results shrink somewhat toward zero.

The FIML maximum likelihood approach can also be used with the structural model by appending the equations for $\bar{\theta}_{jit}$ and $\bar{\Omega}_{jit}$ to (9). Notwithstanding the use of maximum likelihood techniques as a general approach covering all frameworks examined in the paper, it is once again the case that for the SUR model the estimates are not dependent upon the assumption of a normal likelihood. As shown in the on-line appendix, FIML point estimates for the SUR model are all but identical to those found using three stage least squares that inserts predicted values of $\bar{\theta}_{jit}$ and $\bar{\Omega}_{jit}$ into the non-linear SUR system (14) above.

With respect to total factor productivity growth, mismeasurement of this variable due to changes in capacity utilization brought about by demand and supply shocks make it endogenous to price and quantity changes. The year fixed effects, motivated above as adjustment for movements in CES price indices and factor prices that are common to all industries, also adjust for common mismeasurement due to the business cycle. Further corrections for productivity growth mismeasurement, in the form of industry level adjustments for business cycle fluctuations and direct corrections for capital utilization based upon the hours of work per worker, do not have a substantial impact on the results, as shown below. Results using long run industry means, where mismeasurement due to capacity utilization should not be an issue, support the results found using annual panel data. Finally, I completely sidestep the issue of endogeneity and bias in the estimated *βs* on total factor productivity growth by taking these as known and showing that headline results regarding the direction of mismeasurement persist across virtually all possible exogenously imposed values for the response of prices and quantities to productivity growth. While the assumption of common *βs* is used to identify the degree of mismeasurement, this is not equivalent to saying that central conclusions regarding the direction of mismeasurement are sensitive to the estimated values of those *β*. In practice they are not and hence any residual endogeneity of total factor productivity growth beyond that accounted for by business cycle controls and capital utilization adjustments cannot be central to the results.

Finally, it is worth noting that while one might think that there is a lack of identification between mismeasuring the gains from the use of input *j* and mismeasuring, in the opposite direction, the gains from the use of all other inputs *~j*, this is incorrect. While $\theta_{\sim jit}$ = 1 - θ_{jit}, $\Omega_{\sim jit} = \sum_{n=1}^{N}\theta_{nit}\theta_{\sim jnt} = \sum_{n=1}^{N}\theta_{nit} - \Omega_{jit}$, and hence the SUR framework (14) applied to the mismeasurement of all inputs other than *j* yields the equations:

$$(19)\quad \hat{P}_{it}^{M} = \left(1-\theta_{jit}\right)\gamma_{\sim j} + \beta_P\left[\hat{A}_{it}^{M} + \left(1-\textstyle\sum_{n=1}^{N}\theta_{nit} - \theta_{jit} + \Omega_{jit}\right)\gamma_{\sim j}\right] + \mu_i^P + \mu_t^P + \varepsilon_{it}^P$$

$$\hat{D}_{it}^{M} = (\theta_{jit}-1)\gamma_{\sim j} + \beta_D\left[\hat{A}_{it}^{M} + \left(1-\textstyle\sum_{n=1}^{N}\theta_{nit} - \theta_{jit} + \Omega_{jit}\right)\gamma_{\sim j}\right] + \mu_i^D + \mu_t^D + \varepsilon_{it}^D.$$

Were $\sum_{n=1}^{N}\theta_{nit}$, the sum of private sector intermediate input expenditure shares, equal to 1, estimation of (19) would yield $\hat{\gamma}_{\sim j}$ equal to $-\hat{\gamma}_j$ of (14). As primary inputs have non-zero expenditure shares, this is not the case, and in practice below the estimates differ substantially. This highlights the role played by shares of users of users (Ω_{jit}) in identification.

III. The Data and Clarifying Monte Carlos

I use the Bureau of Economic Analysis's industry level total factor productivity estimates covering 61 private sector industries from 1997 to 2023 and input-output tables covering the same period. The BEA productivity estimates provide factor income share and quantity data for 14 inputs, comprised of 9 classes of capital, college and non-college labour, and energy, service and materials intermediates. The input-output tables allow the more detailed calculation of the intermediate input shares of the domestic 61 private sector industries, giving a total of 75 input categories.[5] Our interest lies in those inputs most obviously associated with computer technology, namely (i) computer hardware capital, (ii) software capital, (iii) computer and electronic intermediates and (iv) computer systems design & related intermediates. As the data are available, mismeasurement in the remaining 71 input categories is also examined, albeit parenthetically. I remind the reader that we are measuring mismeasurement of factor augmenting productivity growth in the use of inputs through systematic discrepancies in the relationship between prices & quantities demanded and total factor productivity growth in industries which are users and users of users of these inputs. Thus, repeatedly below the term industry is used to refer to users or user of users of inputs, demand and price refer to demand for and price of such industries, and inputs is used to refer to the inputs whose factor augmenting productivity growth is implicitly being mismeasured.

As dependent variables, I use the measured growth of industry prices (P) and demand for industry output (the D in equations above), broken down into the aggregate categories: consumption (C), exports (X), investment (I), government (G), private intermediate input use excluding own industry use (M), and own industry intermediate input use (O). I separate out own use (O) because this source of demand is likely to depend upon the factor augmenting form of total factor productivity growth, making regressors such as total factor productivity growth and input factor shares endogenous. As noted above, the flexibility of the SUR approach allows me to drop this element of demand. All demand components are net of input-output tables estimated imports by industry for that category of demand, and together they sum to total domestic supply.

Defined growth rates require positive values for these measures in all periods, which is only true for 20 industries. This 20 industry x 26 year sample is referred to as the PMCXIGO sample and model below, or PMCXIG when endogenous O is dropped in SUR estimation. To expand the number of industries, I combine investment and government, which are individually

[5] The BEA input-output tables are not actually a single matrix, but rather separate make tables by industry x commodity and use tables by commodity x industry. As the make table is largely diagonal, I treat commodities as synonymous with industries in the use table in compiling data. The correlation of the 61 industry x 26 year quantity growth in the IO use of commodities with the growth of industry output in the productivity data base is .988, or .982 once industry and year means are removed.

Table 1: Testing Lag Length in the SUR Vector Auto-Regression model
(p-value of lag coefficients by row in specifications indicated by column)

	PMCXR model - 44 industries				PMCXIG model - 20 industries				$PQ_{\sim O}$ model - 61 industries			
	1 lag	2 lags	3 lags	4 lags	1 lag	2 lags	3 lags	4 lags	1 lag	2 lags	3 lags	4 lags
	heteroskedasticity robust Wald statistic evaluated using asymptotic chi-squared distribution											
1st lag	.017	.001	.000	.000	.000	.000	.000	.000	.942	.951	.944	.979
2nd lags		.000	.000	.000		.000	.000	.000		.000	.000	.000
3rd lags			.156	.169			.000	.000			.002	.002
4th lags				.102				.011				.694
	heteroskedasticity robust Wald statistic evaluated using Wild bootstrap distribution											
1st lag	.212	.055	.048	.021	.151	.128	.123	.043	.960	.995	.985	.992
2nd lags		.000	.001	.000		.057	.161	.156		.000	.000	.000
3rd lags			.605	.655			.150	.176			.027	.034
4th lags				.496				.174				.823

Notes: Each row presents tests of the indicated lag coefficients in a regression with the column indicated total number of lags. Sample size equals number of industries times (26 - number of lags) years. Specifications include TFP growth and industry and year dummies, in addition to lagged lefthand-side variables, as regressors. PMCXR model has 25 (5x5) coefficients per lag length, PMCXIG 36 (6x6), and $PQ_{\sim O}$ model 4 (2x2). Wild bootstrap p-values based upon the distribution of the Wald statistic in 1000 iterations with estimated residuals multiplied by iid ±1 Rademacher random variables.

zero in many industries, into a residual category (R), which allows the calculation of growth rates for 44 industries in all years. I take this broad sample as my main sample and refer to it as the PMCXRO or PMCXR sample and model in tables below. Finally, all forms of demand net of imports can be combined to create aggregate domestic quantity demanded and supplied by industry. This provides non-zero growth rates for all 61 industries and is referred to as the PQ sample and model below, or $PQ_{\sim O}$ when own use is subtracted from Q. For the PQ sample, the SUR and structural models are identical, as demand shares (ϕ_{Dit}) are identically equal to 1.

As noted in Section II, OLS regressions provide unbiased or (with stochastic regressors) consistent estimates of average parameter values if parameter heterogeneity is independent of the regressors. In the context of the structural model above, this would be the case if variation in demand shares net of industry and year means is independent of the same for total factor productivity growth. In the data used in this paper, the correlations of residuals net of year and industry fixed effects of total factor productivity growth with the demand shares of consumption, exports, intermediates net of own use, investment, government, and own use intermediates are -.0135, -.0183, -.0032, .0183, .0213 and .0186, respectively, with no correlation commanding a p-value less than .21.

As also noted earlier, serial correlation in shocks might make t or even t-1 factor shares endogenous to t-1 to t price and demand growth. Table 1 presents tests of the statistical significance of lagged dependent variables in SUR specifications regressing the PMCXR , PMCXIG or $PQ_{\sim O}$ dependent variables on TFP growth, year and fixed effects, and lagged values of the vectors of lefthand-side variables. Reported p-values are calculated using the conventional heteroskedasticity robust Wald test alternately evaluated using its asymptotic chi-squared distribution, as well as the Wild bootstrap estimate of its finite sample distribution, as in small finite samples high dimensional tests of this sort using the asymptotic distribution often have sizeable positive size distortions (Young 2022). These tests strongly reject the null of zero 2nd order lags, but evidence in favour of higher order lags is weak. Specifications below err on the safe side; reporting results up to and including 3rd order lags.

Monte Carlos might give the reader some reassurance regarding the validity of the methods described above and used below, while also providing some sense of how asymptotic econometric theory plays out in the finite samples of this paper. Tables 2 and 3 use three data generating processes (*dgps*), based upon the point estimates of the PMCXRO structural model, its SUR counterpart, and the SUR model augmented with 3 lags of the vector of dependent variables. The error disturbances are either iid normal variables, with the covariance structure across the dependent variables found in each model's estimates, or else derived by multiplying the estimated residuals by Rademacher random variables that equal ±1 with 50/50 probability. The latter are referred to as "actual" errors, and take two forms: in one each industry x year vector of errors (for the vector of dependent variables) is multiplied by an independent Rademacher realization, producing independent but heteroskedastic errors, and in the other each industry matrix of errors is multiplied by a single Rademacher realization, producing errors that retain the within industry-cluster residual correlation present in the data and induced by estimation. 100 realizations of each *dgp* for each of 75 estimated mismeasurement models (based upon the 75 inputs described above) are used and PMCXRO structural and SUR PMCXRO & PQ estimation (the last two with and without 3 lags) applied to each *dgp*.

Table 2 reports the average across the 75 mismeasurement models for each *dgp* of the ln mean squared error of the estimated mismeasurement parameter, with the logarithm allowing the interpretation of differences as the average proportional difference per *dgp*. When the structural model PMCXRO is the *dgp*, mean squared error is lowest with structural estimation, even when the errors are cluster correlated in a fashion that is not considered in the structural estimation, but the difference with SUR PMCXRO no lags estimation is only 5 to 12 percent. Mean squared error rises when lags are added in SUR estimation, often by 20 percent or more, even when the *dgp* actually involves lagged values of the dependent variables. The PQ model gives up information by combining the different components of demand into one Q aggregate and tends to have slightly higher mean squared error than models which use disaggregated demand.

Table 3 reports rejection probabilities of both the true null equal to the mismeasurement parameter and the false null equal to 0 effects, to give some sense of size and power. Results using heteroskedasticity robust, industry clustered and homoskedastic covariance estimates are presented in separate panels. As seen, the industry clustered covariance estimate results in large

Table 2: Average ln Mean Squared Error of Mismeasurement Parameter
by Data Generating Process, Error Distribution and Estimation Framework
(each cell based on 100 replications for each of 75 mismeasurement models)

		estimation framework				
dgp	errors	structural PMCXRO	SUR no lags PMCXRO	SUR 3 lags PMCXRO	PQ no lags	PQ 3 lags
structural PMCXRO	normal	-.81	-.72	-.49	-.75	-.51
	actual-id	-.91	-.86	-.59	-.84	-.57
	actual-cl	-1.1	-.98	-.86	-.97	-.80
SUR no lags PMCXRO	normal	-.05	-.71	-.47	-.61	-.37
	actual-id	-.78	-.73	-.47	-.73	-.47
	actual-cl	-.96	-.98	-.76	-.86	-.68
SUR 3 lags PMCXRO	normal	-.20	-.76	-.56	-.67	-.45
	actual-id	-.76	-.75	-.56	-.72	-.54
	actual-cl	-.91	-.93	-.86	-.87	-.72
	mean	-.72	-.83	-.62	-.78	-.57

Notes: *dgps* based upon point estimates of indicated mismeasurement model for each of 75 inputs. Normal errors with estimated error covariance; actual-id (independently distributed) errors equal to vector of residuals for each industry x year multiplied by independent Rademacher ±1 variables; and actual-cl (industry clustered) errors equal to matrix of residuals for each industry multiplied by independent Rademacher ±1 variables.

size distortions. In contrast, the heteroskedasticity robust covariance estimate does reasonably well across the board, even when the simulated errors retain the within industry cluster correlation present in the data or induced by estimation. With normal iid homoskedastic errors its rejection probabilities are somewhat higher than with the homoskedastic covariance matrix, but size distortions are never extreme and its average performance, across all *dgps*, is better.[6] Using the heteroskedasticity robust covariance estimate, SUR estimation without lags and without aggregating demand into one Q category provides more accurate true null rejection probabilities than with lags and/or aggregation, and is comparable to structural estimation in accuracy, even when the *dgp* has lags or is structural. In the same, power is slightly higher with SUR estimation, except when the *dgp* is structural, and falls slightly when demand is aggregated, although differences for the most part are small. Based upon the above, in the analysis below I use heteroskedasticity robust covariance estimates throughout. Clustered covariance estimates are almost always smaller, making results appear more significant.

While I use OLS estimation to cover all 75 inputs, below I apply computationally more costly FIML instrumental variables SUR methods to interrogate the headline results for computer and electronics intermediates. Table 4 uses as its *dgp* the computer intermediates point estimates of the baseline FIML system in (18) above for SUR PMCXR estimation, augmented in some cases with three lags of the PMCXR variables. 1000 iterations are used with normal, actual and

[6]The residuals (of regressions on TFP growth and industry and year fixed effects) are decidedly non-normal, with kurtoses of 37, 11, 29, 40, 14, & 17 for the PMCXRO variables, respectively. Nevertheless, as can be seen in the table by comparing the normal and actual rows, this does not substantially worsen the accuracy of inference using the heteroskedasticity robust covariance estimate.

Table 3: Monte Carlo .01 Level Empirical Rejection Probabilities of Mismeasurement Nulls by Data Generating Process, Error Distribution and Estimation Framework
(each cell = 100 replications for each of 75 mismeasurement models)

		tests of true null = parameter value					tests of false null = 0				
estimation framework:		structural	SUR no lags	SUR 3 lags	PQ no lags	PQ 3 lags	structural	SUR no lags	SUR 3 lags	PQ no lags	PQ 3 lags
dgp	errors	(A) using heteroskedasticity robust covariance estimates									
structural	normal	.017	.016	.031	.018	.031	.153	.141	.142	.142	.147
	actual-id	.014	.011	.026	.015	.027	.148	.152	.141	.129	.128
	actual-cl	.022	.021	.016	.024	.020	.151	.154	.122	.141	.125
SUR no lags	normal	.013	.018	.027	.019	.030	.054	.154	.155	.134	.140
	actual-id	.013	.014	.026	.015	.027	.122	.131	.134	.118	.127
	actual-cl	.022	.014	.017	.022	.020	.131	.127	.128	.134	.133
SUR 3 lags	normal	.008	.018	.028	.019	.031	.043	.114	.163	.104	.138
	actual-id	.027	.023	.026	.021	.028	.123	.106	.148	.098	.146
	actual-cl	.029	.018	.013	.024	.023	.118	.096	.109	.097	.117
mean		.018	.017	.023	.020	.026	.116	.131	.138	.122	.133
		(B) using industry clustered covariance estimates									
structural	normal	.116	.122	.115	.123	.122	.285	.275	.235	.272	.250
	actual-id	.054	.055	.064	.065	.074	.235	.244	.211	.235	.206
	actual-cl	.038	.033	.034	.040	.044	.196	.188	.161	.195	.178
SUR no lags	normal	.077	.118	.113	.124	.119	.147	.289	.249	.267	.237
	actual-id	.052	.057	.065	.069	.074	.207	.238	.203	.237	.207
	actual-cl	.037	.036	.043	.052	.052	.196	.203	.167	.219	.188
SUR 3 lags	normal	.065	.119	.112	.127	.113	.153	.256	.261	.249	.236
	actual-id	.073	.082	.072	.097	.079	.180	.206	.223	.205	.227
	actual-cl	.058	.068	.031	.081	.039	.186	.199	.180	.197	.192
mean		.063	.077	.072	.086	.080	.199	.233	.210	.231	.213
		(C) using homoskedastic covariance estimates									
structural	normal	.011	.011	.021	.011	.019	.141	.127	.128	.131	.135
	actual-id	.028	.027	.046	.030	.050	.150	.141	.153	.142	.154
	actual-cl	.028	.020	.020	.030	.024	.145	.129	.119	.133	.130
SUR no lags	normal	.015	.012	.022	.012	.020	.063	.141	.144	.116	.124
	actual-id	.032	.036	.058	.031	.052	.141	.153	.166	.140	.163
	actual-cl	.036	.026	.030	.037	.033	.124	.133	.140	.129	.142
SUR 3 lags	normal	.007	.012	.021	.008	.021	.064	.112	.149	.086	.123
	actual-id	.037	.029	.055	.031	.052	.137	.128	.167	.121	.164
	actual-cl	.030	.015	.028	.022	.033	.130	.114	.118	.107	.120
mean		.025	.021	.033	.023	.034	.122	.131	.143	.123	.139

Notes: Structural and SUR refer to PMCXRO model. Otherwise, as in Table 2.

actual clustered errors created as described above and rejection probabilities using heteroskedasticity robust covariance estimates reported in the table.

As can be seen in Table 4, the accuracy of inference worsens with instruments,[7]

[7]Although first stage Fs are in the thousands. As shown in Young (2022), first stage F tests provide little assurance of accurate rejection probabilities using instrumental variables when errors are not homoskedastic normal.

Table 4: Monte Carlo .01 Level Empirical Rejection Probabilities and ln MSE
(each cell = 1000 replications for computer & electronics intermediates mismeasurement model)

		rejection probabilities											
		true null = parameter				false null = 0				ln MSE			
		PMCXR		$PQ_{\sim O}$		PMCXR		$PQ_{\sim O}$		PMCXR		$PQ_{\sim O}$	
dgp	errors	0 lags	3 lags	0 lags	3 lags	0 lags	3 lags	0 lags	3 lags	0 lags	3 lags	0 lags	3 lags
FIML no lags	normal	.025	.072	.029	.065	.963	.926	.918	.903	-4.2	-3.4	-4.1	-3.3
	actual-id	.044	.067	.057	.078	1.00	.932	.918	.845	-4.6	-3.3	-4.0	-2.9
	actual-cl	.000	.000	.000	.000	1.00	.975	.943	.950	-5.9	-4.4	-5.2	-3.6
FIML 3 lags	normal	.050	.025	.035	.039	.974	.752	.934	.771	-3.5	-3.7	-3.5	-3.4
	actual-id	.067	.011	.098	.052	.999	.867	.984	.879	-3.5	-3.9	-3.2	-3.1
	actual-cl	.000	.000	.000	.000	1.00	.749	1.00	.931	-3.8	-5.7	-3.4	-4.1
mean		.031	.029	.036	.039	.989	.867	.950	.880	-4.2	-4.1	-3.9	-3.4

Notes: PMCXR FIML *dgp* as in (18) above, augmented with 0 or 3 lags of the PMCXR variables on the right-hand side; estimation using PMCXR or $PQ_{\sim O}$ system, with and without lags. Otherwise as in Table 2.

especially for $PQ_{\sim O}$ estimation, but rejection probabilities .at the .01 level using PMCXR estimation remain below the .05 level when using the appropriate model for the lag structure of the *dgp*. Below I use the nominal .01 level as the assessment of "statistical significance." Power now falls off substantially more with $PQ_{\sim O}$ estimation, especially with lags, where the mean squared error is on average 70 to 80% higher than that found using PMCXR estimation. In the analysis below, headline results become much more volatile, and often insignificant, as lags are added to the $PQ_{\sim O}$ estimation framework, but are more stable and always significant when using the disaggregated demand models.

IV. Results

Table 5 reports estimates of mismeasurement in the gains from using computer related inputs following either the structural specification in (9) above, with true and measured values related as in (13), or the non-structural seemingly unrelated SUR model in (11) and (14). As noted earlier, there are three samples with 44, 20 and 61 industries, based upon the existence of non-zero values to calculate growth rates for the components of demand. SUR estimation allows the dropping of variables, as it does not make use of the structural equation linking the weighted sum of the growth of components of demand to the growth of total supply. As such, in some specifications it drops endogenous own use (O) as a left-hand side variable or removes it from the measure of total quantity ($Q_{\sim O}$). Heteroskedasticity robust standard errors are reported in ().

As seen in the table, estimated mismeasurement in the gains from using software capital varies closely around zero, while mismeasurement in the use of computer systems design intermediates is either strongly negative or strongly positive, often with equally large standard errors, depending upon the sample. In contrast, estimated mismeasurement in the use of both computer hardware capital and computer and electronics intermediates is consistently negative.

Table 5: Mismeasurement Associated with Computer Technology
(each cell a separately estimated model)

	structural model		SUR (seemingly unrelated regressions)					
variables:	PMCXRO	PMCXIGO	PMCXRO	PMCXIGO	PMCXR	PMCXIG	PQ	$PQ_{\sim O}$
industries:	44	20	44	20	44	20	61	61
computer hardware capital	-.30 (.13)	-.48 (.14)	-.32 (.17)	-.45 (.22)	-.37 (.15)	-.46 (.21)	-.54 (.38)	-.54 (.40)
software capital	-.08 (.15)	-.16 (.07)	-.14 (.19)	-.13 (.10)	-.09 (.18)	-.12 (.10)	.06 (.48)	.04 (.50)
computer & electronic intermediates	-.54 (.12)	-.61 (.08)	-.55 (.10)	-.61 (.08)	-.55 (.09)	-.61 (.08)	-.56 (.17)	-.61 (.16)
computer systems design intermediates	-.88 (.65)	-2.5 (.58)	-1.0 (.80)	-2.5 (.61)	-.88 (.75)	-2.5 (.59)	1.7 (1.2)	1.7 (1.3)
everything but comp. & elec. intermediates	.06 (.08)	.44 (.15)	.04 (.07)	.52 (.15)	.15 (.09)	.66 (.11)	.07 (.05)	.06 (.05)

Notes: Mismeasurement parameters as in the structural model (9) and (13) and SUR model (11) and (14). Heteroskedasticity robust errors in (). Observations = number of industries x 26 years. Industries dropped which have 0 demand for some component of demand, as growth rates are then undefined. Right hand side variables = growth of P (price) and domestic demand (excluding imports) components M (private sector intermediate use, excluding own use), C (consumption), X (exports), R (residual = G + I), I (investment), G (government final and intermediate), O (own use intermediate), Q (total demand = supply), and $Q_{\sim O}$ (Q excluding own use).

The absolute t-stats for computer hardware, however, are less than the 2.6 cutoff for significance at the .01 level in all but one specification and are shown to depend heavily on estimated elasticities of demand and supply further below, whereas the negative estimates for computer and electronics intermediates will be seen to be far more robust. The use of structural or SUR estimation, inclusion or exclusion of endogenous own output, or use of 61, 44 or 20 industry samples with varying dependent variables, does little to change the latter, which vary between -.54 and -.61, with absolute t-stats between 3.5 and 8, indicating that we overestimate the gains from using computer and electronic inputs in downstream industries.

Because of the role played by concatenated expenditure shares of users of users in identification, mismeasurement of the gains in the use of one factor is not equivalent to mismeasurement in the opposite direction of the gains from the use of all other factors, as highlighted in (19) above. The bottom row of Table 5 estimates a common rate of mismeasurement in the use of all factors other than computer and electronics intermediates. While estimates for the 20 industry PMCXIGO and PMCXIG models are close to the negative of those for computer & electronics intermediates ($\hat{\gamma}_{\sim j} \approx -\hat{\gamma}_j$), estimates for the 44 and 61 industry models, being near to and statistically indistinguishable from zero, are decidedly not. Thus, the

Table 6: Mismeasurement Associated with Other Inputs
(each cell a separately estimated model)

	structural model		SUR (seemingly unrelated regressions)					
variables:	PMCXRO	PMCXIGO	PMCXRO	PMCXIGO	PMCXR	PMCXIG	PQ	$PQ_{\sim O}$
industries:	44	20	44	20	44	20	61	61
communications	.18	.19	.01	.24	.03	.22	.85	.77
capital	(.33)	(.45)	(.61)	(.47)	(.49)	(.45)	(.95)	(1.0)
r & d	.18	.29	.17	.28	.20	.29	.21	.25
capital	(.09)	(.08)	(.10)	(.08)	(.10)	(.08)	(.15)	(.15)
instruments	.23	1.7	.58	1.7	.18	1.7	.17	.42
capital	(.50)	(.61)	(.58)	(.62)	(.59)	(.62)	(.78)	(.81)
transport	-.16	-.26	-.30	-.30	-.22	-.29	-.22	-.19
equipment	(.16)	(.22)	(.17)	(.22)	(.16)	(.22)	(.24)	(.25)
other	-.10	-.36	-.14	-.44	-.06	-.44	.00	.03
equipment	(.16)	(.24)	(.24)	(.24)	(.20)	(.24)	(.27)	(.29)
art	.07	-.02	.06	-.01	.01	-.02	.10	.05
capital	(.10)	(.08)	(.12)	(.09)	(.12)	(.09)	(.21)	(.20)
structures	-.10	-.21	-.12	-.22	-.10	-.22	-.22	-.22
capital	(.06)	(.05)	(.08)	(.06)	(.07)	(.06)	(.13)	(.15)
college	.22	.24	.20	.25	.22	.25	.24	.29
labour	(.06)	(.06)	(.08)	(.06)	(.07)	(.06)	(.14)	(.14)
non-college	.15	.19	.15	.20	.16	.21	.09	.10
labour	(.05)	(.08)	(.06)	(.08)	(.06)	(.08)	(.10)	(.10)
energy	.02	.04	.01	-.01	.02	.00	.05	.07
intermediates	(.07)	(.09)	(.07)	(.09)	(.07)	(.09)	(.11)	(.11)
materials	-.10	-.20	-.09	-.21	-.10	-.21	.02	.01
intermediates	(.05)	(.05)	(.05)	(.05)	(.05)	(.05)	(.06)	(.06)
services	-.03	-.05	-.02	-.04	-.02	-.04	.01	.00
intermediates	(.03)	(.03)	(.04)	(.03)	(.03)	(.03)	(.05)	(.05)
electrical	-1.5	-1.6	-1.7	-1.7	-1.9	-1.8	-1.1	-1.4
components*	(.68)	(.60)	(.65)	(.59)	(.65)	(.58)	(1.0)	(1.1)

Notes: (*) "Electrical equipment, appliances and components", but when used as intermediate inputs "components" are likely to dominate. Otherwise, as in Table 5.

negative results for computer intermediates in Table 5 should not be reinterpreted as indicating undermeasurement of the positive gains from the use of non-computer intermediates.

As comparison to Table 5, Table 6 reports results for other primary and intermediate inputs available in the data sets used in this paper. These are the five categories of non-computer capital, two categories of labour, and three broad intermediate input factor income share categories given in the BEA total factor productivity data base, as well as 59 other detailed intermediate industry input shares reported in the annual input-output tables. Point estimates of mismeasurement of the gains from the use of these inputs are generally statistically insignificant and sometimes sensitive in terms of sign to the specification. The exception is college labour,

Table 7: Impact of Fixed Effects on Point Estimates
(each cell a separately estimated model)

	SUR PMCXR 44 industries			SUR PMCXIG 20 industries			SUR $PQ_{\sim O}$ 61 industries		
fixed effects:	I	Y	none	I	Y	none	I	Y	none
computer hardware	-.54 (.18)	-.72 (.14)	-.77 (.15)	-.58 (.22)	-.57 (.14)	-.59 (.14)	-.75 (.37)	-1.3 (.27)	-1.3 (.26)
computer & elec. intermediates	-.59 (.10)	-.38 (.05)	-.39 (.05)	-.63 (.08)	-.41 (.04)	-.41 (.04)	-.66 (.17)	-.35 (.08)	-.37 (.08)
communications capital	.32 (.09)	-.10 (.03)	-.07 (.03)	.34 (.08)	-.20 (.03)	-.17 (.03)	.36 (.15)	-.06 (.05)	-.04 (.05)
r & d capital	-.08 (.62)	-.46 (.18)	-.49 (.20)	2.0 (.58)	-.48 (.27)	-.38 (.30)	-.10 (.81)	-.37 (.20)	-.41 (.20)
instruments capital	-.18 (.18)	-.01 (.02)	-.01 (.03)	-.14 (.24)	.20 (.07)	.22 (.09)	-.08 (.25)	-.03 (.04)	-.02 (.04)
transport equipment	-.01 (.20)	.24 (.05)	.24 (.06)	-.56 (.28)	.09 (.09)	.08 (.11)	.02 (.28)	.37 (.08)	.35 (.08)
structures capital	-.06 (.06)	.03 (.01)	.03 (.01)	-.08 (.05)	.03 (.01)	.03 (.01)	-.15 (.13)	.03 (.03)	.03 (.03)
college labour	.31 (.06)	-.05 (.02)	-.05 (.02)	.31 (.07)	-.01 (.01)	.00 (.01)	.36 (.12)	-.09 (.02)	-.08 (.02)
non-college labour	-.02 (.04)	.05 (.02)	.03 (.02)	-.08 (.04)	.13 (.02)	.09 (.02)	-.05 (.05)	.04 (.03)	.02 (.03)
electrical components	-2.5 (.79)	.02 (.09)	.01 (.11)	-2.0 (.78)	.06 (.08)	.05 (.11)	-2.4 (1.2)	.14 (.14)	.10 (.17)

Notes: Included fixed effects are industry (I), year (Y) or none. Otherwise, as in Table 5.

where there are found to be unmeasured positive effects that have t-stats above 2.6 in 6 of 8 specifications. Of the 59 other detailed industry intermediate inputs examined, only one, electrical components, has absolute t-stats greater than 2.6 in more than 3 of the 8 specifications, and its negative point estimates are reported in the table.

The results in Table 6, however, are sensitive to the inclusion of both year and industry fixed effects, as shown in Table 7, which reports SUR model estimates excluding intermediate own-use demand with subsets of fixed effects for those results found to be of a consistent sign in Tables 5 and 6. As can be seen, when industry or year fixed effects are removed all estimates found earlier in Table 6 to be of consistent sign, including statistically significant results for college labour, cease to be so. Thus, belief in these results requires strong adherence to identification from a particular form of residual variation. In contrast, the point estimates for computer hardware and electronics intermediates remain consistently negative, with absolute t-stats for the latter far above 2.6 in all specifications in this table and Table 5 earlier.

Table 8 introduces specification checks for the computer & electronics intermediates results that control for possible endogeneity of factor shares. In panel (A) lags of all dependent

Table 8: Controlling for Possible Endogeneity of Factor Shares: Lags and Initial Shares
(computer & electronics intermediates, each cell a separately estimated SUR model)

	no lags	1 lag	2 lags	3 lags	no lags	1 lag	2 lags	3 lags
	(A) using average factor shares				(B) instrumenting with initial shares			
PMCXR	-.55	-.48	-.60	-.45	-.50	-.42	-.56	-.40
44 industries	(.09)	(.11)	(.12)	(.14)	(.10)	(.11)	(.12)	(.14)
PMCXIG	-.61	-.51	-.50	-.45	-.59	-.49	-.47	-.43
20 industries	(.08)	(.09)	(.10)	(.11)	(.08)	(.09)	(.11)	(.12)
SUR $PQ_{\sim O}$	-.61	-.50	-.67	-.41	-.45	-.33	-.52	-.26
61 industries	(.16)	(.17)	(.17)	(.19)	(.17)	(.19)	(.19)	(.20)

Notes: With growth rates denoting changes between t-1 and t, average factor shares are the average of the two periods and initial are the factor shares in t-1. Specifications as in (14) and (18) with lags of the vector of lefthand side variables added to each equation. Otherwise, as in Table 5.

variables are added to each equation, making them vector autoregressions. These should remove any association between the levels of factor shares and the residuals brought about by the cumulative impact of autocorrelated shocks. As noted earlier, evidence in favour of more than 2 lags is weak, but up to 3 lags are added to be conservative. As in earlier Monte Carlos, efficiency falls and on average standard errors increase with the addition of lags. Here in the sample, point estimates bounce up and down with the addition of successive lags and on average are no different with two lags than with none, but are smallest in absolute magnitude with three lags, where they are -.45 for the two disaggregated demand models and -.41 for the aggregated $PQ_{\sim O}$ specification. Panel (B) adds an additional control for endogeneity, using the FIML equations of (18) above to instrument the average t and t-1 shares used in the analysis with initial t-1 factor shares and avoid possible endogeneity bias from the simultaneity of t factor income shares and t-1 to t growth rates. Comparing with panel (A), we see that point estimates of mismeasurement move a few percentage points toward zero in the PMCXR and PMCXIG specifications. The effects are larger in the $PQ_{\sim O}$ estimates, which are statistically insignificant with 1 or 3 lags, with point estimates of -.33 and -.26, but .01 statistically significant with 0 or 2 lags, with point estimates of -.45 and -.52, respectively.

Changes in capacity utilization with the business cycle or other demand and supply shocks create mismeasurement of TFP growth, which potentially makes this righthand side variable endogenous, biasing the estimates of the response to TFP growth and hence the linked mismeasurement parameter γ_j. The year fixed effects offer a very minimal correction for common effects due to these forces, but panel (A) of Table 9 addresses this issue more fully by allowing for industry heterogeneity. I add the national unemployment rate interacted with an industry indicator to the righthand side, so that the specification (not counting lags of the vector of dependent variables) becomes

Table 9: Controlling for Possible Endogeneity of Total Factor Productivity Growth: Business Cycle Controls, Capital Utilization Adjustment & Estimation using Mean Values (computer & electronics intermediates, each cell a separately estimated SUR model)

	no lags	1 lag	2 lags	3 lags	no lags	1 lag	2 lags	3 lags
	(A) national unemployment level U_t as industry specific control				(B) national unemployment change U_t - U_{t-1} as industry specific control			
PMCXR	-.51	-.47	-.61	-.42	-.56	-.50	-.56	-.37
44 industries	(.09)	(.11)	(.13)	(.14)	(.08)	(.10)	(.11)	(.13)
PMCXIG	-.60	-.51	-.48	-.41	-.62	-.50	-.45	-.40
20 industries	(.07)	(.09)	(.11)	(.12)	(.07)	(.08)	(.10)	(.11)
$PQ_{\sim O}$	-.57	-.51	-.70	-.40	-.62	-.53	-.61	-.30
61 industries	(.16)	(.17)	(.18)	(.19)	(.14)	(.15)	(.16)	(.17)
	(C) unemployment level controls, average shares instrumented with initial				(D) unemployment change controls, average shares instrumented with initial			
PMCXR	-.46	-.42	-.56	-.38	-.51	-.45	-.52	-.33
44 industries	(.10)	(.12)	(.13)	(.14)	(.09)	(.10)	(.11)	(.13)
PMCXIG	-.58	-.49	-.45	-.39	-.60	-.47	-.42	-.37
20 industries	(.08)	(.09)	(.11)	(.12)	(.07)	(.08)	(.10)	(.11)
$PQ_{\sim O}$	-.41	-.34	-.56	-.26	-.49	-.39	-.48	-.17
61 industries	(.17)	(.19)	(.19)	(.20)	(.16)	(.17)	(.18)	(.18)
	(E) capital utilization adjusted TFP growth				(F) capital utilization adjusted TFP growth, average shares instrumented with initial			
PMCXR	-.52	-.43	-.55	-.42	-.46	-.38	-.51	-.37
44 industries	(.09)	(.12)	(.13)	(.15)	(.10)	(.12)	(.13)	(.15)
PMCXIG	-.57	-.48	-.45	-.46	-.55	-.46	-.43	-.44
20 industries	(.07)	(.09)	(.11)	(.11)	(.07)	(.09)	(.11)	(.11)
$PQ_{\sim O}$	-.53	-.44	-.54	-.33	-.37	-.28	-.40	-.16
61 industries	(.17)	(.18)	(.17)	(.21)	(.18)	(.19)	(.18)	(.21)

(G) estimation using industry means (# of observations = # of industries)

PMCXR: 44 industries		PMCXIG: 20 industries		$PQ_{\sim O}$: 61 industries	
average	instrumented	average	instrumented	average	instrumented
-.88	-.83	-.49	-.40	-.72	-.71
(.31)	(.26)	(1.2)	(.36)	(.15)	(.15)

Notes: Unemployment specifications as in (20). Capital utilization adjusted TFP growth equals measured TFP growth minus the change in hours per person engaged times the capital income share. Means specification as in (21), with initial shares equal to those in 1997 for 1997 to 2023 growth. Otherwise, as in Tables 5 & 8.

$$(20)\quad \hat{P}^M_{it} = \bar{\theta}_{jit}\gamma_j + \beta_P\left[\hat{A}^M_{it} + \left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right)\gamma_j\right] + \delta^P_i U_t + \mu^P_i + \mu^P_t + \varepsilon^P_{it}$$

$$\hat{D}^M_{it} = -\bar{\theta}_{jit}\gamma_j + \beta_D\left[\hat{A}^M_{it} + \left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right)\gamma_j\right] + \delta^D_i U_t + \mu^D_i + \mu^D_t + \varepsilon^D_{it}$$

where U_t is the national unemployment rate and the δ_i are industry specific responses to the business cycle. Panel (B) uses the same specification, with the change in the unemployment rate, U_t - U_{t-1}, as the regressor. Comparing with Table 8, we see the effects of these adjustments are inconsistent, raising the mismeasurement parameter in some instances and lowering it in others.

Panels (C) and (D) of Table 9 add the unemployment controls as exogenous variables in the FIML instrumental variables system (18). The effects of instrumenting are analogous to those earlier in Table 8, as coefficients shrink toward 0, albeit mostly for the $PQ_{\sim O}$ sample.

Panels (E) and (F) consider a direct adjustment for capacity utilization, taking the change in hours per person engaged (which are included in TFP calculations) and imputing the same utilization adjustment to capital input (which has no such adjustment) by subtracting the change in hours per person engaged times the capital income share from TFP growth. Relative to baseline results with lags in Table 8, point estimates again move a few points towards zero. Across all panel specifications in Table 9, estimates are at their smallest magnitude in panels (D) and (F) with unemployment change controls or capital utilization adjustment, instrumenting average shares using initial shares and two or three lags. With two lags, these are between -.42 and -.52 for the PMCXR and PMCXIG models and -.40 to -.48 for $PQ_{\sim O}$, shrinking with three lags to between -.33 and -.44 and -.16 to -.17, respectively. PMCXR and PMCXIG estimates are always statistically significant at the .01 level with absolute t-stats greater than 2.6, but with three lags $PQ_{\sim O}$ results are not.

Panel (G) of Table 9 considers a more radical adjustment for capacity utilization, running the analysis using the 26-year industry averages of the variables. This should eliminate any endogeneity from changes in capacity utilization, whether due to business cycles or other price and demand shocks. Naturally, the industry and year fixed effects are dropped, so the specification is

$$(21)\quad \hat{P}_i^M = \gamma_j \theta_{ji} + \beta_P\left[\hat{A}_i^M + \gamma_j\left(\bar{\theta}_{ji} - \bar{\Omega}_{ji}\right)\right] + c_P + \varepsilon_i^P$$
$$\hat{D}_i^M = -\gamma_j \theta_{ji} + \beta_D\left[\hat{A}_i^M + \gamma_j\left(\bar{\theta}_{ji} - \bar{\Omega}_{ji}\right)\right] + c_D + \varepsilon_i^D,$$

where c_P and c_D are constants, growth rates of price, demand and total factor productivity are 1997-2023 industry averages and factor shares are either 26 year industry averages or such instrumented with initial (1997) values in a FIML framework. Point estimates using average shares are generally *more* negative than those found using annual panel data and instrumenting now has virtually no impact on $PQ_{\sim O}$ estimates. The instrumented estimates eliminate any possible endogeneity due to price and demand movements of total factor productivity growth through capacity utilization or factor shares through adjustment costs or equilibrium factor prices and are -.83 (.26) for PMCXR, -.40 (.36) for PMCXIG, and -.71 (.15) for $PQ_{\sim O}$. The large standard errors for PMCXIG are not surprising, as 6 constant terms and 28 covariance parameters are estimated using 20 effective observations each of means and covariance.

Sceptics might still argue that total factor productivity growth can be endogenous in the long run to realized or anticipated demand changes, as these determine market size and the profitability of investment in new technology. The ultimate response to this is to show that the

Table 10: Estimated Supply (ρ) & Demand (σ) Elasticities and Coefficients (β) on Price and Demand Components (computer & electronics intermediates)

	structural models					seemingly unrelated regression models (without own use)					
	PMCXRO		PMCXIGO			PMCXR		PMCXIG		$PQ_{\sim O}$	
	panel	means	panel	means		panel	means	panel	means	panel	means
ρ	.57	30	.66	23	β_P	-.17	-.96	-.06	-.93	-.45	-.79
	(.10)	(74)	(.12)	(61)		(.04)	(.10)	(.05)	(.30)	(.08)	(.14)
σ_M	4.7	1.4	13	2.4	β_M	.53	1.4	.44	2.2		
	(1.0)	(.39)	(8.4)	(.65)		(.10)	(.26)	(.15)	(3.2)		
σ_C	14	1.7	19	2.6	β_C	.29	1.7	.40	2.4		
	(3.5)	(.64)	(13)	(1.4)		(.16)	(.37)	(.26)	(1.1)		
σ_X	2.4	1.7	6.0	1.9	β_X	.21	1.7	.60	1.8		
	(1.0)	(.53)	(4.5)	(1.2)		(.12)	(.27)	(.18)	(1.1)		
σ_O	3.2	2.2	3.6	3.9							
	(1.4)	(.91)	(4.3)	(1.4)							
σ_R	7.4	1.7			β_R	.59	1.6				
	(1.8)	(.45)				(.11)	(.27)				
σ_I			25	3.0	β_I			.58	2.6		
			(17)	(.94)				(.23)	(4.1)		
σ_G			11	2.6	β_G			.44	2.3		
			(7.7)	(.73)				(.17)	(2.7)		
					$\beta_{Q\sim O}$					.61	1.4
										(.08)	(.22)
γ	-.54	-.92	-.61	-.46	γ	-.55	-.88	-.61	-.49	-.61	-.72
	(.12)	(.37)	(.08)	(.32)		(.09)	(.31)	(.08)	(1.2)	(.16)	(.15)

Note: Point estimates from specifications in Table 5.

finding of negative mismeasurement, i.e. an implicit overstatement of factor augmenting technical change in the use of computer and electronics inputs, is robust to variation in the relation between total factor productivity growth and price and demand growth. As a preliminary to this, Table 10 reports the point estimates associated with the response of price and quantity to total factor productivity growth in the baseline estimates of mismeasurement of computer and electronics inputs in Table 5 earlier. For the structural models, with annual panel data the estimated elasticity of supply ρ is found to be around .6 and elasticities of demand σ well in excess of 2, while with long run mean data the elasticity of supply is found to be an order of magnitude larger than the elasticities of demand, which fall somewhat. This pattern could be explained by convex adjustment costs in supply, leading to flatter long run supply curves, and the use of inventories and durable goods services to smooth use, allowing greater demand price sensitivity in the short than in the long run. Standard error estimates, however, are very large and in most cases differences between short and long run estimates are not statistically significant.

A similar pattern, however, is found in the non-structural SUR models. As noted earlier, the coefficient on total factor productivity growth in the SUR price equation, β_P, if given a structural interpretation, equals $-\rho/(\rho+\Sigma_i\phi_i\sigma_i)$, so that $\rho/\Sigma_i\phi_i\sigma_i = -\beta_P/(1+\beta_P)$. Thus, the coefficient in the price equation provides an indication of the ratio of the elasticity of supply to the weighted elasticities of demand, even if not all of those elasticities are actually estimated when a component of demand (i.e. own use) is dropped. Using this, in SUR estimation in Table 10 we find implied estimates of the ratio of supply to weighted demand elasticities in the short and long runs (using panel and means data), respectively, of .20 and 24, .06 and 13, and .82 and 4 in the PMCXR, PMCXIG and $PQ_{\sim O}$ models, respectively. The coefficients on total factor productivity growth in the SUR demand equations, β_D, if given a structural interpretation equal $\sigma_D\rho/(\rho+\Sigma_i\phi_i\sigma_i)$, so that $\sigma_D = -\beta_D/\beta_P$. With this in mind, we see that the PMCXR and PMCXIG models indicate that elasticities of demand are generally smaller in the long run.

For our purposes, however, the most interesting feature of Table 10 is the fact that estimated mismeasurement of computer & electronics intermediates (γ) remains strongly negative across a variety of estimated elasticities and relative elasticities. To explore this further, Table 11 re-estimates the mismeasurement models taking the elasticities and relative elasticities as "known" in each regression but varying across regressions so as to cover the whole range of possible values. For the structural models, I consider supply and demand elasticities that are either 0, ½, 1, 5 or 100. There are 15624 possible combinations in the PMCXRO model and 78124 in the PMCXIGO model,[8] and I separately estimate the mismeasurement parameter for computer hardware and computer and electronics intermediates for each and every one. In the case of the non-structural SUR model, I consider values of β_P ranging in .1 increments along the interval [-1,0], i.e. a relative supply-to-demand elasticity ranging from ∞ to 0, and set the values of $\beta_D = -\sigma_D\beta_P$, where σ_D takes on each of the values (0,½,1,5,100) in the PMCXR and PMCXIG models, with 6251 and 31251 total combinations, respectively, and (0,¼,½,¾,1,2,5,10,100) in the $PQ_{\sim O}$ model, where there are 91 combinations across β_P and $\beta_{Q\sim O}$.[9] Separate estimation is carried out using average factor shares and the same instrumented using initial factor shares.

As can be seen in Table 11, across almost all possible combinations of elasticities and relative elasticities of supply and demand, and across all samples and estimation frameworks, in almost every instance the point estimate of mismeasurement for computer & electronic intermediate inputs is negative. Those rare estimates which are positive involve very high relative elasticities of supply (i.e. values of β_P equal to -1 or nearly so) and elasticities of demand

[8]The structural model is undefined when all elasticities equal 0, i.e. supply and demand are both vertical, thus the number of combinations is 5^k-1, where k equals the number of lefthand side variables.

[9]When $\beta_P = 0$ the estimate of γ does not depend upon σ_D (price does not respond to TFP growth and so the elasticity of demand does not matter).

Table 11: Mismeasurement Estimates' Range Across Combinations of "Known" Elasticities

	computer hardware capital				computer & elec. intermediates				
	average shares		instrumented		average shares		instrumented		combin-
	range	# > 0	range	# > 0	range	# > 0	range	# > 0	ations
struc. PMCXRO									
panel data	-2.3 to .33	5381	-1.9 to 19	5673	-.69 to -.24	0	-9.6 to .00	1	15624
industry means	-3.5 to .27	932	-42 to 4.7	2485	-.84 to -.12	0	-.70 to -.04	0	15624
struc. PMCXIGO									
panel data	-2.0 to .88	114	-15 to 14	3060	-1.0 to -.30	0	-2.7 to -.09	0	78124
industry means	-3.6 to .55	3549	-24 to 8.4	8285	-1.1 to -.01	0	-.84 to .10	8	78124
SUR PMCXR									
panel no lags	-2.9 to .33	4451	-1.9 to 19	4528	-.70 to -.21	0	-10 to .06	1	6251
panel 1 lag	-2.8 to .40	4608	-1.7 to 19	4654	-.66 to -.08	0	-11 to .28	4	6251
panel 2 lags	-4.1 to .63	4655	-2.6 to 19	4714	-.79 to -.22	0	-11 to -.06	0	6251
panel 3 lags	-4.0 to 1.2	4743	-3.0 to 20	4756	-.64 to -.04	0	-13 to .47	9	6251
industry means	-3.0 to .42	3140	-18 to 5.2	4051	-.86 to -.16	0	-.71 to -.11	0	6251
SUR PMCXIG									
panel no lags	-1.9 to 1.0	164	-15 to 15	6413	-1.0 to -.29	0	-2.9 to -.08	0	31251
panel 1 lag	-1.8 to 1.8	11523	-13 to 15	21371	-1.3 to -.15	0	-4.0 to .10	18	31251
panel 2 lags	-3.5 to 1.9	23132	-4.3 to 16	23280	-1.3 to -.14	0	-4.7 to .08	6	31251
panel 3 lags	-5.8 to 2.0	24008	-6.8 to 16	24148	-.99 to .13	6	-5.4 to .80	52	31251
industry means	-3.8 to .57	5815	-9.2 to 5.9	6832	-1.1 to .02	2	-.86 to .06	19	31251
SUR PQ$_{\sim O}$									
panel no lags	-1.0 to 1.4	32	-.70 to 22	35	-.80 to -.55	0	-14 to -.03	0	99
panel 1 lag	-.61 to 2.2	35	-.54 to 23	38	-.78 to -.35	0	-15 to .47	3	99
panel 2 lags	-1.6 to 1.9	32	-1.0 to 24	35	-1.1 to -.47	0	-15 to .20	1	99
panel 3 lags	-2.1 to 2.3	41	-1.4 to 25	35	-1.0 to -.01	0	-17 to 1.0	8	99
industry means	-2.9 to .97	23	-8.9 to 5.8	15	-.96 to -.24	0	-.86 to -.20	0	99

Notes: # > 0 = number of combinations for which the point estimate of mismeasurement is > 0.

between .5 and 1. Appearing for the most part in panel data with identification net of fixed effects for industry and year, the highly elastic short run supply needed for these positive estimates seems implausible and is grossly removed from the short run point estimates found in Table 10, requiring a large degree of endogeneity bias. In contrast, the point estimates of mismeasurement for computer hardware capital, which were consistently negative, albeit statistically insignificant, in the baseline results of Table 5 earlier, are very often positive for a large fraction and wide range of potential combinations.

Table 12 provides further detail, giving the point estimates and associated standard errors for the outcome with the largest share of positive estimates for computer intermediates, in the PQ$_{\sim O}$ specification instrumenting with initial shares using panel data and 3 lags, as well as the estimates that are least susceptible to criticism on the grounds of endogeneity, those instrumenting mean 1997-2023 growth rates with 1997 initial shares. As can be seen, the panel data point estimates of mismeasurement for computer hardware capital are positive with

Table 12: Estimated Mismeasurement for Different "Known" Values of β^P and $\beta_D = -\sigma_{Q\sim O}\beta_P$
(PQ$_{\sim O}$ FIML estimation using initial shares as instruments)

$\sigma_{Q\sim O}$:	0	.25	.50	.75	1	2	5	10	100
β^P	(A) computer hardware – estimation using industry means								
-.00	-8.9 (9.1)	-8.9 (9.6)	-8.9 (9.5)	-8.9 (9.6)	-8.9 (9.6)	-8.9 (9.4)	-8.9 (9.6)	-8.9 (9.6)	-8.9 (9.6)
-.10	-7.4 (6.7)	-7.4 (7.0)	-7.4 (7.2)	-7.3 (7.3)	-7.3 (7.3)	-6.7 (6.0)	-5.0 (3.3)	-3.7 (2.2)	5.7 (1.5)
-.20	-5.7 (5.1)	-5.7 (5.7)	-5.7 (6.1)	-5.6 (6.4)	-5.5 (6.4)	-4.7 (5.2)	-3.2 (2.9)	-2.6 (1.4)	5.6 (1.6)
-.30	-4.1 (5.6)	-4.0 (6.3)	-3.9 (6.8)	-3.8 (7.0)	-3.6 (7.0)	-3.0 (5.4)	-2.2 (2.3)	-2.5 (1.0)	-3.5 (.88)
-.40	-2.6 (6.7)	-2.4 (6.4)	-2.3 (5.9)	-2.2 (5.4)	-2.2 (4.9)	-2.0 (3.5)	-1.8 (1.8)	-2.5 (.91)	-3.5 (.89)
-.50	-1.5 (3.7)	-1.5 (3.1)	-1.6 (2.7)	-1.6 (2.5)	-1.6 (2.4)	-1.5 (1.9)	-1.8 (1.5)	-2.6 (.89)	-3.5 (.95)
-.60	-1.2 (1.6)	-1.3 (1.5)	-1.4 (1.4)	-1.5 (1.4)	-1.5 (1.4)	-1.1 (1.1)	-1.9 (1.2)	-2.8 (1.6)	-3.5 (.86)
-.70	-1.0 (.94)	-1.2 (.90)	-1.4 (.92)	-1.5 (.96)	-1.6 (.97)	-.57 (.85)	-2.2 (1.1)	5.8 (1.6)	-3.6 (.69)
-.80	-.87 (.70)	-1.1 (.66)	-1.4 (.69)	-1.6 (.76)	-1.5 (.85)	.11 (.84)	5.7 (1.8)	5.7 (1.6)	-3.6 (.79)
-.90	-.60 (.71)	-.91 (.64)	-1.2 (.72)	-1.3 (1.2)	-.51 (1.8)	.76 (.92)	5.7 (1.8)	5.7 (1.6)	-3.6 (1.0)
-1.0	-.13 (1.0)	-.33 (.97)	-.24 (1.6)	.86 (2.9)	2.8 (3.1)	1.2 (1.1)	5.7 (1.7)	5.7 (1.6)	-3.6 (.71)
	(B) computer hardware capital – estimation using panel data with 3 lags								
-.00	-.18 (.17)	-.18 (.17)	-.18 (.17)	-.18 (.17)	-.18 (.17)	-.18 (.17)	-.18 (.17)	-.18 (.17)	-.18 (.17)
-.10	-.24 (.19)	-.25 (.19)	-.26 (.20)	-.27 (.20)	-.28 (.20)	-.31 (.22)	-.39 (.26)	-.20 (.21)	7.8 (4.8)
-.20	-.30 (.22)	-.32 (.22)	-.34 (.23)	-.37 (.25)	-.39 (.26)	-.48 (.30)	-.28 (.27)	.98 (.38)	20.7 (3.3)
-.30	-.35 (.24)	-.40 (.26)	-.44 (.28)	-.49 (.31)	-.54 (.33)	-.68 (.42)	.62 (.28)	1.4 (.54)	22.9 (3.0)
-.40	-.40 (.27)	-.48 (.31)	-.56 (.35)	-.64 (.39)	-.72 (.44)	-.80 (.54)	1.3 (.49)	1.7 (.65)	23.8 (3.0)
-.50	-.44 (.30)	-.55 (.36)	-.68 (.42)	-.82 (.50)	-.96 (.58)	-.51 (.57)	1.6 (.59)	2.1 (.82)	24.3 (2.6)
-.60	-.47 (.33)	-.62 (.40)	-.81 (.51)	-1.0 (.64)	-1.2 (.78)	.70 (.54)	1.8 (.65)	2.6 (1.1)	24.5 (3.9)
-.70	-.47 (.34)	-.66 (.45)	-.91 (.60)	-1.2 (.81)	-1.4 (1.1)	2.2 (.79)	1.9 (.70)	3.4 (1.6)	24.7 (3.6)
-.80	-.45 (.35)	-.66 (.48)	-.96 (.68)	-1.3 (1.0)	-1.2 (1.5)	2.8 (1.0)	2.1 (.77)	4.5 (2.4)	24.8 (7.1)
-.90	-.39 (.35)	-.60 (.49)	-.86 (.74)	-.92 (1.2)	1.6 (2.0)	3.0 (1.1)	2.2 (.86)	6.3 (3.7)	24.9 (2.9)
-1.0	-.30 (.34)	-.45 (.47)	-.50 (.73)	.69 (1.3)	9.4 (2.4)	2.9 (1.1)	2.5 (.97)	8.7 (4.9)	25.0 (3.3)
	(C) computer & electronics intermediates – estimation using industry means								
-.00	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.42 (.04)
-.10	-.42 (.04)	-.42 (.04)	-.42 (.04)	-.43 (.04)	-.43 (.04)	-.43 (.04)	-.44 (.04)	-.44 (.04)	-.43 (.04)
-.20	-.43 (.04)	-.43 (.04)	-.43 (.04)	-.44 (.05)	-.44 (.05)	-.44 (.05)	-.46 (.04)	-.45 (.04)	-.52 (.15)
-.30	-.43 (.05)	-.44 (.05)	-.44 (.05)	-.45 (.05)	-.45 (.05)	-.46 (.05)	-.48 (.04)	-.45 (.03)	-.61 (.24)
-.40	-.44 (.05)	-.44 (.05)	-.45 (.05)	-.46 (.05)	-.47 (.05)	-.49 (.05)	-.49 (.04)	-.44 (.03)	-.68 (.30)
-.50	-.43 (.05)	-.45 (.05)	-.46 (.05)	-.47 (.05)	-.49 (.06)	-.52 (.06)	-.49 (.04)	-.43 (.03)	-.72 (.33)
-.60	-.42 (.06)	-.44 (.06)	-.47 (.06)	-.49 (.06)	-.51 (.06)	-.57 (.07)	-.49 (.03)	-.43 (.03)	-.75 (.34)
-.70	-.40 (.06)	-.43 (.07)	-.47 (.07)	-.51 (.07)	-.55 (.08)	-.62 (.07)	-.48 (.03)	-.43 (.03)	-.77 (.35)
-.80	-.35 (.07)	-.39 (.08)	-.45 (.09)	-.53 (.09)	-.61 (.10)	-.68 (.08)	-.47 (.03)	-.44 (.04)	-.79 (.36)
-.90	-.29 (.07)	-.32 (.09)	-.38 (.11)	-.52 (.13)	-.71 (.15)	-.72 (.07)	-.46 (.03)	-.44 (.04)	-.80 (.37)
-1.0	-.21 (.06)	-.20 (.09)	-.23 (.13)	-.40 (.19)	-.86 (.29)	-.71 (.07)	-.46 (.03)	-.45 (.05)	-.81 (.39)
	(D) computer & electronics intermediates – estimation using panel data with 3 lags								
-.00	-.34 (.12)	-.34 (.12)	-.34 (.12)	-.34 (.12)	-.34 (.12)	-.34 (.12)	-.34 (.12)	-.34 (.12)	-.34 (.12)
-.10	-.33 (.12)	-.33 (.12)	-.33 (.12)	-.33 (.12)	-.33 (.12)	-.33 (.12)	-.33 (.14)	-.39 (.15)	-1.6 (.68)
-.20	-.31 (.12)	-.31 (.12)	-.31 (.13)	-.31 (.13)	-.31 (.13)	-.31 (.14)	-.38 (.17)	-.59 (.13)	-12.5 (2.8)
-.30	-.30 (.13)	-.30 (.13)	-.29 (.13)	-.29 (.14)	-.29 (.14)	-.30 (.17)	-.52 (.17)	-.67 (.12)	-15.1 (2.1)
-.40	-.28 (.13)	-.27 (.14)	-.27 (.14)	-.26 (.15)	-.26 (.16)	-.28 (.21)	-.64 (.15)	-.73 (.13)	-15.9 (1.9)
-.50	-.26 (.14)	-.25 (.15)	-.24 (.16)	-.22 (.17)	-.22 (.19)	-.29 (.26)	-.70 (.13)	-.80 (.15)	-16.3 (2.2)
-.60	-.24 (.14)	-.22 (.16)	-.19 (.17)	-.17 (.20)	-.15 (.23)	-.35 (.32)	-.73 (.13)	-.89 (.19)	-16.5 (2.1)
-.70	-.21 (.15)	-.18 (.17)	-.14 (.19)	-.09 (.23)	-.05 (.29)	-.50 (.33)	-.76 (.13)	-1.0 (.25)	-16.7 (2.3)
-.80	-.18 (.15)	-.13 (.18)	-.06 (.22)	.03 (.28)	.11 (.38)	-.68 (.29)	-.79 (.14)	-1.2 (.36)	-16.8 (1.7)
-.90	-.16 (.16)	-.08 (.19)	.03 (.24)	.20 (.35)	.40 (.54)	-.81 (.24)	-.83 (.16)	-1.4 (.53)	-16.8 (1.3)
-1.0	-.13 (.16)	-.03 (.20)	.14 (.27)	.47 (.43)	.97 (.83)	-.87 (.21)	-.87 (.17)	-1.8 (.86)	-16.9 (2.1)

elasticities of demand above 2 and values of β_P below -.5, i.e. a relative elasticity of supply from 1 to infinity, in both short and long run data. In contrast, the estimates for mismeasurement of the gains from the use of computer and electronics intermediate inputs are consistently negative and only approach 0 if the short term (estimated off of annual panel data with year and industry fixed effects and 3 lags) relative elasticity of supply to demand is above 5 ($\beta_P < -.8$) and the elasticity of demand tightly delimited by ½ and 1. For long run means data instrumenting with initial shares, the estimate of mismeasurement using computer intermediates is always negative and, with the exception of extreme elasticity values, statistically significant at the .01 level.

V. Confirmatory Evidence from TFP Growth Projected on Factor Shares

The variation underlying the preceding results is admittedly difficult to intuit. At the least squares-like solution which maximizes each non-linear SUR likelihood, the "regressors" are the derivatives of the non-linear equations with respect to each parameter:

$$(21)\quad \frac{\partial \hat{P}_{it}^{M}}{\partial \beta^{P}} = \hat{A}_{it}^{M} + \gamma_j\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right),\ \ \frac{\partial \hat{P}_{it}^{M}}{\partial \gamma_j} = \beta_P\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right) + \bar{\theta}_{jit}$$

$$\frac{\partial \hat{D}_{it}^{M}}{\partial \beta^{D}} = \hat{A}_{it}^{M} + \gamma_j\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right),\ \ \frac{\partial \hat{D}_{it}^{M}}{\partial \gamma_j} = \beta_D\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right) - \bar{\theta}_{jit}.$$

weighted by the inverse covariance matrix of dependent variable residuals. Thus, at the point estimates, the mismeasurement parameter is determined by the variation of $\beta\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right) \pm \bar{\theta}_{jit}$ that is correlated with $\hat{P}_{it}^{M}$ and $\hat{D}_{it}^{M}$ that is orthogonal to unobserved true total factor productivity growth $\hat{A}_{it}^{M} + \gamma_j\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right)$. Unfortunately, little credibility is likely to be gained by pointing readers to variation that is orthogonal to constructed variation.[10] One might be tempted to gain some insight by regressing $\hat{P}_{it}^{M}$ & $\hat{D}_{it}^{M}$ on $\hat{A}_{it}^{M}$, $\bar{\theta}_{jit}$ and $\bar{\Omega}_{jit}$, but this is senseless, because the whole point of mismeasurement is that it affects $\hat{A}_{it}^{M}$, so not much can credibly be learnt from variation of factor shares that is orthogonal to measured total factor productivity growth.

We can, instead, look for confirmation in variation in factor shares that is not orthogonal to measured total factor productivity growth. Specifically, consider running measured total factor productivity growth on own and upstream factor shares plus industry & year fixed effects

$$(22)\quad \hat{A}_{it}^{M} = \beta_\theta \bar{\theta}_{jit} + \beta_\Omega \bar{\Omega}_{jit} + \eta_i^A + \eta_t^A + \varepsilon_{it}.$$

The mismeasurement model predicts that $\beta_\theta = -\beta_\Omega (= -\gamma_j)$, mismeasurement of what users accomplish with computer inputs should result in opposite effects on measured productivity growth in users of users. While proponents of the unmeasured benefits associated with computer related inputs would expect to find a positive coefficient on own factor shares $\bar{\theta}_{jit}$, non-zero

[10]Even the "OLS" dependent variables are constructed. For a non-linear regression with a single dependent variable, if $y_i = f(\boldsymbol{x}_i, \boldsymbol{\beta}) + \varepsilon_i$, where $f(\boldsymbol{x}_i, \boldsymbol{\beta}) = \boldsymbol{z}_i'\boldsymbol{\beta} + r_i$, with $\boldsymbol{z}_i$ equal to the derivative of f with respect to $\boldsymbol{\beta}$ and r_i the linear approximation error, the estimate of $\boldsymbol{\beta}$ is given by $(\boldsymbol{Z}'\boldsymbol{Z})(\boldsymbol{Z}'(\boldsymbol{y} - \boldsymbol{r}))$. In the system above, $r_i = -\gamma_j\beta_k(\bar{\theta}_{jit} - \bar{\Omega}_{jit})$, for $k = P$ or D and β_k as in (11).

Table 13: Measured TFP Growth Projected on Computer Input Shares (industry means)

	OLS: average shares			IV: initial shares			OLS: average shares			IV: initial shares		
industries	61	44	20	61	44	20	61	44	20	61	44	20
	(A) computer hardware capital						(B) computer software capital					
β_θ	-.02	-.01	.07	-.49	-.40	.14	.13	.16	.12	.03	.01	.07
	(.21)	(.21)	(.27)	(.16)	(.11)	(.27)	(.07)	(.07)	(.07)	(.10)	(.10)	(.04)
β_Ω	.62	.22	-.52	2.4	1.6	2.2	-.49	-.62	-.72	.29	.55	.00
	(1.4)	(1.4)	(2.7)	(1.9)	(1.2)	(1.9)	(.42)	(.41)	(.54)	(.67)	(.76)	(.70)
$\beta_\theta = -\beta_\Omega$	.648	.876	.866	.283	.313	.246	.346	.210	.234	.610	.431	.909
$\beta_{\theta\text{-}\Omega}$	.00	.00	.06	-.40	-.33	.22	.11	.12	.08	.06	.08	.08
	(.20)	(.20)	(.25)	(.10)	(.08)	(.28)	(.05)	(.05)	(.05)	(.07)	(.06)	(.06)
	(C) computer & electronics intermediates						(D) computer systems design intermediates					
β_θ	.44	.42	.43	.42	.39	.42	.47	.53	.17	.74	.54	-.22
	(.05)	(.04)	(.04)	(.05)	(.04)	(.04)	(.29)	(.30)	(.45)	(.34)	(.29)	(.44)
β_Ω	-1.3	-1.0	-1.4	-1.1	-.79	-1.2	-1.2	-1.7	4.3	.57	3.5	22
	(.40)	(.33)	(.40)	(.40)	(.38)	(.36)	(.46)	(2.0)	(5.3)	(1.4)	(2.8)	(14)
$\beta_\theta = -\beta_\Omega$	.016	.041	.019	.043	.232	.013	.183	.553	.386	.378	.151	.115
$\beta_{\theta\text{-}\Omega}$	.32	.33	.30	.32	.34	.31	.49	.46	.39	.72	.67	.67
	(.03)	(.02)	(.03)	(.02)	(.02)	(.03)	(.28)	(.30)	(.37)	(.33)	(.33)	(.40)

Notes: Estimation as in (24). $\beta_\theta = -\beta_\Omega$: p-value of the test. Heteroskedasticity robust standard errors in (). Unconstrained estimates instrumented with initial values of θ and Ω, constrained estimates instrumented with initial value of θ-Ω.

effects of the opposite sign on the concatenated computer factor shares of upstream industries $\bar{\Omega}_{jit}$ are hard to explain as a benefit of computer use. If the mismeasurement model is true, efficiency can be gained by imposing the constraint $\beta_\theta = -\beta_\Omega$ and estimating

$$(23)\ \hat{A}^M_{it} = \beta_{\theta-\Omega}\left(\bar{\theta}_{jit} - \bar{\Omega}_{jit}\right) + \eta^A_i + \eta^A_t + \varepsilon_{it}.$$

As before, these regressions can be run using industry mean data, in the form

$$(24a)\ \hat{A}^M_i = \beta_\theta\bar{\theta}_{ji} + \beta_\Omega\bar{\Omega}_{ji} + c + \varepsilon_i \ \text{ and }\ (24b)\ \hat{A}^M_i = \beta_{\theta-\Omega}\left(\bar{\theta}_{ji} - \bar{\Omega}_{ji}\right) + c + \varepsilon_i,$$

and as before, since I follow customary Tornqvist indices and use average factor shares ($\bar{\theta}$, $\bar{\Omega}$) across the period of growth as regressors, concerns about endogeneity can be addressed by instrumenting with initial (pre-growth) values of θ and Ω.

Table 13 reports such estimates for computer related inputs, using industry means data and the 44, 20 and 61 industry samples used in the analysis earlier above. As seen in the table, the results for computer and electronics intermediates are consistent with the mismeasurement model. The coefficients on θ_{ji} are all positive and those on Ω_{ji} negative, albeit not always significant at the .01 level. The restriction $\beta_\theta = -\beta_\Omega$ is not rejected at the .01 level, and insofar as it is challenged it is because the negative effects of Ω_{ji} are greater in magnitude than the positive effects seen for θ_{ji}. When the restriction is imposed it results in almost identical point estimates

Table 14: Measured TFP Growth Projected on Computer Input Shares
(computer & electronics intermediates)

	61 industry sample			44 industry sample			20 industry sample		
	no lags	1 lag	2 lags	no lags	1 lag	2 lags	no lags	1 lag	2 lags
	(A) OLS using average factor shares								
β_θ	.57 (.22)	.65 (.24)	.89 (.26)	.51 (.21)	.59 (.22)	.80 (.24)	.39 (.21)	.37 (.25)	.56 (.29)
β_Ω	-.84 (.98)	-1.1 (1.1)	-2.0 (1.4)	-.58 (.93)	-.74 (1.1)	-1.5 (1.3)	.10 (1.0)	.20 (1.3)	-.55 (1.7)
$\beta_\theta = -\beta_\Omega$	.729	.643	.355	.929	.866	.515	.561	.591	.993
$\beta_{\theta\text{-}\Omega}$	.50 (.14)	.54 (.15)	.61 (.17)	.49 (.14)	.55 (.15)	.61 (.17)	.52 (.14)	.52 (.17)	.56 (.19)
	(B) IV instrumenting with initial factor shares								
β_θ	.15 (.24)	.17 (.24)	.37 (.25)	.13 (.23)	.15 (.23)	.32 (.24)	.20 (.22)	.14 (.25)	.32 (.28)
β_Ω	1.3 (1.0)	1.4 (1.1)	.80 (1.3)	1.4 (1.0)	1.6 (1.1)	1.0 (1.3)	1.2 (1.1)	1.6 (1.3)	.92 (1.5)
$\beta_\theta = -\beta_\Omega$	.080	.087	.288	.066	.057	.212	.099	.108	.344
$\beta_{\theta\text{-}\Omega}$	.55 (.13)	.59 (.14)	.66 (.16)	.55 (.13)	.61 (.15)	.67 (.16)	.58 (.14)	.58 (.16)	.62 (.17)

Notes: Estimation as in (22)-(23) with panel data, fixed effects and 0 or 2 lags. Otherwise as in Table 13.

across all samples in both OLS and IV formulations, i.e. about .3 estimated exaggeration of the gains from the use of computer and electronics intermediates, with t-stats of 10 or greater. In contrast, for computer systems design intermediates and software the point estimates are all statistically insignificant, while for computer hardware they vary in sign depending upon the sample and OLS/IV specification.

Table 14 reports panel data results for computers and electronics intermediates, using the panel specifications in (22) and (23) augmented with 0, 1 or 2 lags of total factor productivity growth[11]. Estimates of β_θ and β_Ω are mostly very imprecise, with standard errors as large or larger than the coefficients, especially with the IV specification. The statistically insignificant estimates of β_Ω, while mostly negative using average shares, are positive when instrumented. However, when the constraint is imposed, the IV estimates of $\beta_{\theta\text{-}\Omega}$ differ substantively and statistically from the IV estimates for β_θ, and are also much more precise, showing that the variation found from the movement of θ-Ω is substantially different and more informative than that from θ alone. With the restriction $\beta_\theta = -\beta_\Omega$, OLS and IV specifications yield almost

[11]When regressing industry x year TFP growth on year and industry dummies and 3 lagged values of TFP growth, while the 2nd lag of TFP growth is significant at the .01 level, the 3rd lag is completely insignificant (coefficient of -.002 and p-value using a heteroskedasticity robust covariance estimate of .966), and when regressing on 4 lagged values, both the 3rd and 4th lags are insignificant (p-values of .553 and .579, respectively).

Table 15: Fixed Effects, Industry Unemployment Controls, & Capital Utilization Adjustment (estimates of $\beta_{\theta\text{-}\Omega}$ for computer & electronics intermediates)

	fixed effects						industry-level U controls				K utilization adjusted TFP	
	industry		year		none		U_t		U_t - U_{t-1}			
	no lags	2 lags	no lags	2 lags	no lags	2 lags	no lags	2 lags	no lags	2 lags	no lags	2 lags
	(A) OLS using average factor shares											
61	.52	.64	.34	.39	.34	.40	.51	.65	.48	.57	.51	.56
industries	(.13)	(.16)	(.05)	(.06)	(.05)	(.06)	(.14)	(.17)	(.14)	(.17)	(.15)	(.16)
44	.54	.67	.35	.43	.36	.43	.50	.64	.48	.57	.51	.56
industries	(.13)	(.17)	(.05)	(.07)	(.05)	(.07)	(.14)	(.17)	(.14)	(.18)	(.15)	(.16)
20	.55	.61	.33	.34	.34	.36	.53	.59	.51	.53	.53	.48
industries	(.14)	(.18)	(.05)	(.08)	(.05)	(.08)	(.14)	(.19)	(.15)	(.19)	(.16)	(.16)
	(B) IV instrumenting with initial factor shares											
61	.57	.70	.34	.40	.35	.41	.56	.71	.53	.62	.56	.62
industries	(.13)	(.16)	(.05)	(.06)	(.05)	(.06)	(.13)	(.15)	(.13)	(.16)	(.14)	(.15)
44	.60	.73	.36	.44	.37	.44	.55	.69	.53	.62	.57	.63
industries	(.13)	(.16)	(.05)	(.07)	(.05)	(.07)	(.13)	(.16)	(.13)	(.16)	(.14)	(.15)
20	.61	.68	.34	.35	.35	.37	.59	.64	.56	.57	.59	.55
industries	(.13)	(.18)	(.05)	(.07)	(.05)	(.08)	(.13)	(.17)	(.14)	(.17)	(.15)	(.16)

Notes: unemployment controls are interacted with industry dummies, as in (19) earlier. Capital utilization adjustment of TFP growth as in Table 9.

identical point estimates and standard errors. Similarly, when fixed effects are removed, unemployment controls added, or TFP adjusted for capital utilization as specification checks in Table 15, point estimates of $\beta_{\theta\text{-}\Omega}$ are very similar using OLS and IV specifications. All computer & electronics intermediates $\beta_{\theta\text{-}\Omega}$ point estimates in the OLS and IV specifications in Tables 13, 14 and 15 are significant at the .01 level. Of the 74 other inputs examined in this paper, *none* has effects that are similarly consistently .01 significant across either OLS *or* IV specifications.

VI. Implications for Aggregate Productivity Growth

This section calculates the impact of implicit mismeasurement of factor augmenting technical change on aggregate productivity growth. Total private sector productivity growth ($\hat{A}_t^T$) is the sum of the Domar weighted gross output productivity growth measures by sector

$$(25)\ \hat{A}_t^T = \sum_{i=1}^{N} \frac{P_{it}Q_{it}}{GDP_t}\hat{A}_{it}^T,$$

where the ratios of gross output to private sector GDP, $P_{it}Q_{it}/GDP_t$, are the Domar weights. Hulten (1978) provides a rigorous derivation, but a short heuristic proof can be derived by noting that aggregate TFP growth should be the value added share weighted growth of industry TFP growth calculated on a value added basis. If we think of value added as being composed of "price" and "quantity" components whose product equals the nominal value of output minus the nominal value of intermediate inputs, $P_{it}^{VA}Q_{it}^{VA} = P_{it}Q_{it} - \sum_{j=1}^{N} P_{jit}M_{jit}$, then differentiating quantities with respect to time holding prices constant we have

$$(26) \quad \hat{Q}_{it}^{VA} = \frac{P_{it}Q_{it}}{P_{it}^{VA}Q_{it}^{VA}}\left(\hat{Q}_{it}^{T} - \sum_{j=1}^{N}\theta_{jit}\widehat{M}_{jit}^{T}\right)$$

and as value added TFP growth is the growth of real value added minus the value added share weighted growth of primary inputs $j = N+1 .. J$, we have: [12]

$$(27) \quad \hat{A}_{t}^{T}(VA) = \hat{Q}_{it}^{VA} - \sum_{j=N+1}^{J}\frac{P_{it}Q_{it}}{P_{it}^{VA}Q_{it}^{VA}}\theta_{jit}\widehat{M}_{jit}^{T}$$
$$= \frac{P_{it}Q_{it}}{P_{it}^{VA}Q_{it}^{VA}}\left(\hat{Q}_{it}^{T} - \sum_{j=1}^{J}\theta_{jit}\widehat{M}_{jit}^{T}\right) = \frac{P_{it}Q_{it}}{P_{it}^{VA}Q_{it}^{VA}}\hat{A}_{it}^{T},$$

so that weighting by value added shares of nominal private sector GDP we get (25).

Assuming mismeasurement only of factor augmenting productivity growth in the use of factor j, plugging in the relation between $\hat{A}_{it}^{T}$ and $\hat{A}_{it}^{M}$ given in (13) above:

$$(28) \quad \hat{A}_{t}^{T} = \sum_{i=1}^{N}\frac{P_{it}Q_{it}}{GDP_{t}}[\hat{A}_{it}^{M} + (\theta_{jit} - \Omega_{jit})\hat{f}_{jit}^{UO}] \quad \left(\text{where } \Omega_{jit} = \sum_{n=1}^{N}\theta_{nit}\theta_{jnt}\right)$$
$$= \hat{A}_{t}^{M} + \frac{\gamma_{j}}{GDP_{t}}\sum_{i=1}^{N}\left(P_{jt}M_{jit} - \sum_{n=1}^{N}P_{nt}M_{nit}\frac{P_{jt}M_{jnt}}{P_{nt}Q_{nt}}\right)$$
$$= \hat{A}_{t}^{M} + \frac{\gamma_{j}}{GDP_{t}}\left(\sum_{i=1}^{N}P_{jt}M_{jit} - \sum_{n=1}^{N}P_{jt}M_{jnt}\sum_{i=1}^{N}\frac{M_{nit}}{Q_{nt}}\right) = \hat{A}_{t}^{M} + \gamma_{j}\sum_{i=1}^{N}\frac{P_{it}Q_{it}}{GDP_{t}}\theta_{jit}\left(1 - \frac{M_{it}}{Q_{it}}\right),$$

where M_{it} denotes the total use of the output of industry i as private sector intermediate input and we assume that industry x year variation in mismeasurement $(\hat{f}_{jit}^{UO} - \gamma_{j})$ is orthogonal to variation in direct and indirect expenditure on input j, $P_{it}Q_{it}(\theta_{jit} - \Omega_{jit})$. (28) makes the obvious point that insofar as mismeasured output is used as an intermediate input in other sectors, that mismeasurement simply results in a transfer of productivity growth from one sector to another and does not affect aggregate total factor productivity growth. The key summary statistic is the Domar weighted sum of the intensity of mismeasured factor use times 1 minus the intermediate input use share of each sector's output, $\sum_{i=1}^{N}(P_{it}Q_{it}/GDP_{t})\theta_{jit}(1 - M_{it}/Q_{it})$, which in US data averages .011 between 1997 and 2023, falling from .019 in 1997-2000 to .010 in 2000 to 2023. This term also summarizes the mismeasurement of private sector GDP growth.[13]

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[12]The reader is reminded that as θ is the expenditure share out of nominal gross output, $(PQ/P^{VA}Q^{VA})\theta$ is value added income share of a primary input.

[13]Take (26), weight by value added shares of GDP, and apply the summation rearrangements done in (28).

Average annual private sector GDP and total factor productivity growth in the US KLEMS database between 1997 and 2023 are .025 and .0073, or 2.5 and .73 percentage points, respectively. In the dark matter regressions of Section IV, excluding extreme outcomes in both directions, estimates of γ_j range from roughly -.6 in baseline formulations up to -.3 when up to 3 lags, unemployment controls, capacity utilization adjustments and initial share instruments are used. A similar range is found when projecting total factor productivity growth on θ - Ω in Section V. These estimates suggest an adjustment of -.0033 to -.0066 of annual private sector GDP and TFP growth. Thus, at least ⅛ of private sector GDP and ½ of private sector TFP growth in the past 26 years can be attributed to an exaggeration of the gains from the use of computer & electronics intermediate inputs. Of the productivity slowdown from .012 in 1997 to 2000 to .05 in 2000 to 2023 mentioned in the Introduction, again at least ½ can be explained by a reduction in mismeasurement as the role of computer intermediates in producing GDP has fallen.

VII. Summary and Conclusion

The results above show that movements of price and quantities demanded, net of movements implied by total factor productivity growth, vary systematically with the share of computer and electronics inputs in an industry's cost structure and its upstream suppliers in a manner that suggests overestimation of the growth benefits from the use of these inputs of between .3 to .6 per percentage use of these inputs. This result is found with industry and year fixed effects (using within industry time series variation) and when estimated across industry means alone (using cross industry long run variation). It is found in 44 industry, 20 industry and 61 industry samples, using different disaggregations of total demand. It is robust to the addition of lagged values of the dependent variables and instrumenting factor shares using pre-growth initial values. It is not driven by any bias due to endogeneity of total factor productivity growth through capacity utilization mismeasurement, as it is robust to adjustments for business cycle variation and capital utilization and, furthermore, holds for long run 26-year industry averages, where capacity utilization is hardly relevant. The point estimates are also almost universally negative across all possible elasticities of demand and supply, showing that endogeneity and bias in estimating the response of price and demand to total factor productivity growth cannot be driving the results. An alternative, and completely different, empirical strategy that projects total factor productivity growth directly on own and upstream computer intermediates use, finds similar estimates of mismeasured growth of about .3 to .6 per percentage share of these factors using industry means data, panel data with and without fixed effects, instrumentation with pre-growth factor shares, lags, unemployment controls, and capital utilization adjustments in samples of 44, 20 or all 61 industries. No such statistically significant and specification robust relationship is found for any other input.

Industries which use computer and electronics intermediates as inputs are durable goods industries. As such, some perspective on the results above can be found by considering two characteristics of durable goods that impart a downward bias to matched-model and hedonic price indices, two common price deflation techniques used in the US.[14] First, as emphasized by Harper (2007), the prices of durable goods reflect the net present value of the flow of quasi-rents from their use. However, as technology progresses durable goods become obsolete because of issues with interoperability and the shadow value of complementary resources. Thus, old computers are regularly scraped not because they wear out but because they lack the capacity needed to interface with more modern software and, most importantly, because the growing capabilities of alternatives raises the shadow value of users' time. Obsolescence means that the same physical product purchased in later years is not the same product from the point of view of buyers, as it has a shorter expected life. This leads hedonic price indices to overstate the value of increasing characteristics, as there is a hidden characteristic (expected service life) that is correlated with quality, and hence overstate price deflation. Similarly, matching the "same" product through time overstates deflation as later versions of the same good embody a shorter stream of expected rents. The use of the flow rental as the price for the flow value of durable goods services would address this issue, but unfortunately, outside of housing, in our national accounts the benefits of durables are measured using their sales prices and not their rentals.

Second, as emphasized by Aizcorbe and Copeland (2007), durable goods are purchased intermittently and have a product life cycle. When initially introduced higher quality models are purchased by consumers who place the highest valuation on quality. As prices decline over time, either due to cost reducing learning by doing or price discrimination, consumers who place a lower valuation on quality purchase them. Matched-model price indices will overstate gains from price declines because those who place a low value on quality only gain from the part of the price decline that is below their low initial reservation value, while those with a high reservation value may not gain from price declines at all if they go on to purchase newer high quality vintages. Hedonic price indices will also overstate the value of quality and produce downward biased price trends because when comparing the prices and characteristics of contemporaneously sold vintages there is an omitted variable, the value of quality to those buying the goods, that is positively correlated with goods characteristics.

[14]A third technique used heavily in the evaluation of automobiles and other products with frequent model changes (see Groshen et al 2017) asks manufacturers to identify the cost increment associated with new characteristics and treats that cost increment as quality, i.e. assumes cost per unit quality remains constant. This is problematic, not least because it treats government mandated features such as catalytic converters and fuel efficiency as providing quality gains to individual consumers equal to their costs, which would make such mandates unnecessary in the first place.

Methods such as matched-model and hedonic price indices are well suited to measuring price and quality changes in environments where all buyers literally "consume" all products all of the time. Once one allows that products are durable and purchased intermittently by buyers whose characteristics and valuations vary systematically with the product life cycle, it is not hard to see that such techniques could easily produce upward biased estimates of quality-adjusted output growth. Since in the modern era computer intermediates are intimately tied to improvements in the characteristics and quality of goods, these biases could produce the exaggeration of the benefits of computer intermediate use found in this paper.

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