

Firms and Aggregate Dynamics*

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Abstract

We investigate the role of permanent and transitory shocks for firms and aggregate dynamics. We directly model the dynamics of a large panel of firms. We find that permanent shocks to productivity and permanent shifts in the composition of output explain at least 4/5 of firms dynamics. However, these permanent shocks are almost uncorrelated across firms, and are therefore less relevant for aggregate dynamics. Transitory shocks, on the other hand, are not very important at the firm level. However, because they are significantly correlated across firms they account for most of the volatility of aggregate hours and output. We also show that not using firm level data leads to misidentification of the permanent shocks. Finally, we try to make some progress on the interpretation of the shocks. We show that monetary shocks cause only transitory dynamics, while oil shocks also have permanent effects. We find that public spending shocks have a positive transitory effect, and that tax shocks have a negative transitory effect. We also find some evidence suggesting that both spending and tax shocks have negative permanent effects.

Key Words: Technology Shocks, Business Cycles, Long-run Restrictions
JEL Classification: E2, E3

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1 Introduction

We investigate the nature of aggregate shocks. Empirical macroeconomic research has mainly approached this question using aggregate time series. Yet, the conditions that guarantee the existence of a meaningful aggregate production function are unlikely to be satisfied in practice. As a result, shocks identified directly from aggregate data are, at best, hard to interpret. We tackle this problem by directly modeling the dynamics of two panels: one containing 33 sectors covering the entire US private economy, and the other containing 526 large, publicly traded, firms.

We assume that firms' dynamics are driven by three different shocks. First, there are permanent, stochastic technological improvements. Second, there are changes in the composition of aggregate output and in consumers' tastes that translate into changes in the relative demands for the different firms. Finally, there are transitory shocks. We identify each shock using long run restrictions in a structural VAR: transitory shocks cannot have permanent effects on either the productivity or the relative size of firms, while composition shocks cannot have a permanent effect of the productivity of firms.

For each firm, we recover the three time series of structural shocks. We then investigate the relative importance of each shock for firms and aggregate dynamics. We find that permanent technology shocks and permanent changes in the composition of output explain more than $\frac{4}{5}$ of firms dynamics. However, we also find that these shocks are almost uncorrelated across firms. By contrast, the correlation of transitory shocks lies between 23.6% and 27.7%, depending on the specifics of the model we use. In other words, we show the existence of an aggregate transitory shock. This shock explains most of the variations in output and labor input for the US economy, despite being the least important shock at the firm level.

There have been many previous attempts to identify the exogenous sources of the business cycle. One strand of literature follows the lead of Kydland and Prescott (1982) by specifying a dynamic equilibrium model, choosing the primitive source(s) of the fluctuation and defining shock(s) as residual(s)¹ from the equations of the model. Recent papers on this topic (Smets and Wouters, 2003 and Chari, Kehoe and McGrattan, 2004) have found that shocks that changes to the consumption-leisure margin explain most of the fluctuations². Another strand of literature has adopted the long run

¹For instance Prescott (1986) arrives at an estimate of the fraction of output variability that can be attributed to technology shocks using actual Solow residuals to estimate the variance and serial correlation of the underlying technology shocks. Feeding shocks with these properties into a calibrated real-business-cycle model resulted in output variability that was between 50 and 75 percent of actual variability

²Hall (1997) emphasizes that a large fraction of business cycle fluctuations seems to be accounted for by changes in the marginal rate of substitution between consumption and leisure. Chari, Kehoe and McGrattan (2004) label this variable "labor wedge." Smets and Wouters (2003) study a dynamic general equilibrium model with nominal rigidities and allow for various types of shocks, including productivity shocks, preference shocks and mark-up shocks. They found that a sizeable fraction of output volatility is due to preference shocks that induce changes on the consumption-leisure margin.

identification strategy of Blanchard and Quah (1989), and Shapiro and Watson (1988). Gali (1999) uses a bivariate VAR with the growth rate of labor productivity and hours worked, and distinguishes shocks that affect labor productivity in the long run from those that do not. The main findings according to this approach are that the permanent shock has a negative short run effect on hours, and that it explains very little of the business cycle³. Some recent studies (Francis (2001), Chang and Hong (2003)) have used industry data to investigate the robustness of the first finding. Gali and Rabanal (2004) give a comprehensive survey of the existing literature, while Chari, Kehoe and McGrattan (2004b) present a critique.

We make three contributions to the literature. First, we introduce the composition shocks and show that they are very important sources of firm level dynamics. Second, we show that even at the industry level, aggregation poses problems for the identification of the permanent shocks. We show that the permanent shock identified from industry level data contains some transitory component and that it is correlated with monetary shocks. By contrast, our firm level permanent shock is not correlated with monetary shocks. We find that public spending shocks have a positive transitory effect, and that tax shocks have a negative transitory effect. We also find some evidence suggesting that both spending and tax shocks have negative permanent effects. Finally, to the best of our knowledge, we are the first to investigate the co-movements of permanent and transitory shocks at the *firm* level. A similar exercise was performed by Kiley (1996) using industry data for the manufacturing sector.

In section 2, we present a simple, neoclassical model of an economy with sectorial shocks, which we use to derive our identifying restrictions. In section 3 we describe our data, our empirical strategy, and our findings.

2 The Model

The purpose of the model is to derive the structural restrictions that will allow us to identify the different shocks that affect the economy. Since these restrictions apply to the long run effect of certain shocks, we emphasize only the long run properties of the model. Here we present a simple case with no capital and fixed labor supply. The general case is presented in the appendix. Throughout the discussion, letters with an upper bar represent aggregate variables. The representative agent maximizes

$$E_0 \left[\sum_{t=0}^{\infty} \beta^t u(\bar{c}_t) \right],$$

³The negative effect of technology on hours has been disputed by several authors. See for instance Christiano et al (2003).

subject to the budget constraint

$$\bar{c}_t + \bar{b}_t \leq \bar{\pi}_t + \bar{w}_t \bar{n}_t + (1 + \bar{r}_t) \bar{b}_{t-1}.$$

Consumers receive real labor income $\bar{w}_t \bar{n}_t$, the aggregate profits of the firms $\bar{\pi}_t$ and the interest payments \bar{r}_t on their real bond holdings \bar{b}_t . The real bond is in zero net supply. The consumption good is obtained by aggregating the outputs of a continuum of firms:

$$\bar{c}_t = \left(\int_0^1 \tilde{c}_{i,t}^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}}, \theta > 1.$$

The only non-standard feature of this model is the presence of idiosyncratic shocks ω_{it} which we label composition shocks:

$$\tilde{c}_{it} = \omega_{it} \times c_{it}.$$

The consumption of c_{it} physical units of good i delivers the same utility as the consumption of $\frac{\omega_{it} c_{it}}{\omega_{jt}}$ units of good j . The processes ω_{it} are exogenous⁴ and they are assumed to follow a process of the form $\omega_{it} = \omega_{it-1} \exp(\mu_i^\omega + \Phi_i^\omega(L) \eta_{it}^\omega)$ where μ_i^ω is a constant drift, $\Phi_i^\omega(L)$ is a square summable polynomial in the lag operator L and η_{it}^ω is a white noise. We maintain that compositions shocks are an essential to describe the change in the firm and sectorial composition of the economy. The optimal condition for the choices of consumption imply that we can write:

$$\frac{c_{it}}{\bar{c}_t} = \omega_{it}^{\theta-1} \left(\frac{p_{it}}{\bar{p}_t} \right)^{-\theta}$$

where

$$\bar{p}_t = \left(\int_0^1 \left(\frac{p_{it}}{\omega_{it}} \right)^{1-\theta} di \right)^{\frac{1}{1-\theta}}$$

We assume that the goods markets operate under perfect competition, that labor is the only factor of production, and that returns to scale are constant⁵.

$$y_{it} = z_{it} n_{it}$$

The technology of each firms z_{it} is also assumed to follow a process $z_{it} = z_{it-1} \exp(\mu_i^z + \Phi_i^z(L) \eta_{it}^z)$ where μ_i^z is a constant drift, $\Phi_i^z(L)$ is a square summable polynomial in the lag operator L and η_{it}^z is

⁴We use the normalization $\int_0^1 \omega_{it}^{\theta-1} di = 1$. The shocks are conveniently normalized to make \bar{p} a price level (i.e., if all prices are the same, they are also equal to the price level). The normalization is such that idiosyncratic shocks do not directly affect aggregate outcomes. Suppose that you compare two economies with different distributions of ω_{it} . Also suppose that all industries have the same productivity and that the two distributions satisfy the normalization condition. Then the two economies will have identical aggregate outcomes (same capital stock, same labor supply, same interest rate).

⁵See appendix for the case with capital accumulation and endogenous labor supply.

a white noise. Perfect competition implies that real profits are zero and $\frac{p_{it}}{\bar{p}_t} = \frac{\bar{w}_t}{z_{it}}$. Nominal income identity

$$\int \frac{p_{it}}{\bar{p}_t} c_{it} = \bar{w}_t \bar{n}_t$$

together with our definition of \bar{p} , implies that

$$\bar{w}_t \bar{n}_t = \bar{c}_t,$$

which we can use to derive

$$c_{it} = \omega_{it}^{\theta-1} (z_{it} \bar{n}_t)^\theta \bar{c}_t^{1-\theta},$$

the labor market equilibrium

$$\bar{n}_t = \int \frac{y_{it}}{z_{it}} = \int \frac{\omega_{it}^{\theta-1} (z_{it} \bar{n}_t)^\theta \bar{c}_t^{1-\theta}}{z_{it}},$$

and

$$\begin{aligned} \bar{c}_t &= \bar{z}_t \bar{n}_t \\ \bar{z}_t &= \left(\int \omega_{it}^{\theta-1} z_{it}^{\theta-1} \right)^{\frac{1}{\theta-1}} \end{aligned}$$

where \bar{z}_t is the aggregate productivity. From this last expression it is apparent that aggregate labor productivity can also change because of composition shocks. We can rewrite

$$c_{it} = \omega_{it}^{\theta-1} \times z_{it}^\theta \times \bar{z}_t^{1-\theta} \bar{n}_t.$$

By definition the only shock that can affect productivity of firms i in the long run is

$$\frac{y_{it}}{n_{it}} = z_{it},$$

but the share of firms i in total output is affected by both of the permanent shocks:

$$\frac{c_{it}}{\bar{c}_t} = \omega_{it}^{\theta-1} \times \left(\frac{z_{it}}{\bar{z}_t} \right)^\theta,$$

or in nominal terms:

$$\frac{p_{it} c_{it}}{\bar{p}_t \bar{c}_t} = \omega_{it}^{\theta-1} \times \left(\frac{z_{it}}{\bar{z}_t} \right)^{\theta-1}.$$

Finally, we assume that there is a transitory shock η_{it}^T . By [construction], this shock has no permanent effect on the productivity or the relative size of the firms. Therefore the long run restrictions are:

$$\begin{aligned} \lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{n_{it+j}}}{\partial \eta_{it}^\omega} &= 0 \\ \lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{n_{it+j}}}{\partial \eta_{it}^T} &= 0 \\ \lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{\bar{y}_{t+j}}}{\partial \eta_{it}^T} &= 0 \end{aligned}$$

We discuss the role of capital and endogenous labor supply in the appendix.

3 Data

We believe one important issue in our analysis is the choice of a productivity measure: we must trade-off theoretical motivations against measurement error problems. Conceptually, Total Factor Productivity (TFP) is the best measure. However measuring the effective flow of services from the capital stock is extremely challenging. On the other hand, labor productivity (YH) is well measured, especially in the long run, but it is affected by non technological shocks. For instance, shocks to the labor supply schedule (see appendix) would decrease hours in the short run and increase the capital-labor ratio and labor productivity in the long run⁶. We take these issues very seriously, and we check the robustness of our results to different measures of productivity in the sectorial dataset.

We perform the analysis on two different data sets. The first one is a subset of COMPUSTAT database that contains annual data for 526 firms⁷. The second one is the sectorial input-output database developed by Dale W. Jorgenson et al. that covers 33 sectors at roughly the 2-digit SIC level, including 21 manufacturing industries. The sample in the first dataset runs from 1970 to 2003. In the second dataset, the sample runs from 1958 to 1996. Because the first data set, which we have labeled FIRM, is at a more disaggregated level, it has the potential to more effectively disentangle technology shocks from composition shocks. On the other hand the second data set, which we label SEC, contains a careful measure of TFP.

Our baseline specification includes three variables: a productivity measure, the relative weight of each firm and the labor input, which we denote respectively z_i , m_i , and n_i . Our measure of productivity⁸ is YH for the FIRM dataset and both TFP and YH for the SEC dataset. The relative weight series is constructed dividing the quantity of output of each firm by the sum of the output of all firms or sectors. Lastly the labor input is the number of employees in the FIRM data set and the quantity of labor input in the SEC data set.

To determine the correct stationary transformation of the variables we run a battery of tests. We perform an Advanced Dickey Fuller (ADF) unit root test for each series to assess the presence of a stochastic trend in the series. The results for the FIRM data set are summarized in Table 1. For example, in the case of the logarithm of labor productivity, we were able to reject the null of a unit root at the 10, 5 and 1 percent confidence levels for respectively 47, 38 and 8 firms. The ADF test on the first difference of the same series rejected the null of the unit root at the 10, 5

⁶Uhlig (2004) points that changes in taxes on capital income can also affect the long run labor productivity. See Gali and Rabanal (2004) for a discussion.

⁷The 526 firms cover the 33 sectors of the Jorgenson dataset. These are all the firms with non-missing values for the variables of interests between 1970 and 2003.

⁸The precise construction of every variable is described in the data appendix.

and 1 percent confidence levels for 499, 489 and 414 firms, respectively. Similarly, performing a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, we were not able to reject the null of stationarity for the same series at the 10, 5 and 1 percent confidence for 132, 69 and 50 firms, respectively. The KPSS test on the first difference did not reject the null of stationarity at the 10, 5 and 1 percent confidence for respectively 517, 488 and 467 firms. A summary of the results suggests that the large majority of the series is I(1).

4 Results

Our baseline specification is the trivariate VAR with two lags⁹ estimated for each firm or sector i . To remain consistent with the outcome of the previous tests we specify the VAR in first differences. The joint behavior of the three variables is described by the following MA representation where the variables are expressed in natural logarithms:

$$\begin{bmatrix} \Delta z_{it} \\ \Delta m_{it} \\ \Delta n_{it} \end{bmatrix} = \begin{bmatrix} c_{i11}(L) & c_{i12}(L) & c_{i13}(L) \\ c_{i21}(L) & c_{i22}(L) & c_{i23}(L) \\ c_{i31}(L) & c_{i32}(L) & c_{i33}(L) \end{bmatrix} \begin{bmatrix} \eta_{it}^z \\ \eta_{it}^\omega \\ \eta_{it}^T \end{bmatrix}$$

where η_{it}^z , η_{it}^ω and η_{it}^T are structural shocks, which are assumed to be mutually orthogonal and serially uncorrelated with variance normalized to unity¹⁰. The MA is recovered estimating a VAR¹¹ and using the long run restrictions derived in the stylized model of the previous section: the *composition* shock, η_{it}^ω has no long run effect on the productivity which restrict $c_{i12}(1)$ to be 0 and the *transitory* shock η_{it}^T has no long run effect on both the productivity and the relative weight of the firms which restrict $c_{i13}(1)$ and $c_{i23}(1)$ to be both equal to 0.

4.1 Impulse Responses

We discuss the results obtained with the FIRM data set, only highlighting the results for the SEC dataset if they differ. In our specification the three variables have a stochastic trend, therefore no shock has a transitory effect on the *level* of a variable unless we have imposed it.

Permanent technology shock.

Figure 1 shows the estimated effects of a positive permanent *technology* shock η_{it}^z . The left part of the figure displays the graph of the mean impulse response of the level of the three variables to a one standard deviation of the shock. The right part shows the corresponding distribution of

⁹The results estimating the VAR with 1 or 3 lags are very similar.

¹⁰Both the orthogonality and normalization of the structural shocks are part of the identifying assumptions. The normalization assumption just redefines the unit of each shock. The orthogonality assumption is justified on the basis that we are identifying fundamental shocks.

¹¹We are implicitly assuming that the MA is fundamental, see Lippi and Reichlin (1993) for a discussion of this assumption.

impact and Long Run responses for the firms. The mean of the point estimates suggests that a positive *technology* shock increases both productivity and the relative weight but decreases hours. The decline in hours is consistent with the evidence from aggregate and industry data reviewed in Gali and Rabanal (2004). The distribution of responses shows that the impact and the long run effect on productivity is positive for all firms. The effect on the weight is positive on impact and in the long run for 81% and 70% of the firms, respectively. Firms that experience a positive productivity shock becomes more important in the sector. The effect on hours is negative on impact and in the long run for 78 percent and 81 percent of the firms, respectively.

Previously, we have argued that TFP is conceptually a better measure than labor productivity for what concerns our identification. We chose to present the labor productivity results because the TFP series for the FIRM data is unavailable. This is due to the lack of a reliable measure of the capital stock. The concern with TFP is potential long run measurement error due to the difficulty of measuring capital services and quality changes in factors input¹². The advantage of the SEC data set is that the authors have produced series of factor inputs that account for almost any known measurement problem. The results for the *technology* shock identified using the SEC dataset are virtually identical¹³ to one obtained with the FIRM dataset both in the specification with YH and with TFP.

Composition shock.

Similarly Figure 2 shows the estimated effects of a positive *composition* shock η_{it}^{ω} . The impact effect on productivity is equally divided between positive and negative across firms while its long run effect is constrained to zero. The impact and long run effects on the weight are positive for all the firms. The impact and long run effects on hours are positive for virtually all firms: a firm whose weight increases in the long run without an increase in productivity, increases its labor input.

Transitory shock.

Finally Figure 3 shows the estimated effects of a positive *transitory* shock η_{it}^T . The impact effect on productivity is negative for 60 percent of the firms, while its long run effect is constrained to zero. The effect of the transitory on productivity at high frequencies is not surprising given its strong effect on labor input. Using the SEC dataset the impact effect of the transitory shocks becomes positive for 67% and 68% of the sectors using the YH and the TFP measure, respectively¹⁴. The

¹²We are not concerned by the short run measurement error of TFP, due to many reasons such as variable intensity of input utilization.

¹³The identified technology shock has a negative effect on the labor input in both specifications. Figures of the IRF using the SEC dataset are available online at URL.

¹⁴This is consistent with the observation that labor productivity and hours are positively correlated at the sector level, but not at the firm level.

impact effect on the weight is positive for roughly half of the firms while, its long run effect is again constrained to zero. Here, the short run effect is also small. The impact and long run effects on the level of hours are positive for 100% and 81% of the firms, respectively. The large heterogeneity across firms is not surprising, and is perhaps expected. Overall the mean impulse responses look plausible.

4.2 Variance Decompositions

4.2.1 Firm and Industry Dynamics

Figure 4 shows the mean of the variance decomposition for the variables *in level* of each N estimated VAR. From the figure it appears that productivity movements at the firms level are on average overwhelmingly explained by technology shocks. On impact approximately 80% of productivity movements are caused by technology shocks while composition shocks and transitory shocks explain 12% and 8%, respectively. Relative weights movements are dominated by composition (on average 62% of impact movements and 70% of Long Run movements) and technology shocks (roughly 30% at all frequencies). Labor input movements are also dominated by composition (on average 53% on impact and 55% in the long run) and technology shocks (on average 34%). Perhaps not surprisingly we find that the transitory shock is not so important for firms dynamics. Figure 5-6 show that the mean variance decomposition across sectors of the different shocks are similar for the technology and composition shocks, while the transitory shock explains around 45% of the labor input variance using the YH and the TFP measures. As we shall see below, this last observation reflects the fact that sectors are already aggregate units.

4.2.2 Aggregate Dynamics

We now turn to the principal motivation of the paper and investigate the co-movement of the three shocks across firms. For each firms shock, we compute all pair-wise correlations with the same shock of all other firms. This gives us three symmetric $N \times N$ matrices of correlations. We then take the average¹⁵ for each firms and end up with N mean correlations¹⁶. Table 2 shows that for our baseline specification the average of the mean correlations is around 2.6 percent for the technology shock, 2.43 percent for the preference shock and 23.6 percent for the transitory shock. Table 2 also reports the percentage of pair-wise correlations that are significantly different from zero for each shock. For instance, 85 and 91 percent of the pair-wise correlations between the η_{it}^z are not different from zero at the 10 and 5 percent confidence level. These numbers are not very different for the η_{it}^w pair-wise correlations. On the contrary for the η_{it}^T the percentage of insignificant correlations drop to 6.5 and

¹⁵In taking the averages we exclude the 1 on the main diagonal of the correlation matrix.

¹⁶Using the median instead of the mean gives similar results.

10 percent.

Figure 7 plots the average of the three shocks, namely $\eta_t^j \equiv \frac{\sum_i \eta_{it}^j}{N}$ for $j = z, \omega, T$ in order to visualize the implications of the correlations for an *aggregate* shock. One has to keep in mind that these are structural shocks whose variance is normalized to one, and that firms have different weights, so that the average shock of Figure 7 has no meaning beyond making explicit the different levels of correlation between the shocks. The transitory shock appears as a good candidate to explain aggregate short run fluctuations, which are characterized by a high degree of co-movement across firms. Indeed the average of the transitory shock appears to experience more important fluctuations than the technology shock. On the contrary, permanent *technology* and *composition* shocks appear to be idiosyncratic, or relatively uncorrelated, and appear to be poor candidates to explain aggregate short run fluctuations. The regression of the NBER recessions dates on η_{it}^T , η_{it}^z and η_{it}^ω confirms that the *aggregate transitory* shock is potentially a good candidate¹⁷. Interestingly Figure 7 shows that the aggregate *technology* shock exhibits a sustained negative period during the mid 1970's beginning of 1980's¹⁸, and a sustained positive period in the 1990's, while the aggregate *composition* shock is dominated by a large positive shock in 1980.

From the average variance decomposition we conclude that the *transitory* shock is the least important shock at the firm level. However, contrary to the *technology* and the *composition* shock, the *transitory* shock appears to hit many firms contemporaneously. This property implies that at the aggregate level the *transitory* shock is able to explain almost the entire short run fluctuations of the economy. To illustrate this, we use the estimated VARs to simulate a series for each firm shutting down the effect of the *technology* shock and the *composition* shock¹⁹. Figure 8 shows the actual aggregate output and hours series together with the actual series. The transitory shock explains a remarkable large proportion of the fluctuations of both aggregate output and hours. To compute an exact variance decomposition of aggregate hours and output is impossible. This is because transitory shocks of firms are typically correlated with technology and/or composition shocks of other firms. We would have to make an assumption on causality (a technology shock in firms j increases demand and therefore causes a positive transitory shock in firms j' or vice-versa) to be able to order the shocks. The correlation across firms of different shocks is an avenue to pursue but beyond the scope of this paper. Figure 9 shows the simulated series shutting down the effect of the *transitory* shock and the *composition* shock.

¹⁷We find $NBER_t = \frac{35.34}{.7828844} - \frac{.12}{.0038} \eta_{it}^T - \frac{.0319}{.00381} \eta_{it}^Z + \frac{.0165}{.0038109} \eta_{it}^\omega - \frac{.0176}{.0003939} \text{year}_t$ $R^2 = 0.1812$. The number below the coefficients are standard errors. *year* is a time trend. The transitory shocks appear to be the main explanatory shocks of the recessions. Positive permanent technology shocks are also negatively correlated with recessions while positive permanent composition shocks are positively correlated with recessions.

¹⁸This is consistent with the productivity slow down experienced by the US economy.

¹⁹In the appendix we illustrate the exact procedure.

The main result we take from this exercise is that shocks that cause aggregate fluctuations do not imply large fluctuations in productivity, relative demand and labor input relative to permanent shocks. However, they do happen to hit a large fraction of firms contemporaneously.

Table 2 shows that the sectorial technology shocks have their average correlation that increases up to 9.6% percent. This is still much lower than an average of 24.8 percent for the transitory shock. Excluding the technology and composition shocks, the simulated series is qualitatively similar to the one obtained in the first data set .

5 Towards an interpretation of the shocks

Thus far, we have restrained from interpreting the different shocks. We now try to make some progress on this crucial issue. We first compare the shocks identified from sectorial data to the shocks identified from firm data.

Table 3 contains sector-level regressions. Table 3a shows that permanent technology shocks from SEC are significantly related to both permanent technology and transitory FIRM shocks. SEC composition shocks are related to all three FIRM shocks. Transitory SEC shocks are mostly related to transitory FIRM shocks. The first finding is potentially the most troublesome, and suggests that aggregation problems are important. The results are similar if we use TFP in the SEC regressions.

To investigate further, we regress the SEC and FIRM shocks on two well known, identified shocks: the Romer-Romer monetary shocks, and the Hamilton oil price shocks. Table 3b presents the results. The top coefficient in the technology columns is a red flag for the SEC permanent technology shocks. These shocks are caused by monetary shocks, which as theory tells, us should be transitory. The bias seems less severe when we use TFP, but it is still present. By contrast, the first column shows that the FIRM permanent technology shocks are not caused by the Romer shocks. As expected, oil price shocks have both transitory and permanent effects, and monetary shocks have a significant transitory effect. We conclude that SEC shocks suffer from aggregation problems, and we focus on FIRM shocks in the rest of the analysis.

Table 4 shows the results of firm level regressions. Lagged oil shocks are always very significant: an increase in the oil price²⁰ has negative transitory and permanent negative consequences. Monetary shocks do not have a permanent effect, but a transitory one: a contractionary monetary policy induces a negative transitory shock. Next, we introduce fiscal variables, using cyclically-adjusted data from CBO, which should capture true changes in fiscal policy, as opposed to automatic feed-

²⁰The Hamilton (1996) shock is defined as the amount by which the log of oil prices o_t in quarter t , p_t , exceed the maximum value over the previous four quarters and 0 otherwise:

$$\max \{0, o_t - \max \{o_{t-1}, o_{t-2}, o_{t-3}, o_{t-4}\}\}.$$

backs from shocks to GDP. We find that spending and taxes have positive and negative transitory effects, as expected. We also find that both spending and taxes tend to have negative *permanent* effects. To ascertain the validity of these interesting findings, we ran some robustness checks. The negative permanent effects of government spending appear robust across sub-samples, while the negative permanent effects of taxes disappear if we focus on the post 1985 subsample, and include more firms. That taxes decrease long run labor productivity can easily be explained if taxes reduce returns on capital, and therefore investment. Likewise, if government spending crowds out private investment through higher interest rates, one would expect lower labor productivity. These results show that permanent productivity shocks need not come from exogenous changes in technology. This seems a natural topic for future research.

Finally, we also introduce consumer confidence. However, one must keep in mind that unlike the monetary, fiscal and oil shocks that we have discussed so far, this one is not a structural shock. We find that consumer confidence is strongly related to the transitory shocks, but also somewhat related to the permanent shocks, although with a much smaller magnitude. We believe that this exercise confirms the validity of our approach. Using firm level data is a clear improvement. The shocks that theory tells us should not affect long run productivity, do not, and those that should, do. On the other hand, we acknowledge that a good part of the transitory component remains unexplained.

6 Conclusion

We have found that permanent productivity shocks and permanent changes in the composition of output explain at least $\frac{4}{5}$ of firms' dynamics. On the other hand, shocks that are transitory but correlated across firms are responsible for the bulk of aggregate volatility. We have shown that transitory shocks are significantly related to monetary policy, while permanent shocks are not. We have found that oil shocks have both permanent and transitory effects. Finally, we have documented that the expansionary effects of fiscal policy appear in the transitory components, but also that both spending and taxes seem to have negative long run effects.

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A Appendix

A.1 Long run restrictions with a general production function

We now consider general production functions with constant return to scale, and a standard labor supply function. Aggregate output is used for consumption and investment

$$\bar{y} = \left(\int (\omega_i y_i)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

Value added of firms i is given by

$$y_i = f_i(k_i, n_i)$$

Under constant returns to scale, the capital labor ratio depends only on the relative prices of labor and capital:

$$\frac{w}{r + \delta} = \frac{\frac{p_i}{\bar{p}} \frac{\partial f_i(k_i, n_i)}{\partial n_i}}{\frac{p_i}{\bar{p}} \frac{\partial f_i(k_i, n_i)}{\partial k_i}} \equiv \zeta_i^{-1} \left(\frac{k_i}{n_i} \right)$$

This in turn implies that in the long run, the only factors affecting labor productivity are the technology of the firms, and $\frac{w}{r+\delta}$. In particular, composition shocks ω_i do not affect labor productivity in the long run.

$$\frac{y_i}{n_i} = f_i \left(\zeta_i \left(\frac{w}{r + \delta} \right), 1 \right) \equiv g_i^n \left(\frac{w}{r + \delta} \right)$$

The equilibrium interest rate is pinned down by the preferences of the consumers

$$r = \frac{1 - \beta}{\beta}$$

And the price must be equal to the marginal cost²¹

$$\frac{p_i}{\bar{p}} = \chi_i(r + \delta, w)$$

where $\chi_i(\cdot, \cdot)$, the firms marginal cost, is homogenous of degree one. Using the firms demand curve, we get:

$$\frac{y_i}{\bar{y}} = \omega_i^{\theta-1} \chi_i^{-\theta}(r + \delta, w)$$

National income identity (in real terms) is

$$\bar{y} = w\bar{n} + r\bar{k} \tag{1}$$

²¹Of course, in the Cobb-Douglas case where $y_i = z_i k_i^{\alpha_i} n_i^{1-\alpha_i}$, we get $p_i = \frac{1}{z_i} \left(\frac{r+\delta}{\alpha_i} \right)^{\alpha_i} \left(\frac{w}{1-\alpha_i} \right)^{1-\alpha_i}$, and $\zeta_i^{-1} = \frac{1-\alpha_i}{\alpha_i} \frac{k_i}{n_i}$

Product market equilibrium

$$\bar{y} = \bar{c} + \delta \bar{k} \quad (2)$$

Given our definition of the price level, we have that

$$\int \left(\frac{\omega_i}{\chi_i(r + \delta, w)} \right)^{\theta-1} = 1 \quad (3)$$

and labor market equilibrium implies that

$$\bar{n} = \int n_i = \bar{y} \int \frac{\omega_i^{\theta-1} \chi_i^{-\theta}(r + \delta, w)}{g_i^n \left(\frac{w}{r + \delta} \right)} \quad (4)$$

Finally, a labor supply function guaranteeing balanced growth is

$$\bar{n} = \varphi \left(\frac{w}{\bar{c}} \right) \quad (5)$$

We have 5 equations (1, 2, 3, 4, 5) in 5 aggregate unknowns $(\bar{y}, w, \bar{n}, \bar{k}, \bar{c})$ ²².

Identifying restrictions.

Transitory shocks have transitory effects, so the two restrictions still apply:

$$\begin{aligned} \lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{n_{it+j}}}{\partial \eta_{it}^T} &= 0 \\ \lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{\bar{y}_{t+j}}}{\partial \eta_{it}^T} &= 0 \end{aligned}$$

Permanent shock to ω have no effect on TFP by construction, and no effect on labor productivity because firms shocks do not affect the aggregate prices.

$$\lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{n_{it+j}}}{\partial \eta_{it}^\omega} = 0$$

Using TFP, our identification system should pick up technology and composition shocks exactly. Using labor productivity, we would classify as technological shocks that increase $\frac{w}{r + \delta}$, in particular shocks that move the labor supply schedule (5). This may be an issue for interpreting the technology shocks in some specifications.

²²We could also use the equilibrium in the capital market

$$\bar{k} = \int k_i = \bar{y} \int \frac{\omega_i^{\theta-1} \chi_i^{-\theta}(r + \delta, w)}{g_i^k \left(\frac{w}{r + \delta} \right)}$$

where $g_i^k \left(\frac{w}{r + \delta} \right) \equiv f_i \left(1, \frac{1}{\zeta_i \left(\frac{w}{r + \delta} \right)} \right)$. We know from Walras that it is in fact redundant.

A.2 Data Construction

Here we report how to construct the variables used in the analysis using the original data of the two data sets.

FIRM: The labor productivity is $z_{it} = \frac{sales_{it}}{newpo_{it} h_{it}}$ where *sales* stands for value added, *newpo* for the sector output deflator from the Jorgenson dataset that we extend to 2002 and *h* for the number of workers. The real weights $m_{it} = \frac{sales_{it}}{\sum_i^N sales_{it}}$. The labor input n_{it} is simply equal to h_{it} .

SEC: We construct a value added series to make the labor productivity comparable across the two data sets: $vadd_{it} = vq_{it} - vm_{it} - ve_{it}$ where *vq* is the value of output, *vm* and *ve* are respectively the value of materials and the value of energy used in production. The labor productivity is then computed as $z_{it} = \frac{vadd_{it}}{\frac{po_{it}}{vl_{it}} pl_{it}}$ where *po_{it}* the output deflator, *vl_{it}* is the value of the labor input and *pl_{it}* is the deflator of labor input. TFP in the SEC data set is directly computed as a growth rate:

$$\Delta \ln TFP_{it} = \Delta \ln Q_{it} - sk_{it} \Delta \ln K_{it} - sl_{it} \Delta \ln N_{it} - se_{it} \Delta \ln E_{it} - sm_{it} \Delta \ln M_{it}$$

where Q_{it} is real output, K_{it} , N_{it} , E_{it} and M_{it} are the quantity of capital, labor energy and materials used in production and $sk_{it} = \frac{vk_{it}}{vq_{it}}$, $sl_{it} = \frac{vl_{it}}{vq_{it}}$, $se_{it} = \frac{ve_{it}}{vq_{it}}$ and $sm_{it} = \frac{vm_{it}}{vq_{it}}$ are the nominal share of output that goes to the different inputs. The real weights are simply $m_{it} = \frac{Q_{it}}{\sum_i^N Q_{it}}$ and labor input is the original variable contained in the data set.

A.3 Simulations and Aggregation

Here we report how to obtain the aggregate series for output and hours that are implied by the transitory shocks η_{it}^T of each firms. Small caps indicate logarithm. By definition, aggregate hours are:

$$\bar{n}_t = \sum_i n_{it}$$

Which we can rewrite

$$d\bar{n}_t = \log \left(\frac{\bar{n}_t}{\bar{n}_{t-1}} \right) = \log \left(\sum_i \frac{\bar{n}_{it}}{\bar{n}_{t-1}} \right)$$

Because we run the VAR in logs, we can simulate using the estimated parameters and structural shock each $\Delta \ln n_{it}$ for all the firms. Of course by construction each $\Delta \ln n_{it}$ is equal to the original one. We define $\Delta \ln \tilde{n}_{it}$ the series simulated shutting down the productivity and composition shock. The simulated aggregate hours implied by the transitory shocks are:

$$d\tilde{n}_t = \log \left(\sum_i m_{i,t-1}^h \times \exp(\Delta \ln \tilde{n}_{it}) \right)$$

where $m_{i,t-1}^h = \frac{n_{it-1}}{\bar{n}_{t-1}}$. Following similar steps we simulate the aggregate output implied by the transitory shocks:

$$d\tilde{y}_t = \log \left(\sum_i m_{i,t-1}^y \times \exp(\Delta \ln \tilde{n}_{it} + \Delta \ln \tilde{z}_{it}) \right)$$

where the weight for $m_{i,t-1}^y = \frac{y_{it-1}}{\bar{y}_{t-1}}$.

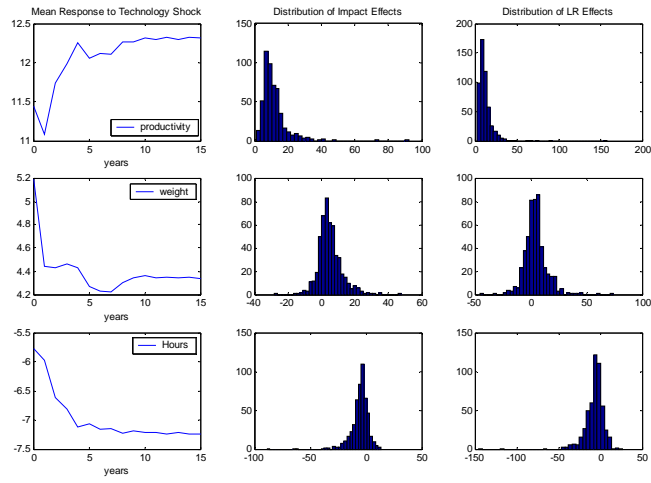


Figure 1: *Firm Dynamics due to the Technology shock*. The first column shows the average of the firms' impulse response. The second and third column show respectively the distribution of impact and Long Run responses. FIRM dataset, Data source: COMPUSTAT.

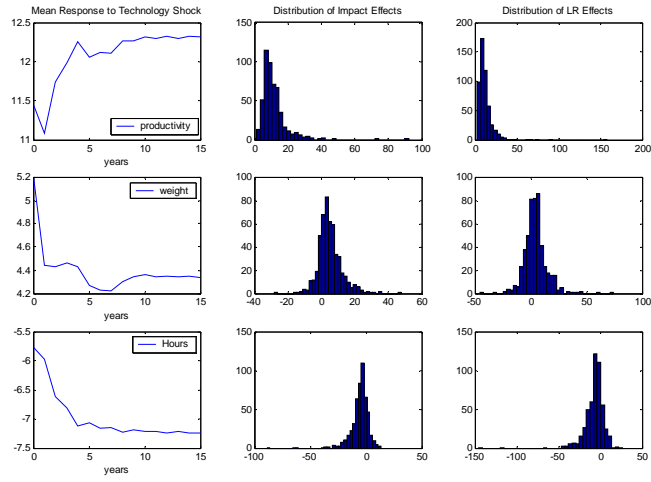


Figure 2: *Firm Dynamics due to the Technology shock*. The first column shows the average of the firms' impulse response. The second and third column show respectively the distribution of impact and Long Run responses. FIRM dataset, Data source: COMPUSTAT.

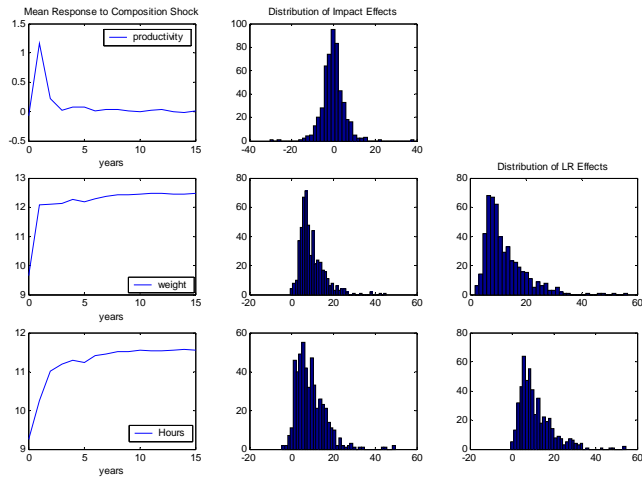


Figure 3: *Firms Dynamics due to the Composition shock*. The first column shows the average of the firms' impulse response. The second and third column show respectively the distribution of impact and Long Run responses. FIRM dataset. Data source: COMPUSTAT.

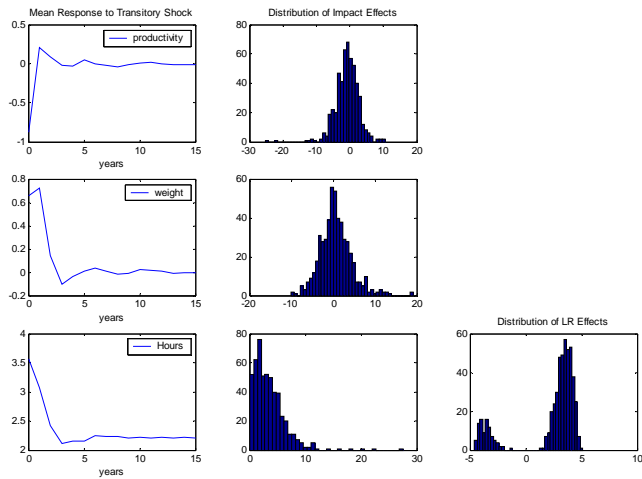


Figure 4: *Firms Dynamics due to the Transitory shock*. The first column shows the average of the firms' impulse response. The second and third column show respectively the distribution of impact and Long Run responses. FIRM dataset. Data source: COMPUSTAT.

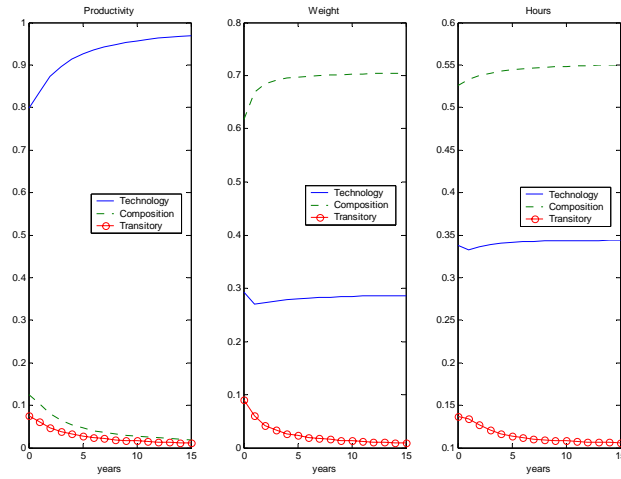


Figure 5: *Firms Dynamics, Variance Decomposition*. Each panel shows the mean of the variance decomposition for the variables *in level* of each N estimated VAR. The first panel shows the percentage of the variance of z_i , m_i and n_i explained on average by the technology shock while the second and the third respectively for the composition and the transitory shock. Firm dataset. Data source: COMPUSTAT.

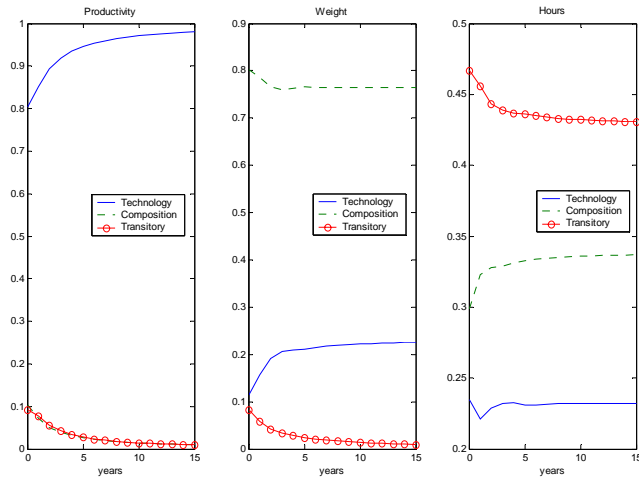


Figure 6: *Industry Dynamics, Variance Decomposition*. Each panel shows the mean of the variance decomposition for the variables *in level* of each N estimated VAR. The first panel shows the percentage of the variance of z_i , m_i and n_i explained on average by the technology shock while the second and the third respectively for the composition and the transitory shock. SEC dataset using YH. Data source: Jorgenson.

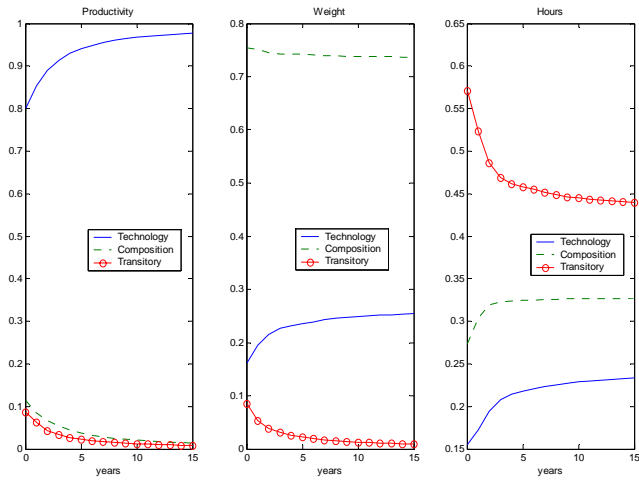


Figure 7: *Industry Dynamics, Variance Decomposition*. Each panel shows the mean of the variance decomposition for the variables *in level* of each N estimated VAR. The first panel shows the percentage of the variance of z_i , m_i and n_i explained on average by the technology shock while the second and the third respectively for the composition and the transitory shock. SEC dataset using TFP. Data source: Jorgenson.

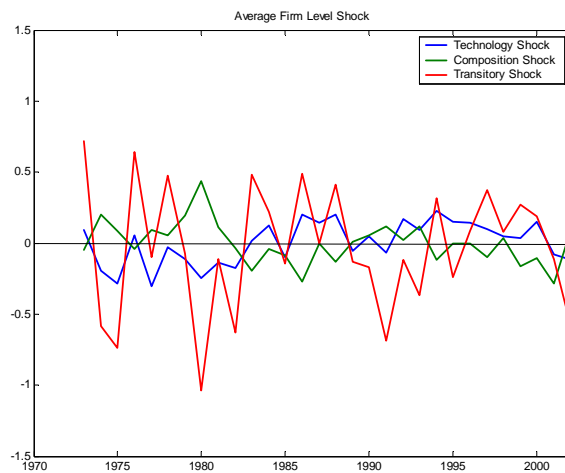


Figure 8: *Aggregate Dynamics*. Average of firm level shocks. Data source: COMPUSTAT.

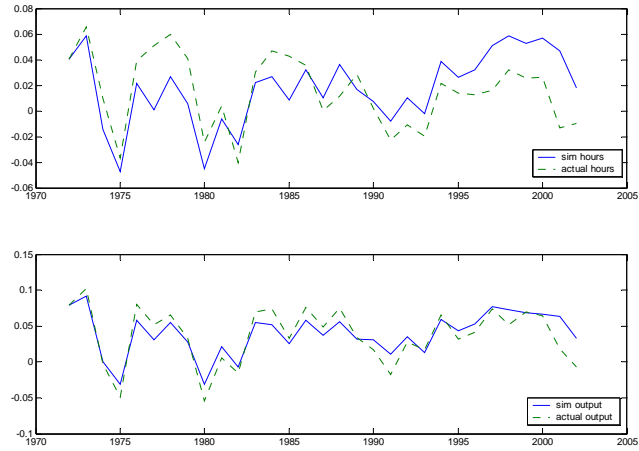


Figure 9: *Aggregate Dynamics*. Aggregate simulated growth rate of hours and output implied by the transitory shock versus the actual series. FIRM dataset. Data source: COMPUSTAT.

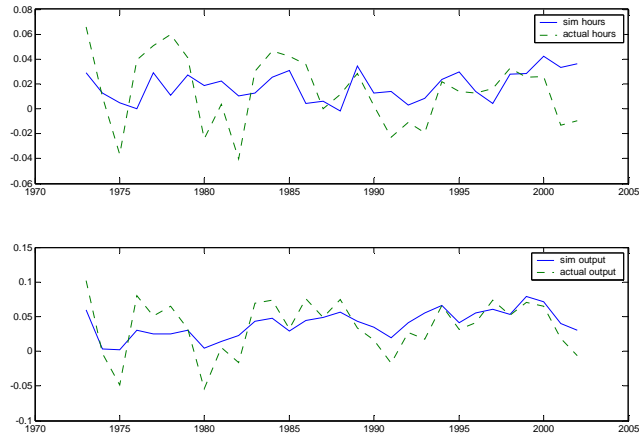


Figure 10: *Aggregate Dynamics*. Aggregate simulated growth rate of hours and output implied by the technology shock versus the actual series. FIRM dataset. Data source: COMPUSTAT.

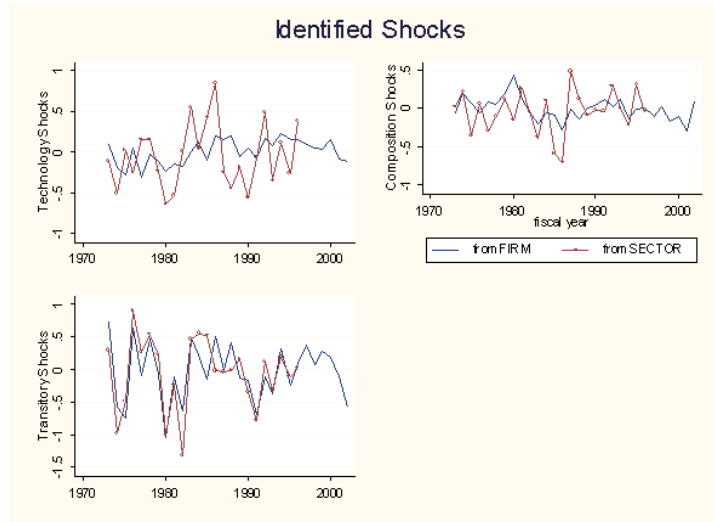


Figure 11: Comparison of shocks identified from COMPUSTAT and shocks identified from Jorgenson's data.

		z	Δz	n	Δn	m	Δm
	CV						
	ADF						
	1%	8	414	12	285	14	351
	5%	38	489	39	408	35	442
	10%	47	499	58	450	55	484
	KPSS						
	1%	50	467	24	397	19	424
	5%	69	488	34	448	41	466
	10%	132	517	84	507	102	506

Table 1: Number of firms for which the null hypothesis of a unit root could be rejected using the ADF test and the null of stationarity could not be rejected using the KPSS test. The total number of firms is 526. All the series are entered in logarithms and Δ indicates the first difference operator. z is labor productivity, m is the relative weight and n is the number of hours.

	η^Z	η^ω	η^T
FIRM $\frac{y}{h}$	0.026 *0.8513,** 0.913,***0.973	0.0243 * 0.8280,** 0.8937,***0.963	0.2360 *0.0656,** 0.1071,***0.229
SEC $\frac{y}{h}$	0.0957 *0.8008,** 0.878,***0.9452	0.0307 * 0.7422,** 0.8262,***0.918	0.248 *0.5273,** 0.623,***0.7988
SEC TFP	0.0476 *0.8237,**0.8916,***0.9725	0.0227 *0.7759,**0.8512,***0.9725	0.2763 *0.4968,** 0.5739,*** 0.7833

Table 2: For each specification the first line reports the average of the mean correlations of the three identified shocks across Firms/Sector and the second line the percentage of pairwise correlations non significantly different form zero. * indicates a 10 percent and ** a 5 percent level of significativity.

Table 3: Shocks identified from Sector versus Firm level data

3a: Regression of Sector-Shocks on Firm-Shocks. Dependent Variable is Shock Identified from Sector Level Data

Sector-Average of Firm Level Shocks	Shocks Identified from Sector Data & Labor Productivity			Shocks Identified from Sector Data & TFP		
	Technology	Composition	Transitory	Technology	Composition	Transitory
Technology	0.146 <i>0.085</i>	0.178 <i>0.078</i>	-0.148 <i>0.079</i>	0.475 <i>0.083</i>	0.094 <i>0.081</i>	-0.017 <i>0.078</i>
Composition	0.014 <i>0.089</i>	0.72 <i>0.082</i>	0.034 <i>0.083</i>	0.263 <i>0.088</i>	0.592 <i>0.086</i>	0.195 <i>0.083</i>
Transitory	0.143 <i>0.065</i>	0.206 <i>0.06</i>	0.657 <i>0.061</i>	0.16 <i>0.064</i>	0.129 <i>0.062</i>	0.61 <i>0.06</i>
N	744	744	744	744	744	744

3b: Explaining Transitory & Technology Shocks

	Sector-Average of Firm Level Shocks		Shocks from Sector Data & Labor Productivity		Shocks from Sector Data & TFP	
	Technology	Transitory	Technology	Transitory	Technology	Transitory
Romer-Romer Shock	0.137 <i>0.283</i>	-0.967 <i>0.323</i>	-1.941 <i>0.64</i>	-2.541 <i>0.597</i>	-1.257 <i>0.655</i>	-2.086 <i>0.593</i>
Romer-Romer (lagged)	0.135 <i>0.308</i>	-0.373 <i>0.35</i>	1.072 <i>0.696</i>	-0.158 <i>0.649</i>	0.352 <i>0.712</i>	-0.288 <i>0.644</i>
Hamilton-Oil Shock	-0.753 <i>0.462</i>	-1.479 <i>0.527</i>	-4.502 <i>1.046</i>	-1.802 <i>0.975</i>	-2.142 <i>1.07</i>	0.548 <i>0.968</i>
Hamilton (lagged)	-2.43 <i>0.462</i>	-7.77 <i>0.526</i>	-2.608 <i>1.045</i>	-10.002 <i>0.974</i>	-3.932 <i>1.069</i>	-10.09 <i>0.967</i>
N	744	744	744	744	744	744

Notes: Standard Errors are in italics, under the regression coefficients. Sample period is 1970-1996 (because Romer-Romer shocks are not available in recent years). Sectoral Data from Jorgenson, Firm Level Data from Compustat.

Table 4: Explaining Firm Level Shocks

	Technology Shock			Transitory Shock		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Hamilton Oil Shock	-0.401 <i>0.247</i>	-0.227 <i>0.192</i>	-0.218 <i>0.188</i>	-1.994 <i>0.253</i>	0.089 <i>0.186</i>	0.175 <i>0.185</i>
Hamilton (lagged)	-2.044 <i>0.244</i>	-0.895 <i>0.188</i>	-0.833 <i>0.197</i>	-8.714 <i>0.249</i>	-2.336 <i>0.183</i>	-4.414 <i>0.194</i>
Romer-Romer Shock	-0.061 <i>0.149</i>			-1.086 <i>0.152</i>		
Romer-Romer (lagged)	0.155 <i>0.162</i>			-0.31 <i>0.166</i>		
Consumer Confidence		0.004 <i>0.001</i>			0.029 <i>0.001</i>	
Consumer Confidence (lagged)		-0.001 <i>0.001</i>			0.001 <i>0.001</i>	
Growth Rate of Public Spending, cyclically adjusted			-1.365 <i>0.367</i>			0.798 <i>0.361</i>
Growth Rate of Public Spending (lagged)			0.332 <i>0.345</i>			5.235 <i>0.339</i>
Growth Rate of Taxes, cyclically adjusted			-1.033 <i>0.283</i>			-3.991 <i>0.278</i>
Growth Rate of Taxes, cyclically adjusted, (lagged)			0.385 <i>0.28</i>			2.76 <i>0.275</i>
N	10489	12483	12483	10489	12483	12483

Notes: All regressions include Firm Fixed Effects and a Linear Time Trend. Government Spending and Taxes are cyclically adjusted by CBO. Standard errors are in italics below the regression coefficients.