

FIRMS AND AGGREGATE DYNAMICS

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Abstract—We investigate the role of permanent and transitory shocks for firms and aggregate dynamics. We find that permanent shocks to productivity and permanent shifts in the composition of output explain at least four-fifths 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, but they account for most of the volatility of aggregate hours and output, because they are significantly correlated across firms. Finally, we try to make some progress on the interpretation of the shocks.

I. Introduction

WE investigate the nature of firms and 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 a panel of large, publicly traded companies.

We assume that firm dynamics are driven by three different shocks. First, there are permanent, stochastic technological improvements. Second, there are permanent 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 the three shocks with long-run restrictions in a structural VAR: we impose that transitory shocks do not have permanent effects on productivity and market share, and that composition shocks do not have a permanent effect on productivity.

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 four-fifths of firm dynamics. However, we also find that these shocks are almost uncorrelated across firms. By contrast, the correla-

tion of transitory shocks lies between 20.5% and 26.8%, 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 U.S. 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 & Wouters, 2003; Chari, Kehoe, & McGrattan, 2004a) have found that shocks to the consumption-leisure margin explain a large fraction of the fluctuations.² Another strand of literature has adopted the long-run 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 of this approach are that the permanent shock has a negative short-run effect on hours, and that it explains very little of the business cycle.³ Some recent studies have used industry data to investigate the robustness of the first finding (Francis, 2001; Chang & Hong, 2003). Gali and Rabanal (2004) give a comprehensive survey of the existing literature, while Erceg, Guerrieri, and Gust (2005) and Chari, Kehoe, and McGrattan (2004b) present a critique.

¹ For 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% of actual variability.

² Hall (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 (2004a) 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 markup shocks. They find that a sizable fraction of output volatility is due to preference shocks that induce changes on the consumption-leisure margin.

³ The negative effect of technology on hours has been disputed by several authors. See for instance Christiano, Eichenbaum, and Vigfusson (2004).

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We make three contributions to the literature. First, we compare the relative importance of permanent and transitory shocks for micro- and macrodynamics. Kiley (1998) performed a similar exercise using industry data for the manufacturing sector, but we are the first to investigate the comovements of permanent and transitory shocks at the *firm* level. Second, we introduce the composition shocks and show that they are important sources of firm-level dynamics. Third, we investigate whether aggregation poses problems for the identification of permanent shocks, and we make some progress in the interpretation of shocks. We find that monetary shocks only induce transitory dynamics. Tax shocks appear to have negative transitory effects. We also find some evidence suggesting that tax shocks have negative permanent effects.

In section II, we present a simple, neoclassical model of an economy with sectorial shocks, which we use to derive our identifying restrictions. In section III we describe our data. In section IV we present our empirical strategy, and our findings. In section V we perform some robustness checks and in section VI we try to give an economic interpretation to the identified shocks.

II. 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

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

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 $\bar{w}_t \bar{n}_t$, where \bar{w}_t is the real wage and \bar{n}_t the amount of labor supplied, 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 0 net supply. The consumption good is obtained by aggregating the outputs of a continuum of firms:

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

The only nonstandard feature of this model is the presence of idiosyncratic taste parameters ω_{it} that evolve stochastically:

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

The consumption of c_{it} physical units of good i delivers the same utility as the consumption of $\omega_{it}c_{it}/\omega_{jt}$ units of good j . The shocks 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. The first-order conditions for consumption imply that

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

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 constant.⁵

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

where y_{it} denotes output and n_{it} the labor input of firm i . The technology of each firm 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 a white noise. Perfect competition implies that real profits are 0 and $p_{it}\bar{p}_t = \bar{w}_t/z_{it}$. Nominal income identity

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

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

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

⁴ We use the normalization $\int_0^1 w_{it}^{\theta-1} di = 1$. The shocks are conveniently normalized to make \bar{p} a price level (that is, 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 w_{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).

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

and

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

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

where \bar{z}_t is the utility-based measure of aggregate productivity. We emphasize that this utility-based measure is not the one that is constructed in the national income and product accounts. Note that ωz is unambiguously defined in our setup, even though, of course, the units of ω and z are arbitrary.⁶ We see that \bar{z} depends on the preference shocks. To understand this dependence better, fix the units, and differentiate with respect to ω :

$$\bar{z}_t^{\theta-2} \times d\bar{z}_t = \int (\omega_{it} z_{it})^{\theta-1} \frac{d\omega_{it}}{\omega_{it}}.$$

Thus, changes in preferences have a positive impact of total factor productivity (TFP) when ω grows more for goods with a higher initial value of ωz . Note that, in this experiment, there is no change in technology in any industry. For lack of a better name, we refer to these changes in preferences as composition shocks.

Let us 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 affects productivity of firm i in the long run is z_{it} , but the share of firms i in total output is affected by both technology and composition 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 . This shock has no permanent effect on the productivity or the relative size of the firms. Therefore the long-run restrictions are

⁶ Suppose ω is the preference for a kilogram of chocolate, and z is the number of kilograms produced per hour of work. Now, change the units to grams. This corresponds to multiplying z by 1,000 and dividing ω by 1,000. This does not change anything real in our economy: it changes neither \bar{c} nor \bar{z} . The same applies to comparisons across industries: the levels of z_i are arbitrary and cannot be compared, while the products $w_i z_i$ are directly comparable.

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

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

$$\lim_{j \rightarrow \infty} \frac{\partial \ln \frac{y_{it+j}}{\bar{y}_{t+j}}}{\partial \eta_{it}^T} = 0.$$

III. Data

In this section, we describe our sample, and we discuss the representativeness and statistical properties of our data.

Our sample includes the 526 firms in COMPUSTAT that have nonmissing data for sales and number of employees from 1970 to 2002, and that did not experience a large merger.⁷ Our baseline specification includes three variables: labor productivity, relative size, and labor input. An important issue in our analysis is the choice of a productivity measure. We must trade off theoretical motivations against measurement problems. Conceptually, TFP would be 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 can be affected by non-technological shocks. For instance, Uhlig (2004) points out that permanent changes in taxes on capital income can affect long-run labor productivity.⁸

For the labor input we use the log of the number of employees

$$n_{it} = \log(\text{employees}).$$

We use sales instead of gross output for lack of data on intermediate inputs and inventories.⁹ We do not have price data at the firm level. We must therefore use sector output deflators, which we take from Jorgenson and Stiroh (2000), and which we extend to 2002. For firm i in sector I with deflator p_{It} , we define labor productivity as

$$z_{it} = \log \left(\frac{\text{sales}_{it}}{p_{It}} \right) - n_{it}.$$

Finally, we define relative size (or market share) as¹⁰

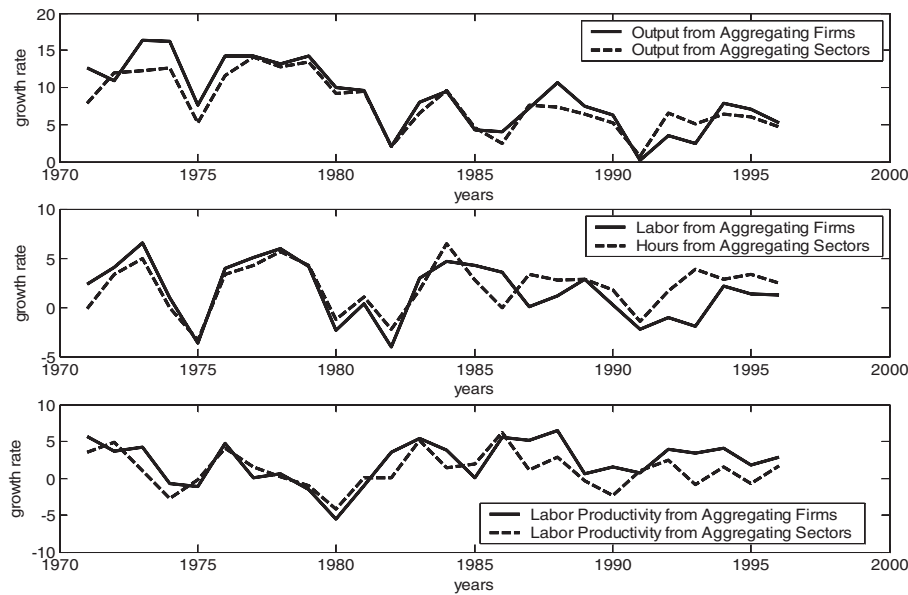
⁷ A large merger is a merger that increases the assets of the company by more than 50%.

⁸ See Gali and Rabanal (2004) for a discussion.

⁹ We have data on finished goods inventories for 153 firms. We have constructed an alternative data set in which we subtract the change in inventories in finished goods from sales before deflating to obtain a more precise measure of value added. The results are virtually identical.

¹⁰ We have performed the analysis using both real weights and nominal weights. The results are very similar.

FIGURE 1.—AGGREGATE REPRESENTATIVENESS OF THE FIRM-LEVEL DATA SET



Notes: Sector-level data are from the Jorgenson data set. Firm-level data are from COMPUSTAT.

$$m_{it} = \frac{sales_{it}}{\sum_{i=1}^{526} sales_{it}}$$

We now assess the representativeness of our sample by constructing two synthetic data sets. We first aggregate up to the sector level, for which we have price deflators, and we compare our synthetic data series to the ones in Jorgenson and Stiroh (2000). We have 32 sectors, roughly at the two-digit SIC level, including 21 manufacturing industries. The number of firms per sector varies from one to one hundred. To have a sense of the representativeness of our data, we regress the growth rate of n , m , and z of each sector onto the synthetic growth rate we have obtained from the firms. The R^2 of the regressions varies from 0.01 to 0.83.¹¹ We also compare the completely aggregated data, and we find that our sample is representative of the whole economy, for both employment and labor productivity, as shown in figure 1. The Jorgenson data set is used only for the comparison in figure 1 and for the deflators, otherwise sectorial and aggregate data are aggregated from the firm-level 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

¹¹ The R^2 for $z \in [0.01, 0.62]$, for $m \in [0.03, 0.83]$, and for $n \in [0.01, 0.74]$. In the case of n the lowest R^2 is for the sector labeled "Textile mill products" for which we have two firms, while the highest R^2 is for the sector labeled "Machinery nonelectrical" for which we have 37 firms. The firm data from COMPUSTAT and the Jorgenson-Stiroh sectorial data set are derived from different source data/surveys; they have different definitions (for example, number of workers at a firm level; a quality-adjusted index of labor input at an industry level).

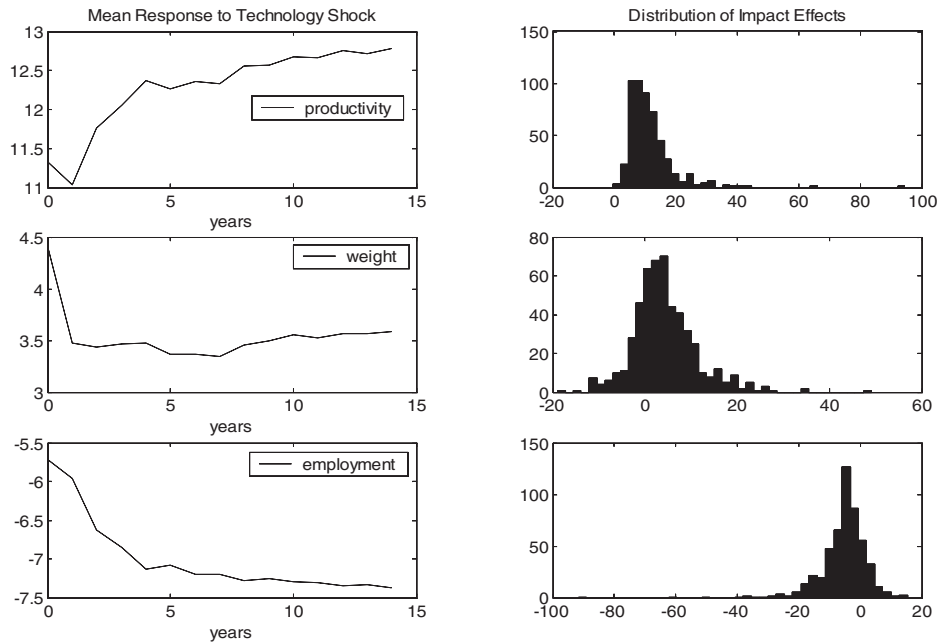
the presence of a stochastic trend in the series. The results for the firm data set are summarized in table 1. For example, in the case of the logarithm of labor productivity, we were able to reject the null of a unit root at the 10%, 5%, and 1% confidence levels for respectively 47, 38, and 8 firms. The ADF test on the first difference of the same series rejected the null of the unit root at the 10%, 5%, and 1% 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% confidence levels 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% confidence levels for respectively 517, 488, and 467 firms. We perform the same analysis on both the relative weight measure m_i and the labor input n_i . A summary of the results suggests that for the large majority of firms both series are again I(1).

TABLE 1.—UNIT ROOT TESTS

		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

Notes: 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.

FIGURE 2.—FIRM DYNAMICS DUE TO THE TECHNOLOGY SHOCK



Notes: The first column shows the average of the firms' impulse response. The second column shows the distribution of impact responses. Firm data set, data source: COMPUSTAT.

IV. Results

Our baseline specification is the trivariate VAR with two lags estimated for each firm or sector i .¹² 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 unity.¹³ The MA is recovered estimating a VAR 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 restricts $c_{i12}(1)$ 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 restricts $c_{i13}(1)$ and $c_{i23}(1)$ to be both equal to 0.¹⁴

¹² The results estimating the VAR with one and three lags are similar.

¹³ Both 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. We define positive productivity shock as a shock that raises productivity in the long run, and positive composition shock as a shock that raises the relative weight in the long run.

¹⁴ We are implicitly assuming that the MA is fundamental; see Lippi and Reichlin (1993) for a discussion of this assumption.

A. Impulse Responses

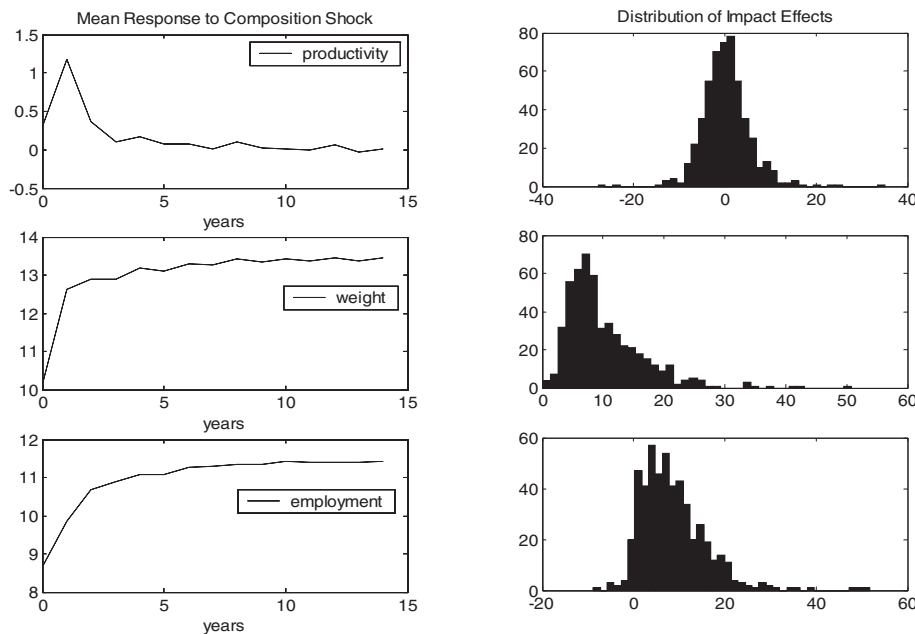
We discuss the results obtained with the firm data set, only highlighting the results for the sector data set if they differ. In our specification the three variables have a stochastic trend, therefore no shock has a transitory effect on the *level* of a variable unless we imposed it.

Figure 2 shows the estimated effects of a positive permanent *technology* shock η_{it}^z . The left part of the figure displays the mean impulse response of the level of the three variables to a 1-standard-deviation shock. The right part shows the corresponding distribution of impact 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 Galí and Rabanal (2004). The distribution of responses shows that the impact effect on productivity is positive for all firms. The effect on the weight is positive on impact for 79% of the firms. Firms that experience a positive productivity shock gain market shares. The effect on hours is negative on impact for 81% of the firms.

Similarly, figure 3 shows the estimated effects of a positive *composition* shock η_{it}^ω . The empirical effect on labor productivity of the composition shock is equally distributed around 0 as one can observe from the impact distribution in figure 3. The effects on the weight are positive for all the firms. The effects on hours are positive for virtually all firms.

Finally, figure 4 shows the estimated effects of a positive *transitory* shock η_{it}^T . The mean effect on productivity is again not different from 0 (the negative blip on impact is

FIGURE 3.—FIRM DYNAMICS DUE TO THE COMPOSITION SHOCK



Notes: The first column shows the average of the firms' impulse response. The second column shows the distribution of impact responses. Firm data set, data source: COMPUSTAT.

mainly due to an outlier). Using the sector data set the impact effect of the transitory shocks on productivity is still 0 but becomes positive for 68% of the sectors in the second and third periods.¹⁵ The impact effect on the weight is also positive for roughly half of the firms, which shows that the short-run effect is also small. The impact on the level of hours is positive for all firms.

B. Variance Decompositions

Firm and Industry Dynamics. Figure 5 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 firm level are on average mostly 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 weight 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 firm dynamics. We present the results obtained using the synthetic sectorial data set.

Figure 6 shows that the mean variance decomposition across the sectors of the different shocks are similar for the technology and composition shocks, while the transitory shock explains around 33% of the labor input variance. As we shall see below, this last observation reflects the fact that sectors are aggregate units.

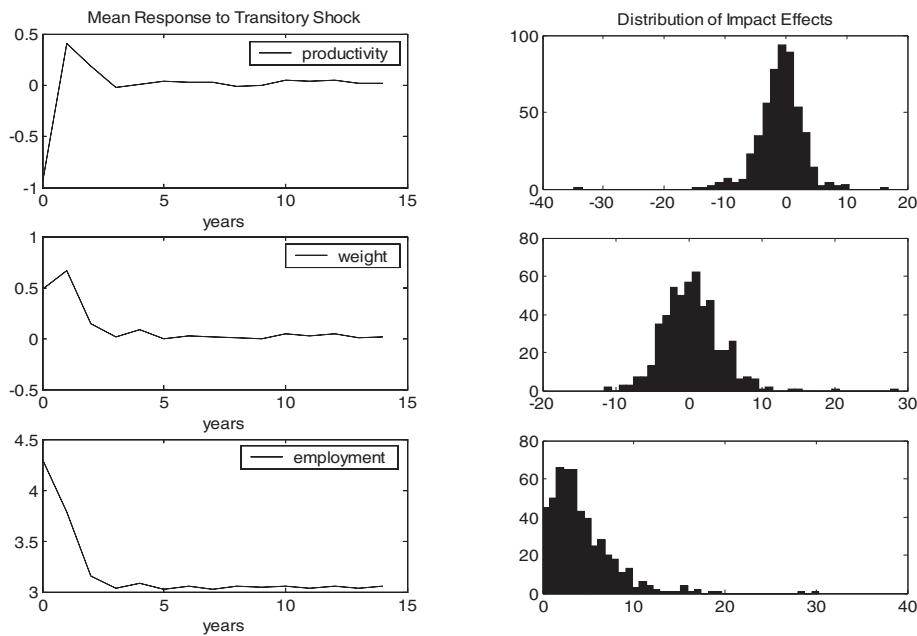
Aggregate Dynamics. We now turn to the principal motivation of the paper and investigate the comovement of the three shocks across firms. For each shock, we compute all pairwise correlations with the same shock of all other firms. This gives us three symmetric $N \times N$ matrices of correlations. We then take the average¹⁶ for each firm and end up with N mean correlations.¹⁷ Table 2 shows that for our baseline specification the average of the mean correlations is around 2.8% for the technology shock, 1.59% for the preference shock, and 20.4% for the transitory shock. Table 2 shows that the sectorial technology shocks have their average correlation that increases up to 4.7%. This is still much lower than an average of 24% for the transitory shock.

¹⁵ This is consistent with the observation that labor productivity and hours are positively correlated at the sector level, but not at the firm level. In the synthetic aggregate firm-level data set, the correlation between the growth rate of labor productivity and the growth rate of workers is positive and equal to 0.17 (in the Jorgenson data set the correlation between the growth rate of aggregate labor productivity and the growth rate of aggregate labor input is 0.13 [it is 0.45 using TFP]). At the firm level, the average correlation between labor productivity and labor input is -0.13 (in the Jorgenson data set the average industry correlation between labor productivity and labor input is -0.18). This apparent paradox between aggregate productivity being procyclical and disaggregated productivity being countercyclical is clearly interesting, but we feel it has no room in this paper. Moreover, the correlations are small, which indicates that productivity is probably mainly acyclical.

¹⁶ In taking the averages we exclude the 1 on the main diagonal of the correlation matrix.

¹⁷ Using the median instead of the mean gives similar results.

FIGURE 4.—FIRM DYNAMICS DUE TO THE TRANSITORY SHOCK

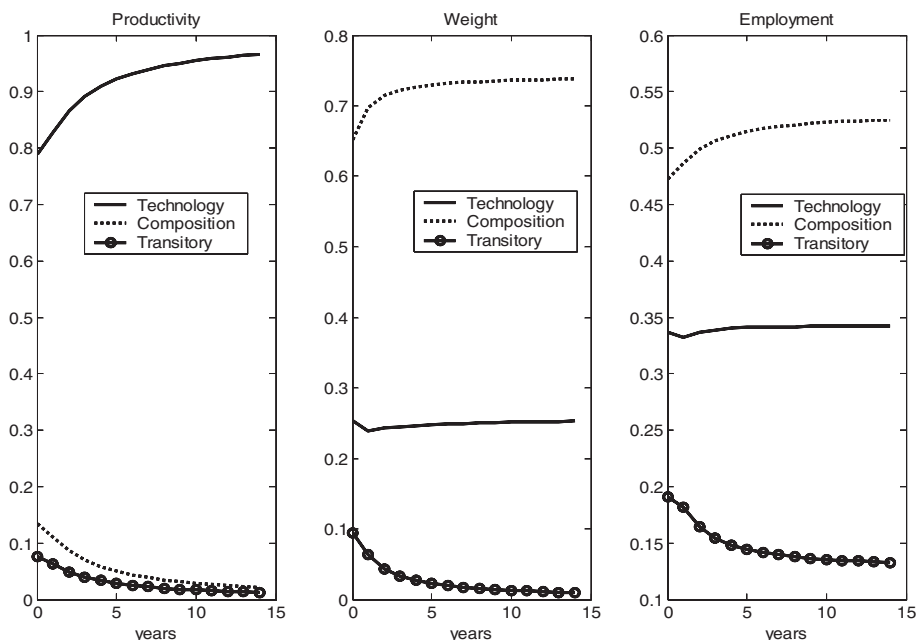


Notes: The first column shows the average of the firms' impulse response. The second column shows the distribution of impact responses. Firm data set, data source: COMPUSTAT.

Figure 7 plots the average of the three shocks, namely $\eta_t^j \equiv (\sum_i^N \eta_{it}^j)/N$ 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 1, 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 ap-

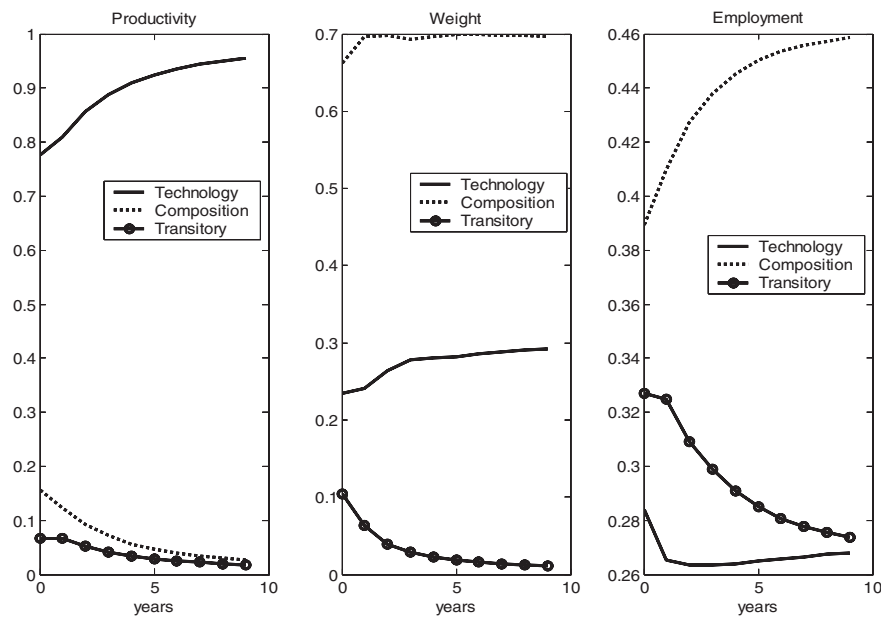
pears to be a good candidate to explain aggregate short-run fluctuations, which are characterized by a high degree of comovement across firms. Indeed the average of the transitory shock appears to experience more important fluctuations than the technology shock. On the contrary, permanent technology and composition shocks appear to be mostly idiosyncratic. Interestingly, figure 7 shows that the aggregate technology shock exhibits a sustained negative period

FIGURE 5.—FIRM DYNAMICS, VARIANCE DECOMPOSITION



Notes: 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 $z, m,$ and n explained on average by the technology shock while the second and the third respectively for the composition and the transitory shock. Firm data set. Data source: COMPUSTAT.

FIGURE 6.—SECTORAL DYNAMICS, VARIANCE DECOMPOSITION



Notes: 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 , m , and n explained on average by the technology shock while the second and the third respectively for the composition and the transitory shock. SEC synthetic data set. Data source: COMPUSTAT.

during the mid-1970s and the beginning of 1980s,¹⁸ and a sustained positive period in the 1990s.

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 *composition* shocks, the *transitory* shock appears to hit many firms contemporaneously. This property implies that at the aggregate level the *transitory* shock is able to explain most of the short-run fluctuations of the economy. To illustrate this, we use the estimated VARs to simulate a series for each firm shutting down the *technology* and *composition* shocks. The exact procedure is discussed in the appendix. Figure 8 shows the actual aggregate output and hours series together with the simulated series. The transitory shock explains a large proportion of the fluctuations of both aggregate output and hours.

¹⁸ This is consistent with the productivity slowdown experienced by the U.S. economy.

TABLE 2.—MEAN CORRELATIONS OF THE THREE IDENTIFIED SHOCKS ACROSS FIRMS OR SECTORS

	Technology Shocks	Composition Shocks	Transitory Shocks
Firm data	0.0281	0.0159	0.2045
Sectoral data	0.0470	0.0156	0.2400
Firm data with bi-VAR	0.0245	-	0.0473
Firm data controlling for inventories	0.0481	0.0294	0.2686

Notes: For each specification we report the average of the mean correlations of the three identified shocks across firms/sectors. Firm: shocks identified using the firm-level data set. Sec: shocks identified using the synthetic sectoral level. Firm bi-VAR: shocks identified from firm-level data using a bi-VAR. Finally, firm with inventories: shocks identified using the subset of firms for which inventory data are available.

Figure 9 shows the simulated employment and output implied by the technology shock. 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 a topic for future research.

V. Discussion

We now discuss the robustness of the results.

A. The Lack of Firm-Level Price Deflators

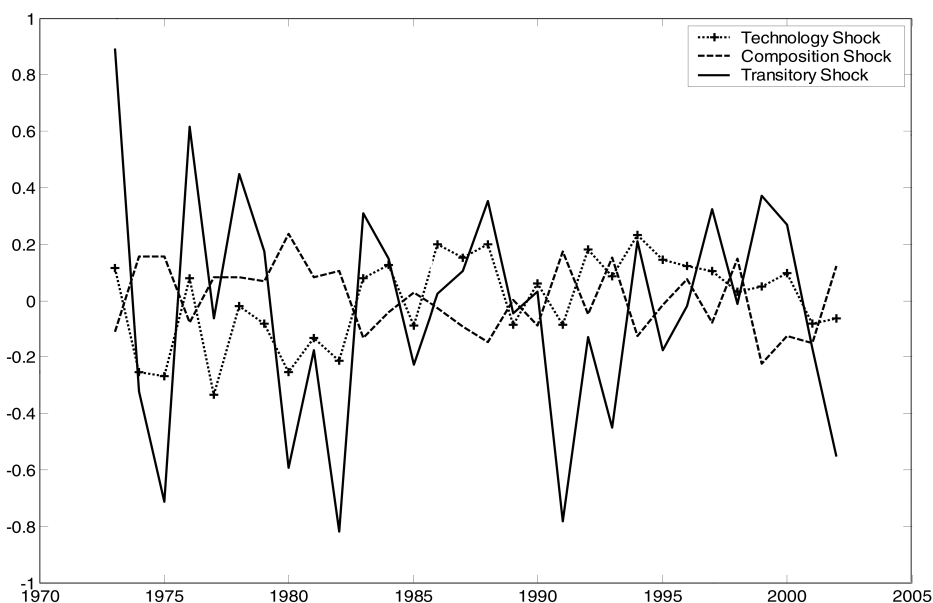
We do not have price data at the firm level. The implication is that our approach might mix up technology shocks and composition shocks at the firm level.¹⁹ To see this, consider the long-run size of the firm

$$\frac{n_i}{\bar{n}} = \left(\frac{\omega_i z_i}{\bar{z}} \right)^{\theta-1}.$$

This shows that one cannot disentangle ω from z by looking only at relative sizes. However, this issue does not prevent

¹⁹ Klette and Griliches (1996) explore the inconsistency of common scale estimators when output is proxied by deflated sales, based on a common output deflator across firms.

FIGURE 7.—AVERAGE OF FIRM-LEVEL SHOCKS



Notes: The figure shows the average of the three shocks in order to visualize the implications of the correlations for an aggregate shock. Data source: COMPUSTAT.

us from identifying the transitory shocks. Consider our tri-VAR

$$\Delta x_t = A(L)\Delta x_t + G\eta_t,$$

where

$$\Delta x_t = [\Delta z_t, \Delta m_t, \Delta n_t]', \quad \eta_t = [\eta_t^z, \eta_t^m, \eta_t^n]'$$

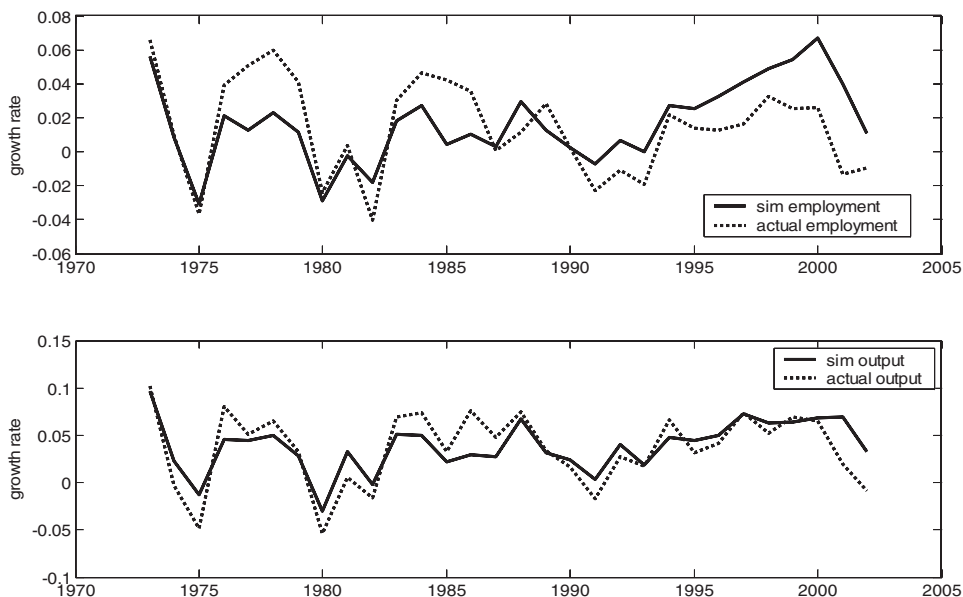
with the structural shocks such that $E\eta_t\eta_t' = I$, and $GG' = V$ the covariance matrix of the reduced-form innovations. Our main long-run restriction is that the transitory shock

affects neither the weight nor the productivity in the long run, in other words

$$R \equiv (I - A(1))^{-1}G.$$

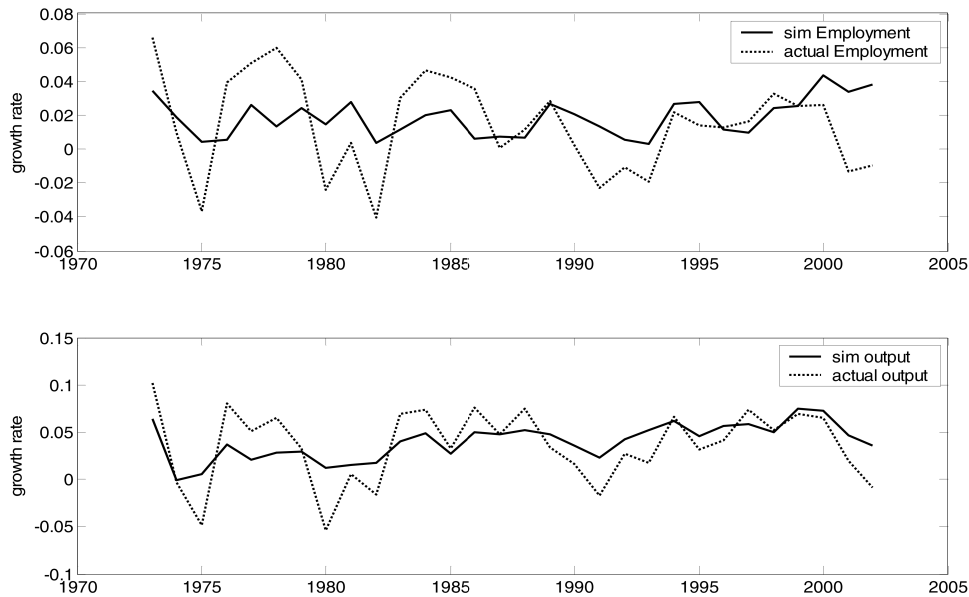
Many 3×3 matrices R satisfy these restrictions, but they all have the same third column. This pins down the third column of G , and therefore the impulse response to the transitory shock, irrespective of how mixed up the first two shocks are. So we may not be able to say whether technological improvements or permanent changes in relative

FIGURE 8.—AGGREGATE DYNAMICS, TRANSITORY SHOCK



Notes: Aggregate simulated growth rate of employment and output implied by the transitory shock versus the actual series. Data source: COMPUSTAT.

FIGURE 9.—AGGREGATE DYNAMICS, TECHNOLOGY SHOCK



Notes: Aggregate simulated growth rate of hours and output implied by the technology shock versus the actual series. Data source: COMPUSTAT.

demands drive most of the firm dynamics, but we can still learn about the role of transitory shocks at the firm level and in the aggregate.

Given that we cannot always disentangle the two permanent shocks, one would be tempted to run a simpler bi-VAR model with only one transitory and one permanent shock. However, in the presence of two permanent shocks, we generally need a tri-VAR in order to correctly identify the transitory shock. Blanchard and Quah (1989) give necessary and sufficient conditions for a bivariate representation not to produce misleading results when the number of shocks is greater than two.²⁰ In words, we would correctly identify the transitory shock only if the distributed lag effects in productivity and relative size are sufficiently similar across the technology and composition shocks. Interestingly, if we run bi-VAR in our data set using labor productivity and hours or relative weights and hours, the identified transitory shock becomes much less correlated across firms. The third line of table 2 reports that in this case the correlation across firms of the permanent shock is on average 0.0245 and the correlation across firms of the transitory shock is only 0.0473.

B. Aggregation

We now compare the shocks identified in our firm-VARs with the shocks one would identify if one were to run VARs on more aggregated data. Table 3A compares the shocks identified from synthetic sector data to the average of the shocks identified at the firm level. For each sector, we compute the average of the shocks hitting the firms in that sector, weighted by sales to take into account

the relative importance of the different firms in the sector. We then regress each sector-level shock on the three firm averages. Table 3A shows that there is no systematic aggregation bias. The second column shows that permanent composition shocks from the sector-level data are significantly related to both permanent average technology and composition shocks at the firm level. However the coefficient on the permanent technology shock is much smaller than the coefficient on the permanent composition shock and much less significant. Here the bias is statistically significant but small and probably not relevant economically. Table 3B presents similar results at the aggregate level. In this case, we run a bi-VAR on aggregate synthetic data, and we compare the identified shocks to the average of the shocks identified at the firm level. Note that the shocks are normalized to have a variance of 1. Thus, the average of the shocks, on the right-hand side, has a variance less than 1. So we would expect the coefficients for the regression of a shock on its own average to be more than 1, as is the case in table 3. Note, however, that the typical national income and product account (NIPA) measure of productivity growth would not pick up the effect of the composition shocks.²¹ To understand the issue, take the total differential of \bar{c} :

$$\frac{d\bar{c}_t}{\bar{c}} = \int \left(\frac{\omega_i c_i}{\bar{c}} \right)^{\theta-1} \left[\frac{dc_{it}}{c_i} + \frac{d\omega_{it}}{\omega_i} \right].$$

Substituting in from the equation for c_i/\bar{c} , we find that $(\omega_i c_i/\bar{c})^{\theta-1} = p_i c_i / (\bar{p}\bar{c})$, which is the nominal share, which we have called m_i . Thus,

²⁰ Blanchard and Quah (1989, p. 670).

²¹ We thank our referee for pointing this out.

TABLE 3A.—COMPARISON OF SECTOR-LEVEL SHOCKS WITH SHOCKS IDENTIFIED FROM FIRM-LEVEL DATA

	Dependent variable is shock identified from synthetic sector data		
	Technology	Composition	Transitory
Weighted average of firm technology shocks	1.206 <i>0.038</i>	0.095 <i>0.037</i>	-0.065 <i>0.039</i>
Weighted average of firm composition shocks	-0.028 <i>0.037</i>	1.203 <i>0.035</i>	0.007 <i>0.038</i>
Weighted average of firm transitory shocks	0.037 <i>0.032</i>	-0.012 <i>0.031</i>	0.988 <i>0.033</i>
<i>N</i>	900	900	900

Note: Regressors are sector averages of firm shocks, weighted by sales. Standard errors are in italics below the regression coefficients. Bold coefficients are significant at the 5% level.

$$\frac{d\bar{c}_t}{\bar{c}} = \int_i m_i \frac{dc_{it}}{c_i} + \int_i m_i \frac{d\omega_{it}}{\omega_i}$$

The first term is the NIPA measure of aggregate consumption growth, and it corresponds to the weighting scheme that we adopt to construct our synthetic data. In both cases, the contribution of composition shocks to aggregate productivity growth is missed. The fact that we do not find aggregation biases is of some interest regardless what our model predicts. CRS and perfect competition rule out most of the aggregation effects by assumption, while the empirical finding of no aggregation biases constitutes a green flag for the use of aggregate data by macroeconomists.

VI. Robustness

We have estimated different models to test the quality of the VAR estimates. We have found that using real weights instead of nominal weights gives similar results. We also have performed the analysis on a subset of firms for which data on finished good inventories are available and found again very similar results. In table 2 we report the average correlations of the firm shocks for this last case.

Another issue concerns the small sample properties of our estimates: How well can we identify the shocks and how well are our impulse responses and variance decompositions estimated given the limited data we have? The small sample problems of structural VARs that achieve identification through long-run restrictions have been emphasized by Faust and Leeper (1997) and Erceg et al. (2005). To answer these important questions, we generate Monte Carlo simulations using a panel of artificial data²² to test the quality of the VAR estimates of impulse responses and variance decomposition. A discussion of the results would take us too far from the focus of the paper. In short we found that, even if the number of observations in the time dimension is relatively small, the relatively large cross section enables us to recover remarkably well the structural shocks and rather well the average impulse responses and average variance

²² The data-generating process for each firm is an MA.

TABLE 3B.—COMPARISON OF AGGREGATE SHOCKS WITH SHOCKS IDENTIFIED FROM FIRM-LEVEL DATA

	Dependent variable is shock identified from synthetic aggregate data	
	Technology	Transitory
Weighted average of firm technology shocks	2.891 <i>0.752</i>	0.281 <i>0.466</i>
Weighted average of firm composition shocks	-1.023 <i>0.83</i>	0.434 <i>0.515</i>
Weighted average of firm transitory shocks	-0.221 <i>0.372</i>	2.012 <i>0.231</i>
<i>N</i>	30	30

Note: Regressors are averages of firm shocks, weighted by sales. Standard errors are in italics below the regression coefficients. Bold coefficients are significant at the 5% level.

decompositions. In the case of the variance decompositions the confidence intervals are large, but we nevertheless are always able to rank the relative importance of the three shocks.

VII. Interpretation of the Shocks

Thus far, we have restrained from interpreting the different shocks. We now try to make some progress on this issue by regressing the firm shocks on well-known, identified macroshocks: the Romer-Romer monetary shocks, the Hamilton oil price shocks, and fiscal shocks, using cyclically adjusted data from the Congressional Budget Office (CBO), which should capture true changes in fiscal policy, as opposed to automatic feedbacks from shocks to GDP. The macroshocks are common across firms, so we really only have as many observations as number of years. We therefore cluster our residuals by years to obtain robust standard errors.

Table 4 shows the results of firm-level regressions. The table is divided into two panels. In the first column of each panel, we regress the firm shocks on contemporaneous and lagged values of all our macro shocks. We next eliminate the jointly statistically insignificant macroshocks using a joint *F*-test until we stay with only significant regressors. The second column of each panel presents the final specification.

Lagged oil shocks are always very significant: an increase in the oil price 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 find that taxes have positive and negative transitory effects, as expected. We also find that taxes tend to have negative *permanent* effects. That taxes decrease long-run labor productivity can easily be explained if taxes reduce returns on capital, and therefore investment. These results show that permanent productivity shocks need not come from exogenous changes in technology. This seems a natural topic for future research.

We believe that this exercise confirms the validity of our approach. The shocks that theory tells us should not affect

TABLE 4.—EXPLAINING FIRM-LEVEL SHOCKS

	Technology Shock		Transitory Shock	
	(i)	(ii)	(iii)	(iv)
Hamilton oil shock	-0.538		2.033	
	<i>0.442</i>		<i>0.855</i>	
Hamilton (lagged)	-1.628	-1.367	-7.74	-4.973
	<i>0.447</i>	<i>0.607</i>	<i>1.026</i>	<i>1.85</i>
Hamilton (lagged twice)	-1.255	-1.728	-2.541	-5.203
	<i>0.441</i>	<i>0.57</i>	<i>1.616</i>	<i>1.985</i>
Romer-Romer shock	-0.033		-0.016	
	<i>0.03</i>		<i>0.08</i>	
Romer-Romer (lagged)	-0.014		-0.158	-0.242
	<i>0.021</i>		<i>0.068</i>	<i>0.075</i>
Romer-Romer (lagged twice)	-0.036		-0.109	
	<i>0.02</i>		<i>0.051</i>	
Growth rate of public spending, cyclically adjusted	-1.334		1.65	
	<i>0.882</i>		<i>1.95</i>	
Growth rate of public spending (lagged)	-0.026		1.784	
	<i>0.5</i>		<i>2.426</i>	
Growth rate of taxes, cyclically adjusted	-2.265	-1.719	-5.101	-5.526
	<i>0.426</i>	<i>0.698</i>	<i>1.531</i>	<i>1.593</i>
Growth rate of taxes, cyclically adjusted (lagged)	0.951		3.124	
	<i>0.53</i>		<i>1.53</i>	

Notes: All regressions have the observations clustered by years. Government spending and taxes are cyclically adjusted by the Congressional Budget Office. Standard errors are in italics below the regression coefficients. Bold coefficients are significant at the 5% level.

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.

VIII. Conclusion

We have found that permanent productivity shocks and permanent changes in the composition of output explain at least four-fifths of firm-level dynamics. However, these shocks are essentially uncorrelated across firms, and therefore explain little of aggregate fluctuations. 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, taxes seem to have negative long-run effects.

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Appendix A

Long-Run Restrictions with a General Production Function

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

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

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:

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

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 w_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 cost²³

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

where $\chi_i(\cdot, \cdot)$, the firms' marginal cost, is homogenous of degree 1. 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

$$\bar{y} = w\bar{n} + r\bar{k}. \tag{A1}$$

Product market equilibrium is

$$\bar{y} = \bar{c} + \delta\bar{k}. \tag{A2}$$

Given our definition of the price level, we have that

$$\int \left(\frac{\omega_i}{\chi_i(r + \delta, w)} \right)^{\theta-1} di = 1, \tag{A3}$$

and labor market equilibrium implies that

$$\bar{n} = \int n_i = \bar{y} \int \frac{\omega_i^{\theta-1} \chi_i^{-\theta}(r + \delta, w)}{g_i^n \left(\frac{w}{r + \delta} \right)} di. \tag{A4}$$

Finally, a labor supply function guaranteeing balanced growth is

$$\bar{n} = \varphi \left(\frac{w}{\bar{c}} \right). \tag{A5}$$

²³ Of course, in the Cobb-Douglas case where $y_i = z_i k_i^{\alpha_i} n_i^{1-\alpha_i}$, we get the following:

$$p_i = \frac{1}{z_i} \left(\frac{r + \delta}{\alpha_i} \right)^{\alpha_i} \left(\frac{w}{1 - \alpha_i} \right)^{1-\alpha_i},$$

and

$$\zeta_i^{-1} = \frac{1 - \alpha_i}{\alpha_i} \frac{k_i}{n_i}.$$

We have five equations in five aggregate unknowns $(\bar{y}, w, \bar{n}, \bar{k}, \bar{c})$.²⁴

Identifying Restrictions

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

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

$$\lim_{j \rightarrow \infty} \frac{\partial \ln \frac{\bar{y}_{t+j}}{\bar{y}_t}}{\partial \eta_{it}^T} = 0.$$

Permanent shocks 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 change the return on capital such as capital taxes or the depreciation rate. This may be an issue for interpreting the technology shocks in some specifications.

Appendix B

Data Appendix

We construct a synthetic sectorial data set aggregating firm-level data to a sectorial level (corresponding to the Jorgenson two-digit level, which is also the level of disaggregation of our price deflators). Some of the sectors are under-represented.

The firm-level data set appears to be representative of the aggregate economy. We show the growth rate of aggregate nominal output (sales), labor input, and labor productivity obtained from the firm-level data set and compare it with the aggregate series obtained from the Jorgenson and Stiroh (2000) sectorial data set. Aggregate nominal output is the sum of nominal sales in firm and the sum of nominal gross output in Jorgenson and Stiroh (2000). The aggregate labor input and labor productivity from the Jorgenson data set are obtained through a weighted average of the sectors' growth rates, more precisely:

$$\Delta \ln x = \sum_i \bar{w}_i \Delta \ln x_i, \bar{w}_i = \frac{1}{2} \left(\frac{P_{i,t} Q_{i,t}}{P_t Q_t} + \frac{P_{i,t-1} Q_{i,t-1}}{P_{t-1} Q_{t-1}} \right),$$

where \bar{w}_i is the Domar weight and x is the growth rate of the industry variable. The aggregate labor productivity for the firm-level data is the ratio of the sum of sales deflated by an aggregate index deflator obtained

²⁴ We 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.

by applying the above formula, to the sum of employees. We interpret this as evidence that our firm sample is representative of the aggregate economy.

Romer-Romer is the exogenous monetary policy shock calculated by Christina Romer and David Romer (2004). The original series is monthly; to obtain an annual series we sum the shocks in each year.

CBO fiscal variables are cyclically adjusted revenues and spending published by CBO (available from the CBO Web site).

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

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

Appendix C

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}^r of each firm. 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 $\Delta \ln \bar{n}_{it}$ as the series simulated shutting down the productivity and composition shock. The simulated aggregate hours implied by the transitory shocks are

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

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

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

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