Expansionary and Contractionary Technology Improvements*

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Abstract

This paper examines the effects of contractionary (or factor-saving) improvements as opposed to improvements in total factor productivity (TFP). We think of contractionary improvements as process innovations and motivate the difference to TFP improvements in a simple DSGE model. Both shocks increase productivity in the long run, but have different effects on, e.g., labor input. We use these predictions to identify these two shocks in a structural VAR with a combination of long-run zero and short-run sign restrictions. Contractionary shocks account for the largest part of fluctuations in labor productivity, while TFP shocks have a stronger impact on output fluctuations. We further interpret our empirical results in terms of a small-scale RBC model with managerial capital.

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1 Introduction

What drives business cycles? Although disagreeing about their exact contribution, a large body of literature assigns a substantial role to technology-induced changes in productivity in explaining economic fluctuations.[1] Despite their commonly acknowledged importance, there is considerable discord about their effects on key economic variables, at least in the short run. Specifically, there has been a recent fervid dispute around the issue whether technological improvements are contractionary or expansionary. Contradicting the results of the early real business cycle literature, Galí (1999) has argued on the basis of U.S. time series that after a positive improvement in aggregate technology, output changes little, while labor falls in the short run. Similarly, Basu et al. (2006) has answered the question 'Are technology shocks contractionary?' positively. In this paper, we argue that there is no clear answer on this matter. Rather, we turn the question around and ask 'Which technology improvements are contractionary?' Specifically, we explicitly allow for the joint existence of two different technology shocks, affecting short-run labor input either positively (conventional TFP shocks) or negatively (contractionary technology shocks). Based on a minimum set of identifying restrictions, we show empirically that both shocks are important drivers of the business cycle variance of key macroeconomic variables. In addition, these shocks trigger different reactions of certain variables, which can help explain why existing evidence on technology shocks does not deliver clear results. In a small theoretical model, which is consistent with our identifying restrictions, we argue that the contractionary technology shocks are different from existing technology or non-technology shocks in the literature. We also provide an economic interpretation, based on anecdotal evidence about the effects of rationalization.

We present time-series evidence for expansionary and contractionary technology shocks that is estimated from a structural VAR with a combination of long-run zero and short-run sign restrictions. In the spirit of Galí (1999), technology shocks are the only shocks that drive up labor productivity in the long run. The restriction that technology shocks are the only shocks that affect labor productivity in the long-run holds in a large class of models, encompassing real-business cycle models as well as New Keynesian models. We then proceed by separating conventional and contractionary technology shocks through their short-run effect on labor input. In the empirical part, we are agnostic about the interpretation of these shocks. More precisely, we first document the business cycle properties of shocks that induce either a positive or a negative correlation between labor productivity and labor input and then interpret these shocks based on their properties.

We find a sufficient number of responses that satisfy our identifying restrictions and induce significant and significantly different responses on hours worked. Conventional technology shocks trigger the dynamics familiar in a real-business-cycle context: an increase in hours, output, investment and consumption. Contractionary technology shocks lead to a fall in hours worked, output and investment. Conventional TFP shocks account for the largest part of fluctuations in output, while contractionary technology shocks drive labor productivity and the short-run dynamics of hours to a large extend.

In order to account for the difference between standard and contractionary shocks, we develop a simple dynamic general equilibrium model. In standard models, shocks to technology enhance productivity of inputs employed by raising the average and marginal product of labor and capital. As an optimal reaction, firms wish to employ more labor and capital. As Galí (1999) pointed out, nominal rigidities can limit the firm's ability to increase sales, such that factor inputs can fall in the short run.[2]

[1] The early RBC literature argued for contributions of technology shocks to fluctuations in aggregate output as high as 70, see Kydland and Prescott (1991). More recent studies, such as Altig et al. (2005) and Chari et al. (2008), found lower values, but typically not below one quarter.

[2] This observation was the starting point of the debate around the so called 'hours puzzle'. Since a negative response of hours worked to a positive technology shock runs contrary to the dynamics of a conventional shock to total factor produc-

In the long run, however, optimal factor input will be unambiguously higher, which is not in line with our empirical results for contractionary technology shocks.

Contrary to this demand-driven temporary reduction in factor input, we have a different technology shock in mind; one which is quite distinct in nature and reduces the optimal factor input despite the firm's ability to freely set prices. This corresponds in broad terms to what is commonly understood as 'rationalization'. There is a lot of anecdotal evidence of firms or whole sectors enhancing efficiency by redesigning their business processes and cutting costs.[3] Productivity is typically increased by these operations. It is not the case, however, that production is expanded given the existing resources. Instead of producing more with the same input factors, these improvements in organization and processes rather focus on producing at most the same amount with less inputs, i.e. at lower costs. In terms of economic language, the average product of labor and capital increases while their marginal product *decreases*, which implies that the marginal unit of capital or the marginal hour is made redundant. The workload previously done by this marginal worker can be reallocated to the remaining ones, due to their increased efficiency. The same is valid for capital goods. As a reaction, either these marginal workers are then dismissed, or average hours worked are reduced. Innovations to business organization and processes shift and rotate the labor and capital demand curves simultaneously. In our view, traditional TFP shocks are better suited to capture innovations to technologies, such as computers, which enhance general productivity and therefore shift the labor and capital demand curves upwards. In standard models of the business cycle, 'cutting costs' is not a well-defined exercise. Average labor costs correspond to the labor share, which is held constant. Average total costs as a share of output are typically equal to one. In the model of this paper, average costs vary after factor-saving shocks.

In order to model the process of rationalization, we introduce the concepts of managerial capacity and factor-saving technology in our model. Relative to a textbook-style RBC model, only the production function is changed. Managerial capacity acts as a new input factor to production, enhancing productivity of all employed factors, similar to TFP. Factor-saving technology, on the other hand, describes to which degree the input factors can be saved by making use of managerial capacity. Hence, an increase in factor-saving technology corresponds to an increase in the relative importance of managerial capacity. The theoretical model implies different reactions of macroeconomic aggregates to shocks to TFP on the one side and shocks to factor-saving technology (contractionary technology shocks) on the other. Most prominently, while both shocks increase labor productivity in the long run, the reaction of factor employment is opposite after these two shocks.

The remainder of this paper is organized as follows. Section 2 explains the empirical identification strategy and documents business cycle dynamics of expansionary and contractionary technology shocks. Section 3 describes the theoretical model with a focus on our concept of contractionary technology shocks. Section 4 discusses an interesting extension on the extensive margin on labor input. Section 5 concludes.

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tivity in a real-business-cycle model, Galí's empirical observation has been taken as evidence in favor of New Keynesian frameworks in order to explain the aggregate dynamics in the data. Later studies that either support or challenge this result include Francis and Ramey (2005a), Francis and Ramey (2005b), and Canova et al. (2008).

[3] Many consultant firms base their success on guiding firms in doing so. McKinsey describes its activities in a case study on its homepage as "The strategy required that the company focus on core products, operate at 20 to 40 percent lower cost than competitors, and eliminate businesses that were inconsistent with the new direction." Another case study gives a similar description of its strategy: "...our team scrutinized the company's operations and identified multiple cost-reduction opportunities, which would involve consolidating plants..." Common to these examples is the focus on cutting costs, with a possible reduction of activity.

2 Time-Series Evidence

2.1 Identification and Specification

The evidence we provide on conventional and factor-saving technology shocks is based on structural VARs with a combination of long-run zero and short-run sign restrictions. Generally, identification involves finding a mapping A of the residuals from a reduced form VAR into structural residuals such that these can be interpreted as structural shocks in (a class of) models. More precisely, the relationship between the structural and reduced form residuals is $e_t = Av_t$ which induces that $A\Sigma_e A' = \Omega$, reduced form variance-covariance matrix.

In order to pin down A uniquely, we assume that the structural shocks are orthogonal and normalize their variance to one, $\Sigma_e = I$, and we impose our identifying restrictions:

1. Technology shocks are allowed to affect labor productivity in the long-run.
    a. Out of these, conventional technology shocks affect hours positively in the short-run.
    b. Out of these, contractionary technology shocks affect hours negatively in the short-run.
2. All other shocks do not affect labor productivity in the long-run.

Note that restrictions 1. versus 2. corresponds to the identification of technology and non-technology shocks as in Galí (1999). Note that Galí identifies two (groups of) shocks, while we seek to identify three (groups of) shocks, two with a long-run effect on labor productivity and one with no long-run effect on labor productivity. We separate the two technology shocks by an additional restriction on the sign of their short-run effect on employment, here total hours worked. This means that we need to add at least a third variable to Galí's minimal bivariate VAR. That is, we use the additional degree of freedom of the extra variable to impose an additional short-run sign restriction on top of the the zero long-run restrictions. Note that this also means that we can not exactly nest the Galí shocks in our framework, but that the sum of the two types of technology shocks should a good approximation of the originally identified Galí shocks.

The restriction that technology shocks are the only shocks that affect labor productivity in the long-run holds in a large class of models and the resulting technology shocks are often interpreted as encompassing any effect that shows up as total factor productivity. There exists some doubt about the interpretation of these shocks as aggregate neutral technology shocks. Examples include demand shifts between sectors, identified as investment-specific technology shocks by Fisher (2006), or demand shifts in favor of more productive inputs such as skilled labor, identified as skill-biased technological change in Balleer and van Rens (2009). Further, preference shocks or, more generally, labor supply shocks that are permanent or at least very persistent can affect long-run labor productivity as well. Even though we label the estimated shocks technology shocks in the identification, following Galí's convention, we are agnostic about their interpretation at this point.

In order to implement out identifying restrictions, consider a VAR in which labor productivity and labor input are ordered first. Our long-run restrictions imply that $l_{13} = l_{14} = ... = l_{1n} = 0$ and $l_{23} = l_{24} = ... = l_{2n} = 0$ in the matrix of long-run effects $L \equiv \sum_{i=0}^{\infty} \Phi_i A_i$, with Φ_i being impulse-response coefficients. This is for example satisfied in a decomposition of the long-run forecast revision variance such that

$$LL' = \Sigma^{\infty} = (\sum_{i=0}^{\infty} \Phi_i)\Omega(\sum_{i=0}^{\infty} \Phi_i)'.$$

We use this to determine the non-technology shocks and to derive an upper left 2-by-2 short run variance matrix that is consistent with these long-run restrictions. Next, we implement the sign restrictions

in a similar fashion as in Peersman (2005). This involves a rotation of the upper left 2-by-2 short-run variance using an orthonormal matrix Q (i.e. $QQ' = I$):

$$Q = \left[\begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix} \right].$$

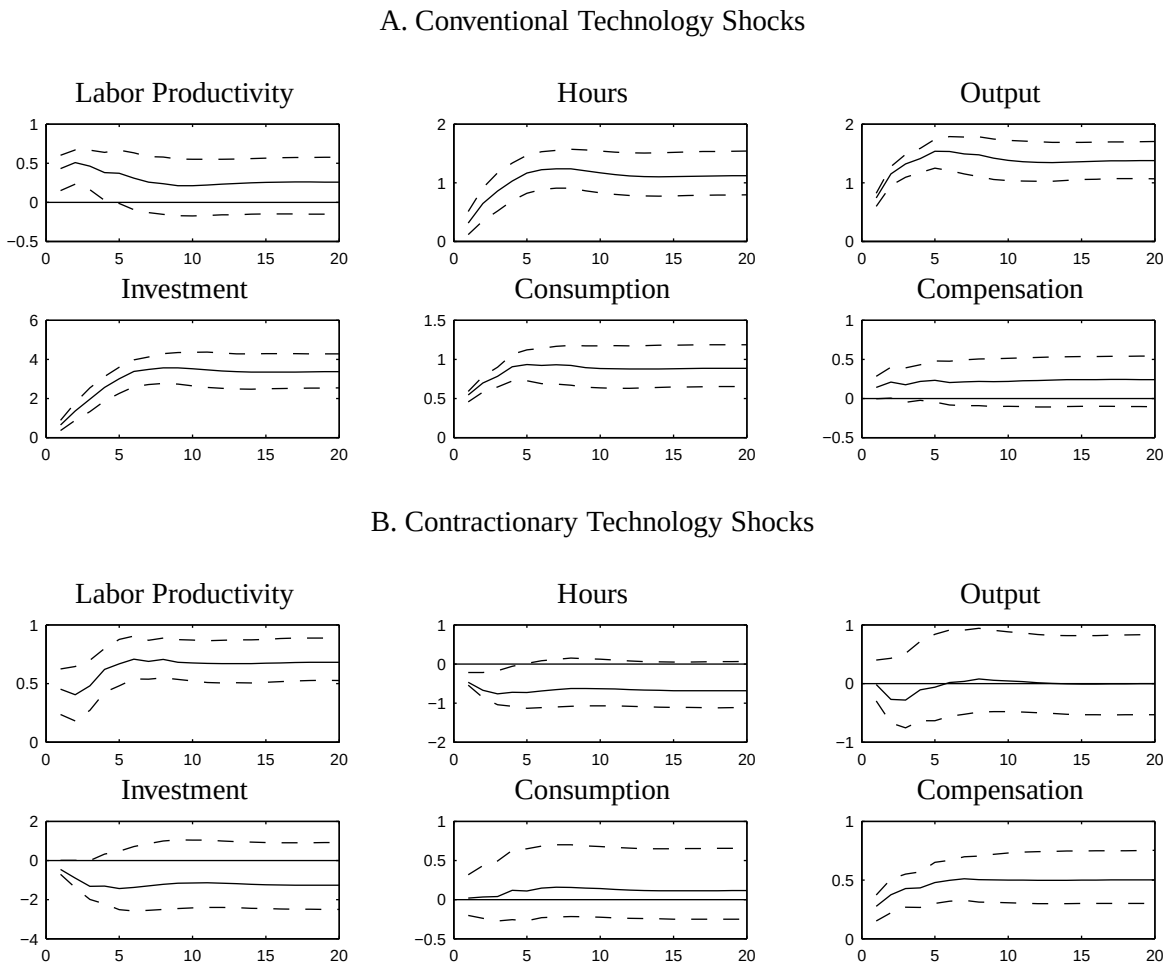
As in Peersman (and similar to Uhlig (2005)), our VAR is estimated in a Bayesian framework. For each draw of the posterior distribution of the reduced form VAR coefficients, we calculate the long-run forecast revision variance. We then randomly draw θ from a uniform distribution $[0, \pi]$, use Q to calculate the upper left elements of the matrix L and check whether our sign restrictions are satisfied. In the application, we draw 100 candidates from the posterior distribution of the reduced form coefficients and another 100 values of θ for the rotation. We compute the impulse responses for all draws that satisfy the sign restriction and report the 16th and 84th percentile from the resulting distribution as confidence intervals. The point estimate that we report is based on the OLS estimate of the VAR coefficients which are then rotated and checked to satisfy the sign restrictions.In the application, the evidence is based on about 4000 draws that satisfy the sign restrictions.
We estimate the reduced form VAR with a flat prior for which the median corresponds to the OLS estimate. Further, we incorporate 4 lags of variables into the VAR as is usually done with quarterly data. We use quarterly U.S. time series data ranging from 1947:1 to 2004:4. Labor productivity, total hours worked as well as real hourly compensation are the nonfarm business measures from the BLS. We then deduct the dynamics of output from the productivity and hours dynamics. Fixed nonresidential investment and personal consumption expenditures are taken from the NIPA data provided by the BEA. Last, we include the relative price of investment as an additional control in our VAR. Here, we use the quarterly series generated by Fisher (2006) that is based on the measure of Cummins and Violante (2002) and that takes these flaws into account.[4] All series are seasonally adjusted. For all of the series included in our baseline VAR, we cannot reject the existence of a unit root in a standard ADF test. This is why we include all variables in first differences in our VAR. We can further statistically reject cointegration between these variables, specifically between consumption, investment and output as well as compensation and productivity.

2.2 Evidence

Figure 1 shows estimated impulse-responses to the identified conventional and contractionary technology shocks. The responses of labor productivity and hours worked to both shocks exhibit the identifying assumptions. After a conventional technology shock hours worked, output, investment, consumption all go up significantly. Labor productivity and compensation are positive, but insignificant, in the long-run. The responses after a contractionary shock are very different. Here, output and investment fall, while consumption goes up. These responses are not significant, however. Note that wages increase significantly. Further, effect of this shock on labor productivity is very strong. Note that adding the responses of these two orthogonal shocks delivers almost identical results to the technology shocks identified with the original Galí identification[5].
How important are these shocks over the cycle? Table 1 exhibits the variance decomposition of the variables in the VAR to the two identified shocks. Both shocks explain a large amount of the business cycle fluctuations in productivity and hours. The contractionary technology shock explains 46% of the impact response of hours worked, while the conventional technology shock is more important in

[4]The series by Jonas Fisher was extended by Ricardo DiCecio. We thank both for making their data available.
[5]See Figure A-1 in the Appendix

Figure 1: Impulse-responses to conventional and contractionary technology shocks



Notes: Quarterly responses in percent to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

the medium run. As already indicated by the impulse-responses, the contractionary shock explains the biggest part of labor productivity. The conventional technology shock explains the largest part of investment, consumption and output fluctuations. The contractionary shock drives about 30% of the business cycle variation in wages.

To summarize, what has been identified and interpreted as technology shocks in the existing literature can be described as an amalgum of two, orthogonal components with quite distinct business cycle properties. Most of the business cycle variation of the key macroeconomic variables is driven by shocks that induce a positive correlation between labor input and productivity. The responses to these shocks are reminiscent of the dynamics generated by technology shocks in a standard real-business-cycle model. In addition, most of the variation in labor productivity, i.e. the variable used for the identification of these shocks, is driven by shocks which induce a negative correlation between productivity and labor input. The shocks are much less important for the business cycle variation of the key macroeconomic variables.

How can we understand the responses to these contractionary shocks? In section 3, we develop a model with contractionary technology shocks which generates the estimated dynamics. To preview, we argue that our estimated shocks can not be interpreted as technology shocks under nominal rigidities, since investment would fall in this scenario. Further, the estimated shocks can also not be interpreted as permanent shocks to preferences, since output and consumption fall.
The results have been checked for robustness along a number of dimensions. In section 4, we extend our analysis to the extensive margin of labor input by considering the effects on job finding and separation rates as well as unemployment. Appendix A further documents robustness with respect to the specification such as omitted variables, structural breaks, etc.

Table 1: Variance Decomposition for conventional and contractionary shocks

Variable	Horizon				Horizon			
	1	8	16	32	1	8	16	32
	Contractionary shock				Conventional shock			
Productivity	39.26	67.77	76.99	81.08	27.25	22.02	17.50	16.12
	(10.5,66.2)	(30.3,85.9)	(40.4,90.8)	(44.5,94.3)	(3.1,57.8)	(4.7,59.9)	(4.2,54.4)	(3.0,52.8)
Hours	46.87	19.75	18.53	19.03	33.91	72.87	77.80	79.24
	(12.2,77.0)	(3.3,59.5)	(2.9,60.1)	(2.2,61.1)	(4.2,70.2)	(33.3,90.2)	(36.6,93.7)	(36.9,96.1)
Investment	5.59	9.95	10.88	11.27	12.63	55.47	64.05	66.99
	(0.5,18.5)	(1.6,34.2)	(1.8,36.3)	(1.4,38.4)	(3.1,27.9)	(31.1,70.4)	(39.6,78.0)	(42.1,80.9)
Consumption	8.91	10.99	11.80	12.02	69.44	75.58	73.14	72.53
	(0.9,27.8)	(1.6,37.4)	(1.6,38.5)	(1.4,39.4)	(51.1,83.4)	(49.5,86.6)	(47.3,85.6)	(46.3,85.5)
Compensation	19.27	30.99	30.88	31.20	4.88	7.24	7.81	8.31
	(5.8,35.3)	(12.6,47.7)	(12.6,49.2)	(11.8,49.6)	(0.4,18.5)	(0.9,25.7)	(1.0,28.1)	(0.9,29.9)
Output	6.70	11.37	11.98	12.20	51.19	78.55	82.77	85.12
	(0.6,20.8)	(2.3,30.9)	(2.2,34.2)	(1.8,35.8)	(36.2,66.2)	(59.9,88.9)	(60.9,92.8)	(61.6,95.5)

Notes: The values for the displayed shocks and the (omitted) residual disturbances add up to 100 for each variable at each time horizon. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. All numbers are percent.

3 Model

In order to interpret our empirical findings, we use a textbook-type small RBC model, with a modification of the production function. The closed economy is inhabited by a representative household and a representative firm. The household consumes, works, and accumulates capital, which it rents to the firm. The firm uses a production technology with the input factors capital, labor, and managerial know-how to produce a final good, which can be used for consumption or investment.

Firms The only innovation of the model lies in the production function. Additional to the standard input factors capital and labor, we assume that managerial know-how is needed for the organization of input factors. The task of this management is to design operational schedules and to structure business processes, thereby avoiding idle resources, overlapping responsibilities and similar inefficiencies. It is modeled as a stock of knowledge M in the production function, similar to TFP. As the latter, we treat

this knowledge as exogenous. A better organization allows the firm to make better use of the existing input factors. We also assume that this management layer has to grow with the other input factors in order to maintain constant returns to scale. Put differently, if capital and labor are doubled without increasing managerial capacities, inefficiencies arise necessarily.[6]

$$Y_t = M_t^{\eta_t} \left[K_t^{\alpha} (A_t L_t)^{1-\alpha} \right]^{1-\eta_t} . \tag{1}$$

Importantly, the weight of management capability relative to the other input factors η_t is not fixed. The variable η_t hence represents labor- and capital-saving technology. This is where restructuring takes place. By redesigning business structures, i.e. raising η_t, the firm can reduce inefficiencies and produce the same output with less inputs. The first-order conditions of the firm are thus

$$W_t = (1-\alpha)(1-\eta_t)\frac{Y_t}{L_t}, \tag{2}$$

$$r_t = \alpha(1-\eta_t)\frac{Y_t}{K_t} - \delta, \tag{3}$$

with r_t being the real interest rate and δ the depreciation rate. The firm takes both factor prices as given. Figure 2 visualizes these first-order conditions. On the axis are (log) factor input and the (log) factor price. A standard TFP shock pushes Y_t upwards, thereby increasing factor demand on all levels. A factor-saving shock potentially also increases Y_t, but rotates the demand curve. If the impact on Y_t is not too large, optimal factor input is actually reduced.

Households The representative household maximizes lifetime utility

$$E_t \sum_{\tau=t}^{\infty} \beta^{\tau} \frac{C_t^{1-\sigma}}{1-\sigma} - b\frac{L_t^{1+\Psi}}{1+\Psi},$$

where C_t and L_t are consumption and labor, respectively. In doing so, it has to obey a series of period budget constraints

$$C_t + K_{t+1} = (1+r_t)K_t + W_t L_t + \Pi_t,$$

with Π_t representing potential profits of the firms, which are owned by the household. The resulting first-order conditions are the familiar Euler equation

$$C_t^{-\sigma} = \beta E_t (1+r_{t+1}) C_{t+1}^{-\sigma}, \tag{4}$$

and a labor-leisure trade off

$$C_t^{-\sigma} W_t = b L_t^{\Psi}. \tag{5}$$

Equilibrium In equilibrium, all markets clear. Hence, labor supply, defined in (5), equals labor demand in (2) and the goods market clears

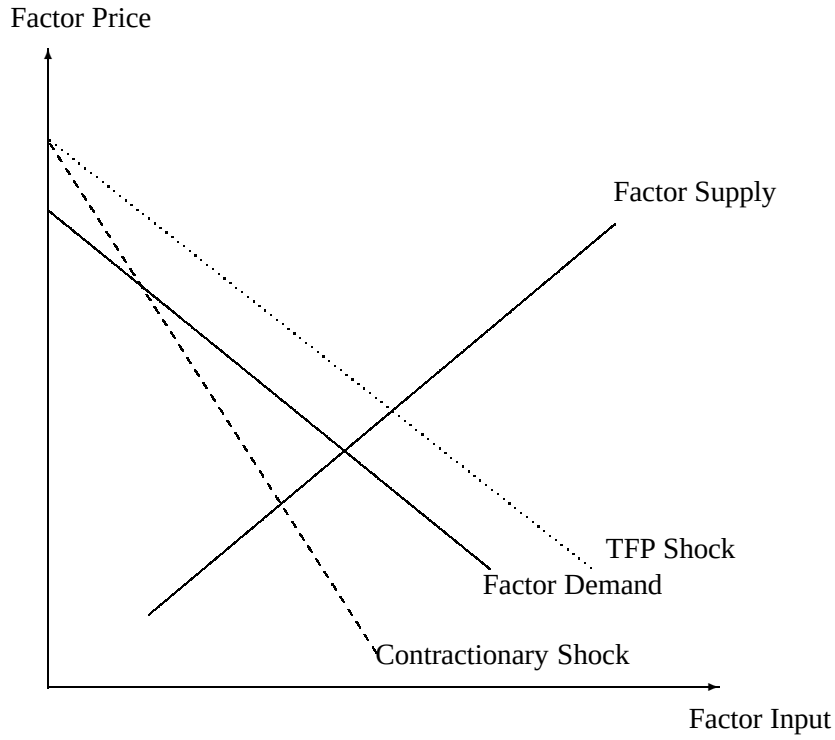
$$Y_t = C_t + K_{t+1} - (1-\delta)K_t. \tag{6}$$

Furthermore, average costs are

$$AC_t = (W_t L_t + r_t K_t)/Y_t = 1 - \eta_t.$$

[6] Also in the textbook example of building an existing factory again to reach constant returns to scale, management has to be reproduced as well.

Figure 2: Factor demand before and after a standard and a contractionary technology shock.



Hence, increasing η_t means cutting costs. Note the difference to standard models, in which an operation like 'cutting costs' is not well defined. Average labor costs in these models typically correspond to the fixed labor share α, while total costs equal output. Profits are thus always zero. In the present model, profits are

$$\Pi_t = Y_t - W_t L_t - r_t K_t = Y_t \eta_t.$$

As visible, restructuring business by increasing efficiency, i.e. raising η_t, is a fruitful enterprize for consultancies. We leave the question of when this is possible and which factors trigger such an adjustment to future research.[7] We focus on the effects of a changing η by assuming that the input-saving technology evolves in logs exogenously according to a simple AR(1) process

$$\eta_{t+1} = \eta_t^{\rho_\eta} \varepsilon_t,$$

with ε_t being a i.i.d. shock with mean one. Also standard TFP technology in logs follows an AR(1) process

$$A_{t+1} = A_t^{\rho_A} \nu_t,$$

3.1 Calibration

We use a standard calibration of the model. The baseline parameters used for the simulation of the model are summarized in table 2. We use a value of 1 for σ to ensure balanced growth. The Frisch

[7] For example, lacking demand might be responsible for a large part of restructuring activities.

Table 2: Baseline calibration of the model

Parameter		Value	Calibration Target	
Coefficient of rel. risk aversion	σ	1	Balanced growth	
Labor supply coefficient	Ψ	1/2	Frisch Elasticity	1/2
Parameter in UF	b	0.019	Labor supply in SS	1/3
Discount factor	β	0.99	SS interest rate	4%
Parameter in PF	α	1/3	Capital share	0.32
Factor saving technology SS	$\bar{\eta}$	.05	SS profits	5%
Autocorrelation of η	ρ_η	.99	Near unit root	
Autocorrelation of A	ρ_A	.99	Near unit root	
Managerial technology SS	$\bar{M}$	e	ΔY *cet. par.*	$\Delta\eta$

elasticity of labor supply was estimated between 1/3 and 1/2 by Domeij and Flodén (2006). We use $\Psi = 1/2$. Additionally, we present results of the case of $\Psi = 1$. Note that these parameters do not have a strong impact on the investigated equilibrium dynamics. The discount factor implies an annual interest rate of four per cent. We set $\alpha = 1/3$. Because of the presence of a third input factor, this implies a capital share of 0.32 for the following value for $\bar{\eta}$, which is set such that the steady-state share of profits equals the observed value from 1970-2008 in the U.S. Its autocorrelation is set to 0.99, since we are interested in the long-run effects of a change in η. Regarding the managerial technology M, there is no clear calibration target to choose. We try to be transparent about the transmission mechanism by setting it to $e\bar{Y}$. By this, the production function (1) in logs changes to $y_t = \alpha k_t + (1-\alpha)(a_t l_t) + \eta_t/(1-\eta)$ with lower-case letters representing logs.

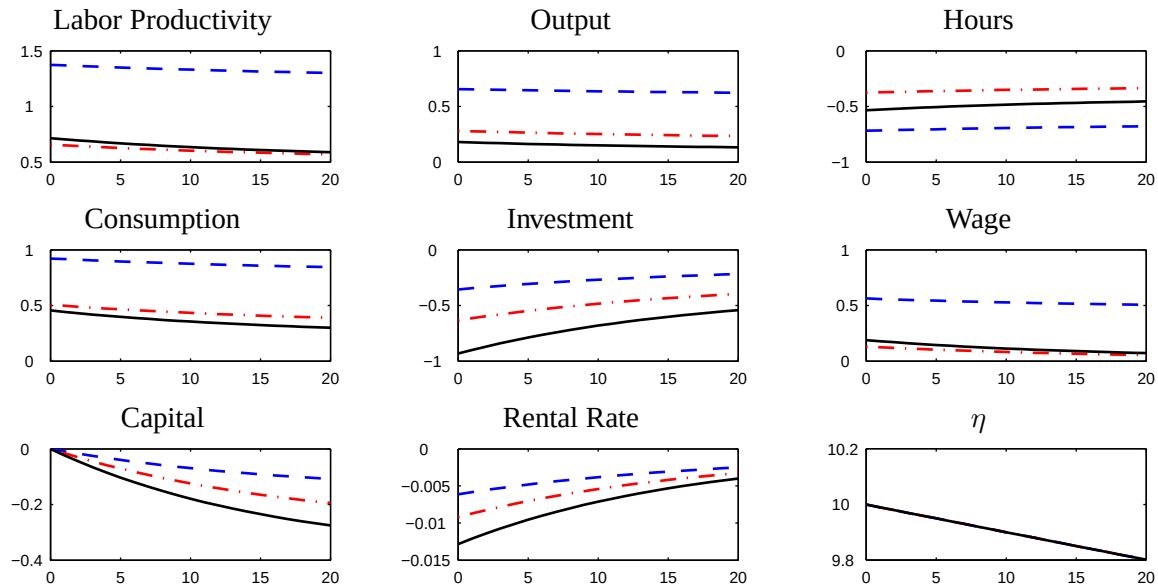
3.2 Impulse-Response Functions to Shocks to Factor-saving technology

Figure 3 shows the responses of several variables to a unanticipated, one-time shock of $\varepsilon_1 = 10\%$, i.e. η jumps from 0.05 to 0.055.The black lines represent the baseline calibration. As visible, labor and investment fall after such a shock, since they can be substituted by re-organizing production. While the rental rate falls, however, the wage increases. This due to the pre-determines of capital. Its marginal product cannot adjust as quickly as the one of labor. According to equation (3), a fixed capital stock with a hardly changing output reduces the rental rate after an increase in η. A falling rental rate leads to rising consumption, see equation (4). On the other hand, labor adjusts quickly, with hours falling sharply. The raises the marginal product of labor, such that we can observe an increase in the wage, see equation (2). Output reacts very mildly, since more can be produced with an higher importance of managerial capacity, but input factors fall at the same time. Importantly, labor productivity rises. Profits (not plotted) rise. However, with a longer-lasting restructuring process, i.e. a slowly increasing η, they fall on impact. The red dashed dotted lines show the impulse-responses for the case of $\Psi = 1$. While some responses are weaker, especially those of investment and the hours, there is no qualitatively difference.

3.3 Impulse-Response Functions to Shocks to Total-Factor Productivity

In order to compare the effects of factor-saving technology shock to standard TFP shocks $\nu_t = 1\%$, figure 4 plots the responses of the same variables as in figure 3 after an unanticipated 1% shock to A_t

Figure 3: Impulse-responses to a contractionary technology shock



Notes: Horizontal axis denotes quarters, vertical axis shows log deviations from steady state. Black solid lines: baseline calibration. Red dashed-dotted lines: $\Psi = 1$. Blue dashed lines: Labor-saving shock.

in period 1. We assume an AR(1) process for TFP with an autocorrelation coefficient of 0.99 as well. The most prominent difference between the two shocks is the reaction of hours worked. While the factor-saving shock reduces employment, a positive TFP innovation triggers a surge. Consumption increases after both shocks due to the increased efficiency. Output clearly rises after TFP shocks, while it does not react very much after factor saving shocks. The impulse-response functions are qualitatively the same under the alternative calibration of $\Psi = 1$, represented by the red dashed-dotted lines. Based on the above insights, we develop an empirical identification strategy in section 2.

3.4 Robustness

3.4.1 Labor-saving shocks

The model so far assumes that contractionary technology shocks reduce the marginal product of labor *and* capital, while increasing their average products. An alternative are labor-saving technology shocks. These can obtained by changing the production function (1) to

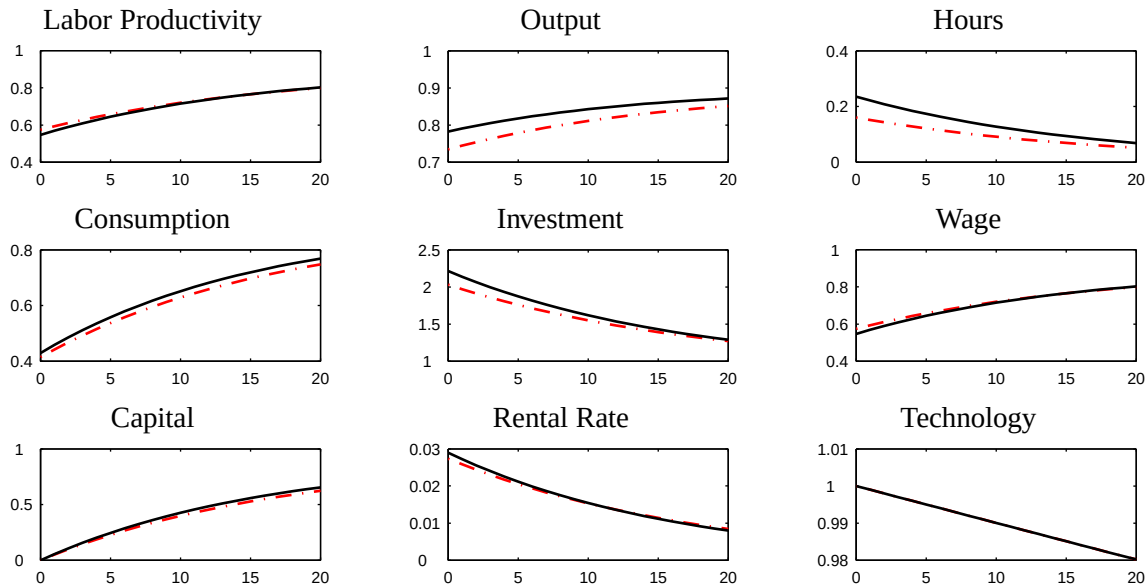
$$Y_t = K_t^{\alpha} \left[M_t^{\eta_t} (A_t L_t)^{1-\eta_t} \right]^{1-\alpha}. \tag{7}$$

While the first-order condition for labor (2) is unchanged, the corresponding equation determining capital demand (3) is the same as in a standard model.

$$W_t = (1-\alpha)(1-\eta_t)\frac{Y_t}{L_t}, \tag{8}$$

$$r_t = \alpha \frac{Y_t}{K_t} + \delta. \tag{9}$$

Figure 4: Impulse-responses to a TFP shock



Notes: Horizontal axis denotes quarters, vertical axis shows log deviations from steady state. Black solid lines: baseline calibration. Red dashed-dotted lines: $\Psi = 1$.

The blue dashed lines in figures 3 and 4 show the responses to $\varepsilon_1 = 10\%$ and $\nu_1 = 1\%$. As can be seen, the responses are qualitatively the same as under the more general factor-saving specification.

3.4.2 Comparison with other shocks

The above newly introduced contractionary technology shocks increase labor productivity in the long run and lower hours worked in the short run. However, possible shocks which which induce the same dynamics are technology shocks under sticky prices and preference shocks. As shown in the appendix, long-run labor productivity depends only on $\alpha, \sigma, \Psi, \beta, \delta, b, M, A$, and η. Permanent TFP shocks move A in the long run (which has the same effect as permanently shocking M), permanent contractionary technology shocks affect η, while permanent preference shocks can be interpreted as a change in b. All three shocks lower hours worked in the short run, as will be shown below. In the following, we show that our estimated shocks can really be interpreted as documented in the model, by looking at the predictions of these shocks to other macroeconomic variables. We thereby argue that the contractionary technology shocks dominate the dynamics of our empirically identified shocks.

Technology shocks under nominal rigidities Galí (1999) identifies technology shocks via an long-run restriction on labor productivity and shows that hours worked fall in response to the identified shocks. He interprets these results in favor of a New Keynesian model. In order to simulate the effects of technology shocks under nominal rigidities, we introduce monopolistic competition and sticky prices in our model. In doing so, we follow Galí (2008) but keep capital in the model. Specifically we assume that each period 75% of firms cannot reset their prices. In order to close the model, we assume a standard Taylor rule of the type

$$\hat{i}_t = \phi_\pi \pi_t + \phi_y \hat{y}_t,$$

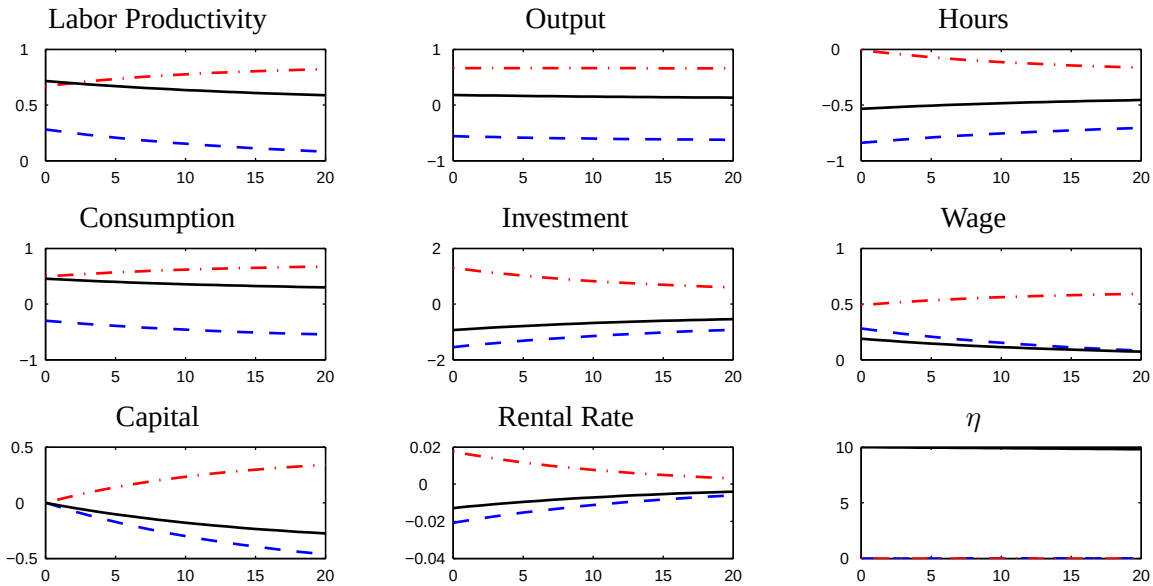
with π denoting inflation and i the nominal interest rate. Hats represent log deviations from steady state. We use standard values for parameterizing the monetary policy rule, $\phi_\pi = 1.5$ and $phi_y = 0.5$. The reaction of the variables of interest to a 1 % shock to TFP is plotted in figure 5 with red dashed dotted lines. Focusing on the differences to the reactions to a contractionary technology shock, depicted by black solid lines, output increases much more and hours react little. Most importantly, investment falls, while the rental rate rises. This is not the case for our identified contractionary technology shocks.

Preference shocks In order to include preference shocks into the model, we change equation (5) to

$$C_t^{-\sigma} W_t = e^{\upsilon_t} b L_t^{\Psi},$$

such that a preference shock υ reduces labor supply. We assume that υ follows an AR(1) process with an autocorrelation coefficient of 0.99, since we are interested in the long-run effects of (almost) permanent shocks. The response of the usual variables to a 1% innovation to υ_1 is shown in figure 5 by blue dashed line. Comparing again to responses to a contractionary technology shock, we see that output and consumption fall. This is in contrast to our empirical findings for the contractionary technology shock. Figure A-2 in the Appendix further documents the empirical results when imposing additional short-run sign restrictions on output and investment on the estimated contractionary technology shocks.

Figure 5: Impulse-responses to different shocks



Notes: Horizontal axis denotes quarters, vertical axis shows log deviations from steady state. Black lines: contractionary technology shock. Red dashed-dotted lines: standard TFP shock under sticky prices. Blue dashed lines: preference shock.

4 The extensive margin of labor market adjustment

Our baseline specification restricts total hours worked to react positively or negatively to technology shocks in the short run. Since the dynamics of total hours worked consists of the adjustment of hours per worker and employment, it is interesting to differentiate between these two margins of labor input. As motivated in our model, contractionary shocks decrease the marginal product of labor and thus make the marginal hour worked redundant. In terms of the extensive margin, contractionary shocks make the marginal worker redundant. It is therefore straightforward to impose the identifying short-run restriction on employment, i.e. we identify conventional shocks by a fall in the separation rate and contractionary shocks by an increase in the job separation rate. This specification is in some sense closer to the original idea in Galí (1999), as we do not impose any restrictions on hours worked directly and use a third variable for identification. The data series that we add to the baseline specification are the job separation and finding rates are taken from Robert Shimer.[8] The unemployment rate can then be approximated by the dynamics of the finding and separation rate via the steady state unemployment rate $\tilde{u} = \frac{js}{js+jf}$.

Figure 6 shows impulse-responses to the identified conventional and contractionary technology shocks. After a conventional technology shock, the job finding rate increases and unemployment falls. Hours worked increase, but not as strong and significant as before. Note that labor productivity and compensation now respond stronger and significant to a conventional technology shock, while investment increases less strongly. After a contractionary shock, hours worked now fall much stronger than in the baseline specification. The job finding rate falls, while unemployment increases. Output and investment fall, while consumption goes up. These responses are not significant, however. Wages increase significantly. Table 3 exhibits the variance decomposition of the variables in the VAR to the two identified shocks. Both shocks explain a large amount of the business cycle fluctuations in productivity and separation. The contractionary technology shock explains 20% of the impact response of hours worked. In turn, the conventional technology shock plays a more prominent role for the fluctuations in the job separation rate, while both shocks are equally important for the job finding rate and unemployment. The conventional technology shock explains over 20% of the business cycle variance in consumption and output.

In order to interpret these responses, consider an extension of the model presented in section 3 that features search-and-matching on the labor market like in Mortensen and Pissarides (1994). Generally, extending a real-business-cycle framework to model employment and unemployment dynamics in this way does not qualitatively change the impulse-responses of aggregate macroeconomic variables to technology shocks. The model we have in mind features both a job creation as well as an endogenous job destruction margin in order to replicate our empirical findings on the job finding and separation rate (as in den Haan et al. (2000)). In this study, job or match-specific productivity shocks induce a productivity distribution such that aggregate productivity shocks change the efficient cutoff for job destruction and therefore induce business cycle fluctuations of the separation rate. Hence, a technology shock in this model drives the separation rate down, the job finding rate up and unemployment down as a consequence, exactly as in our estimated responses. A contractionary technology shock increases the average productivity of all jobs (matches), decreases the productivity of the marginal job and therefore increases the separation rate.

5 Conclusion

[8] This is the worker flow data officially posted on the website of Robert Shimer and documented in Shimer (2007). For additional details, see http://home.uchicago.edu/∼shimer/data/flows.

Table 3: Variance Decomposition with the Extensive Labor Margin

Variable	Horizon				Horizon			
	1	8	16	32	1	8	16	32
	Contractionary shock				Conventional shock			
Productivity	22.20	37.47	46.84	50.80	35.59	45.67	44.28	44.85
	(2.7,47.3)	(8.1,68.3)	(10.9,79.4)	(11.9,85.1)	(12.0,59.6)	(14.1,75.3)	(11.6,80.1)	(10.5,83.8)
Separation	26.44	23.29	21.48	20.41	48.74	56.98	65.17	72.05
	(3.1,58.4)	(4.9,54.8)	(4.2,57.1)	(3.2,59.4)	(16.6,74.7)	(25.2,77.7)	(29.6,84.0)	(32.8,89.8)
Finding	6.42	11.80	10.64	10.67	1.86	13.50	13.71	13.70
	(0.8,15.2)	(2.6,27.6)	(2.2,26.8)	(1.9,27.5)	(0.1,6.5)	(3.0,29.8)	(2.7,31.4)	(2.3,31.8)
Hours	20.00	18.73	16.12	15.50	3.66	7.83	7.40	6.94
	(7.5,38.3)	(6.3,36.3)	(4.4,33.6)	(3.7,33.1)	(0.3,13.5)	(1.5,23.1)	(1.4,23.3)	(1.2,23.5)
Consumption	3.38	4.76	5.10	5.06	24.60	29.63	26.77	25.81
	(0.3,13.3)	(0.9,16.6)	(0.9,19.0)	(0.7,20.1)	(11.4,41.8)	(14.3,49.3)	(10.8,46.9)	(9.1,46.2)
Investment	1.61	6.59	6.09	6.15	2.07	7.79	8.68	8.31
	(0.1,7.0)	(1.3,19.9)	(1.3,19.4)	(1.0,19.8)	(0.2,8.0)	(1.3,21.8)	(1.3,24.5)	(1.0,24.7)
Compensation	9.74	20.29	22.44	23.18	14.91	18.19	17.83	17.36
	(1.2,26.2)	(4.6,40.5)	(5.0,42.3)	(5.1,43.2)	(3.7,32.3)	(3.7,38.3)	(3.3,39.4)	(2.8,41.6)
Output	2.58	5.16	5.38	5.32	16.65	28.45	28.61	28.57
	(0.2,9.9)	(1.5,15.3)	(1.4,16.2)	(1.0,17.3)	(6.3,31.9)	(13.2,44.8)	(13.3,46.5)	(12.4,47.8)
Unemployment	8.73	12.51	11.06	11.14	1.75	14.72	15.42	15.37
	(1.2,18.1)	(2.7,28.9)	(2.3,28.1)	(2.0,28.9)	(0.1,6.6)	(3.4,31.8)	(3.2,33.5)	(2.5,33.8)

Notes: The values for the displayed shocks and the (omitted) residual disturbances add up to 100 for each variable at each time horizon. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. All numbers are percent.

In this paper we argue that there is no clear answer to the question if technology shocks are expansionary or contractionary. Rather, we think that there coexist different shocks, which fundamentally differ in nature. In particular, shocks that allow firms to cut costs can have contractionary effects. Since they increase the average product and decrease the marginal product of input factors simultaneously, marginal workers and capital goods are made redundant. This is commonly referred to as rationalization. The marginal input factors can then be dismissed or their usage can be reduced, leading to a reduction in average hours worked. At the same time, standard innovations in technology uniformly increase efficiency of all factors employed, leading to higher labor and capital demand.

In order to formalize these concepts, we develop a theoretical model. Relative to a standard small-scale RBC model, we impose only two modifications. On the one hand, we introduce the concept of managerial capacity as a new input factor. On the other hand, the relative weight of this new variable is subject to shocks. Consequently, an increased importance of managerial capacity in the production process allow the firm to produce the same amount with less input factors by means of a better workflow. We then simulate shocks to this weight (contractionary technology shocks) and find that the model predicts indeed a fall in hours worked and investment, while output hardly moves. Additionally, wages increase slightly and the real interest rate falls. Labor productivity increases.

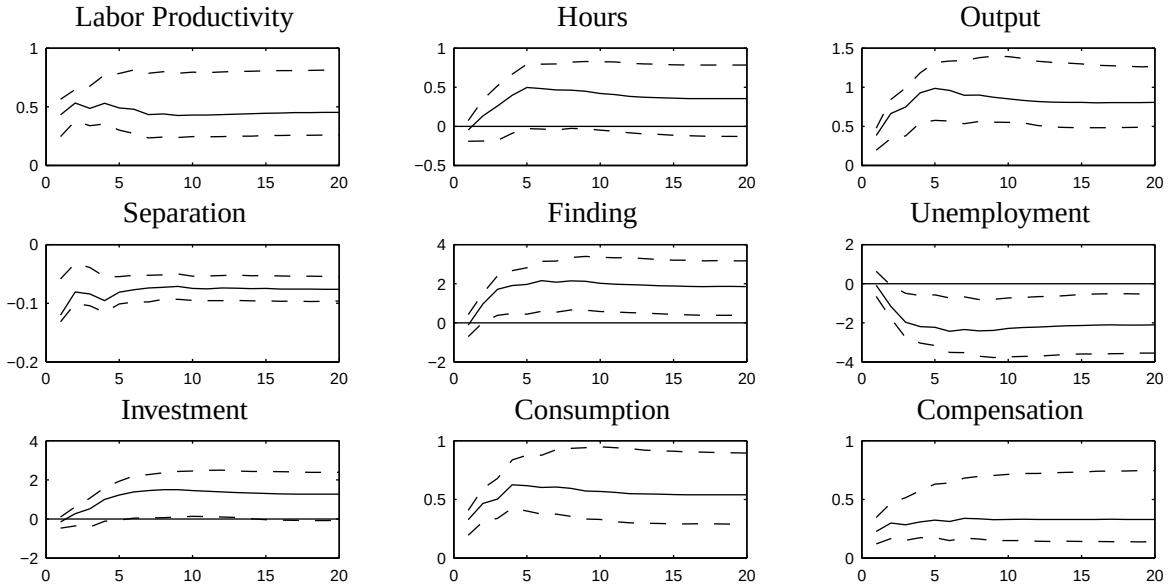
We identify the contractionary technology shocks in the data, based on a minimum set of identifying restrictions. Specifically, we use a combination of zero long-run and sign restrictions, identifying

technology shocks as the only shocks that affect labor productivity in the long run. The simultaneous usage of sign restrictions allows us to distinguish standard TFP shocks, driving separations upwards in the short run, and contractionary technology shocks, reducing separations. We use quarterly U.S. time series for labor productivity, output, investment, consumption, wages, separations, finding rates, and the unemployment rate from 1947:1 through 2004:4. The empirical impulse-response functions confirm the above mentioned predictions of the model. While there are other shocks that satisfy our identifying restrictions, such as preference shocks or TFP shocks under sticky prices, theoretical simulations show that their implications for the remaining variables are at odds with our empirical findings.

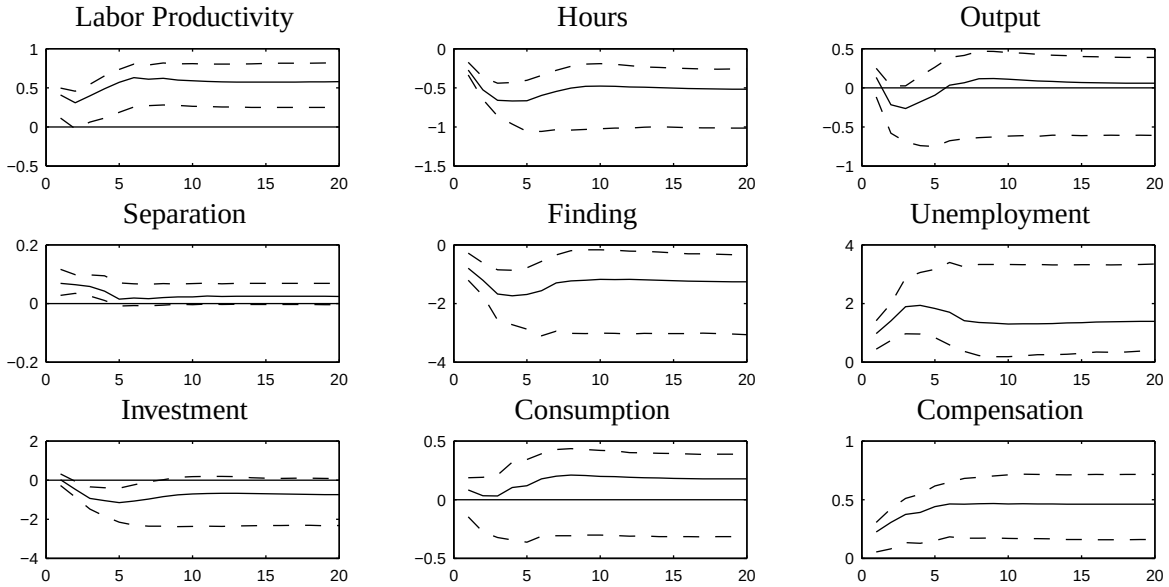
Conducting a business-cycle variance decomposition, we find that both TFP and contractionary technology shocks explain large parts of the observed fluctuations in labor productivity. While TFP shocks are responsible for the largest chunk of fluctuations in output, contractionary technology shocks account for double the amount of fluctuations in hours worked. We therefore conclude that contractionary technology shocks are an important explanation for the behavior of some key variables. Future work will concentrate on endogenizing these shocks.

Figure 6: Impulse-responses with the Extensive Labor Margin

A. Conventional Technology Shocks



B. Contractionary Technology Shocks



Notes: Quarterly responses in percent (percentage points for the job separation, job finding and unemployment rate) to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

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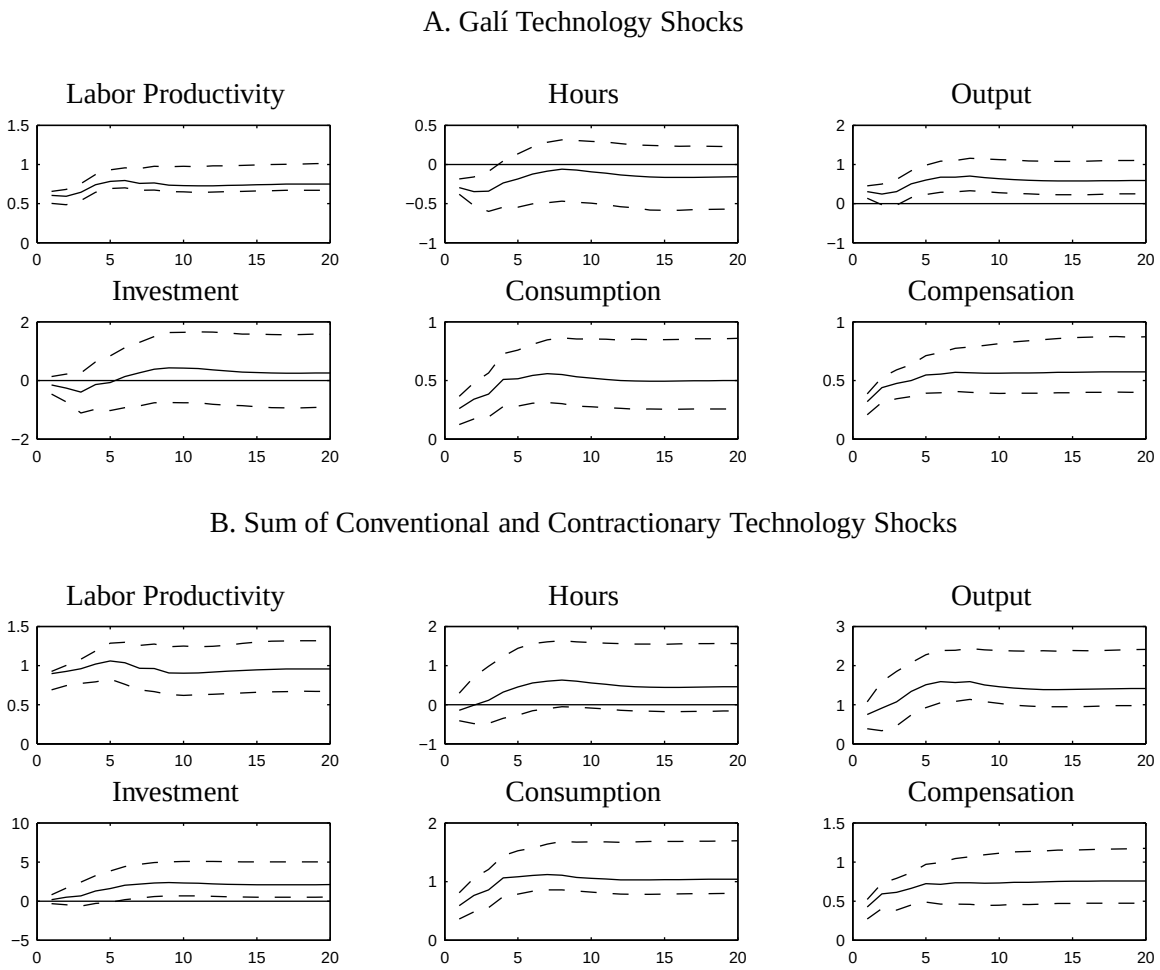
A Robustness and Additional Evidence

Comparison to Galí identification Figure A-1 compares the responses to a technology shock that is identified with the standard Galí assumption on the long-run effect of labor productivity only and the sum of conventional and contractionary technology shocks. The two are not exactly the same. This is not surprising as our identification potentially takes into account two variables, hence a different variation in the data. However, the sum of our two shocks serves as a good approximation of the original Galí shocks.

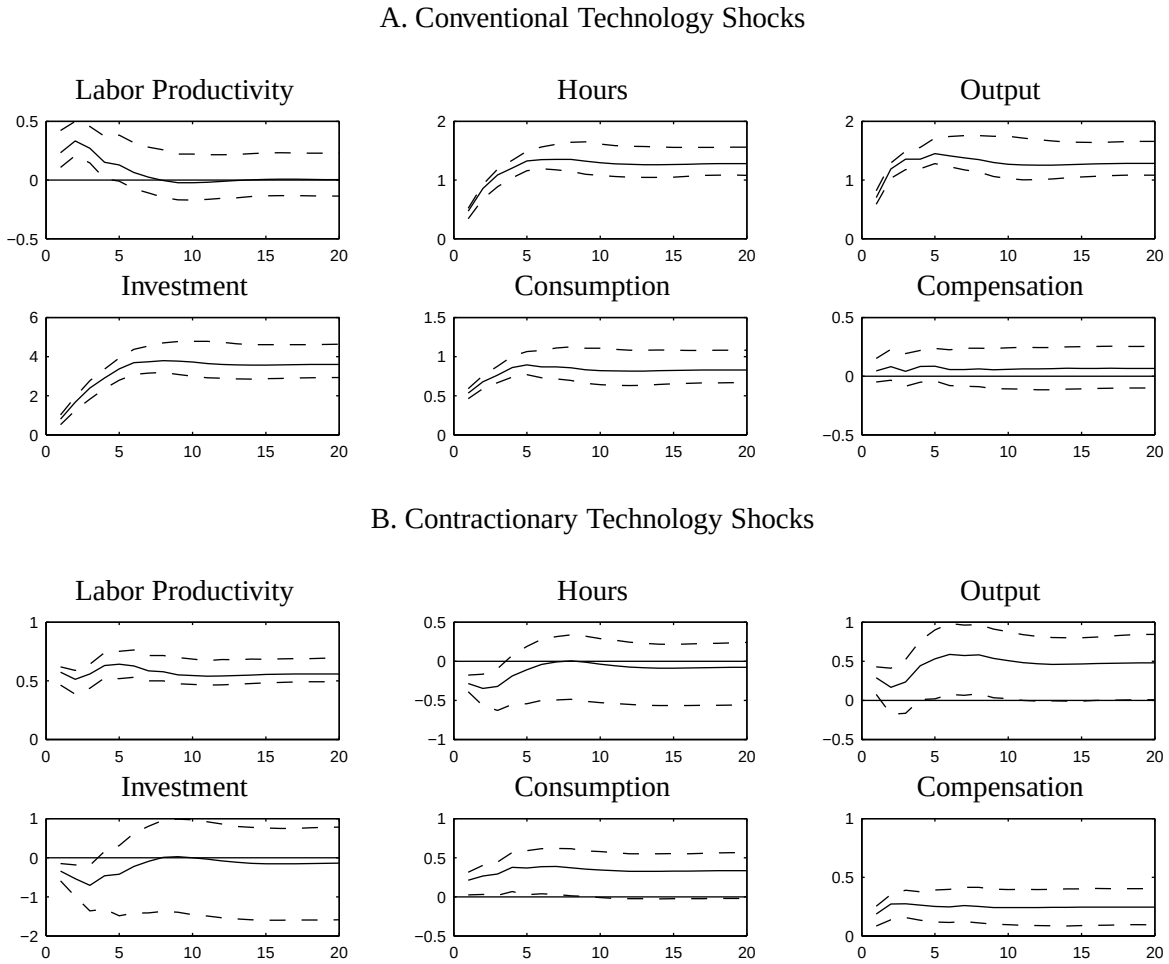
Figure A-1: Comparing responses from Galí and sign identification



Notes: Quarterly responses in percent to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Overidentifying restrictions Figure A-2 is equivalent to Figure 1 but estimated with overidentifying restrictions on a positive effect on output of both technology shocks as well as a positive effect of investment of the conventional shocks and a non-positive effect on investment of the contractionary technology shock. Via these additional assumptions, we can make sure that we do not confuse persistent preference shocks with our technology shocks in the identification as can be seen from Figure 5.

Figure A-2: Impulse-responses with overidentifying restrictions

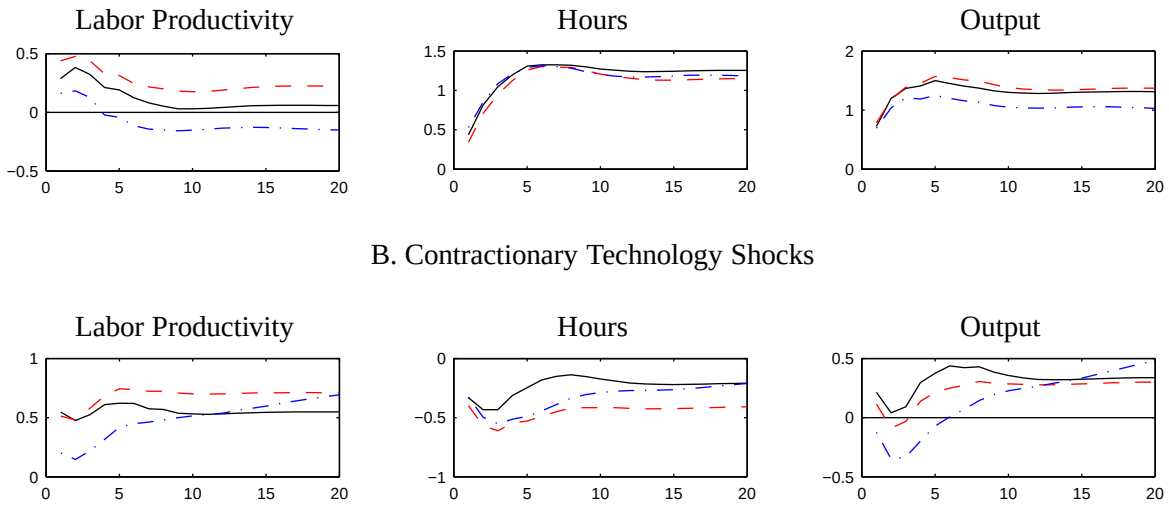


Notes: Quarterly responses in percent to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

Robustness of the results to the specification Figure A-3 shows robustness of productivity, hours and output responses to various specifications. First, we address potential structural breaks (black solid line). Fernald (2007) and Canova et al. (2009) argue that 1973:2 and 1997:1 are break points in the growth literature, in particular productivity growth. Our robustness check therefore includes these dates as dummy breaks in the specification. The other two checks add potentially omitted variables to the VAR such as profits (red dashed line) and inflation and inventories (blue dash-dotted line).

Figure A-3: Robustness to various specifications

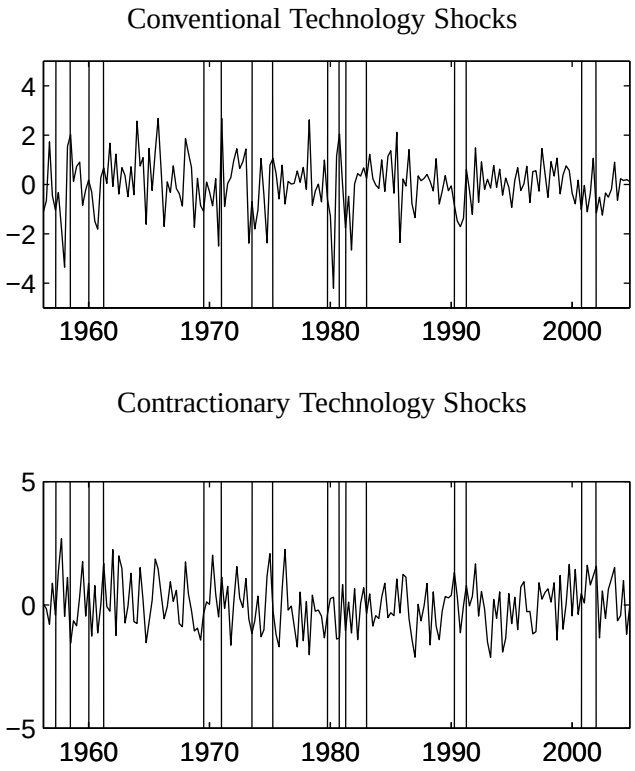
A. Conventional Technology Shocks



Notes: Quarterly responses in percent to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.
Black solid line: structural breaks at 1973:2 and 1997:1. Red dashed line: Including profits. Blue dash-dotted line: Including inflation and inventories.

Historical decomposition Figure A-4 plots the estimated structural shocks over time together with the NBER recession dates.

Figure A-4: Historical decomposition of shocks



B Long-run determinants of labor productivity

Inserting the steady-state production function (1) in the steady-state version of the capital-demand equation (3), solving for K and dividing by L yields

$$K = \left(\frac{r+\delta}{\alpha(1-\eta)\tilde{A}}\right)^{\frac{1}{\alpha(1-\eta)-1}} L^{\frac{(1-\eta)(\alpha-1)}{\alpha(1-\eta)-1}}. \tag{B.1}$$

where all variables denote steady-state values, and $\tilde{A} = M^{\eta} A^{(1-\alpha)(1-\eta)}$. Divide the production function (1) by L and insert the above, also divided by L, to get

$$\frac{Y}{L} = \tilde{A}^{\frac{1}{1-\alpha(1-\eta)}} L^{\frac{\eta}{\alpha(1-\eta)-1}} \left(\frac{p/\beta - 1 + \delta}{\alpha(1-\eta)}\right)^{\frac{(1-\eta)\alpha}{\alpha(1-\eta)-1}}. \tag{B.2}$$

The steady-state value of L can be found implicitly by combining labor supply (5) with labor demand (2), substituting out consumption with the goods-market condition (6) and inserting the production function (1) for Y

$$L^{\Psi - \frac{\sigma[1-\alpha(1-\eta)-\eta]+\eta}{\alpha(1-\eta)-1}} = (1-\eta)(1-\alpha)(1-\tau)X^{\alpha(1-\eta)} \frac{\tilde{A}}{b}\left[\tilde{A}X^{\alpha(1-\eta)} - (1-p+\delta)X\right]^{-\sigma}.$$

Using the above equation (B.1) to substitute out capital and collecting terms gives

$$L^{\Psi - \frac{\sigma[1-\alpha(1-\eta)-\eta]+\eta}{\alpha(1-\eta)-1}} = (1-\eta)(1-\alpha)(1-\tau)X^{\alpha(1-\eta)} \frac{\tilde{A}}{b}\left[\tilde{A}X^{\alpha(1-\eta)} - (1-p+\delta)X\right]^{-\sigma}, \tag{B.3}$$

where

$$X = \left(\frac{p/\beta - 1 + \delta}{(1-\tau)\alpha(1-\eta)\tilde{A}}\right)^{\frac{1}{\alpha(1-\eta)-1}}.$$

Combining equations (B.2) and (B.3) shows that steady-state labor productivity depends on $\alpha, \eta, \sigma, \Psi, \beta, \delta, B, A, b$. Hence, in our model long-run labor productivity is only affected by deep parameters, permanent shocks to TFP or managerial know-how (changing A or B), by contractionary technology shocks (changing η), and by preference shocks (which can be modeled as affecting b).