Online Appendix for "The Dynamics of Hours Worked and Technology"

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Contents

1 Data construction **ii**

2 Sample Statistics over Time: Robustness **iv**

3 Structural Vector Autoregression **xii**
3.1 Transmission of technology shocks with SVAR: Robustness . . . xii
3.2 Transmission of Shocks across Datasets . . . xiii
3.2.1 GG database . . . xiii
3.2.2 CDS database . . . xiv
3.2.3 RR database . . . xv
3.2.4 FR database . . . xvi
3.3 Transmission of technology shocks on filtered hours and different window lengths . . xvi
3.4 Transmission of technology shocks using a measure of technology . . . xx

4 A Complementary Empirical Analysis: Robustness **xxi**

5 Estimates of the structural parameters of the RBC-CES model. **xxii**
5.1 Identification of σ . . . xxiii
5.2 Rolling windows estimation . . . xxiii
5.3 Rolling windows estimation with non uniform weighting scheme. . . . xxvi

6 Can changes in capital-labor elasticity reproduce the SVAR evidence? **xxix**

7 Estimation Robustness: Adding the Great Recession. **xxx**

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8 Competing Structural Interpretation I: the role of Monetary Policy. xxxiii
8.1 General results xxxiii
8.2 Model setup xxxv
8.2.1 Model with a Taylor rule xxxviii
8.2.2 Model with a constant money growth rule xxxviii
8.3 Calibration, theoretical IRFs, simulated data and RBC-CES estimation xxxix

9 Competing Structural Interpretation II: the role of investment adjustment costs xliii
9.1 RBC model with investment adjustment costs xliii

10 Competing Structural Interpretation III: habit formation xlv
10.1 RBC model with habit formation and investment adjustment costs xlvi

1 Data construction

In this section, we explore the robustness of our key empirical results and other sample moments to the use of alternative databases and data filters. For all databases the time span covers the period from 1948:Q1 until 2009:Q1 and times series are obtained from the FRED database. Labor productivity is computed as the ratio between the measure of output and hours, and we take logarithms of both series. We indicate with p_t^j labor productivity and with h_t^j hours of database j. In parenthesis, we indicate the ID series in the FRED database of the Federal Reserve Bank of Saint Louis.

The first database (GG) follows closely the data construction in Galí and Gambetti (2009) (a similar database is used also in Galí and Rabanal (2005)). We consider output in the non-farm business sector (OUTNFB), and hours of all persons in the non-farm business sector (HOANBS) and the civilian non-institutional population of 16 years and over (CNP16OV). We thus have

$$\Delta p_t^{GG} = \Delta \left(\ln \frac{OUTNFB_t}{CNP16OV_t} \right),$$
$$hobs_t^{GG} = \ln \frac{HOANBS_t}{CNP16OV_t}.$$

An alternative database (CDS) is considered following the work in Chang, Doh and Schorfheide (2007). We employ Average Weekly Hours of non-farm Business Sector (PRS85006023), total non-farm employees (PAYEMS), Civilian non institutional population of 20 years and over (CNP20OV = LNU00000025 (men) + LNU00000026(women)), real GDP (GDPC96). Hence, we obtain the CDS data as:

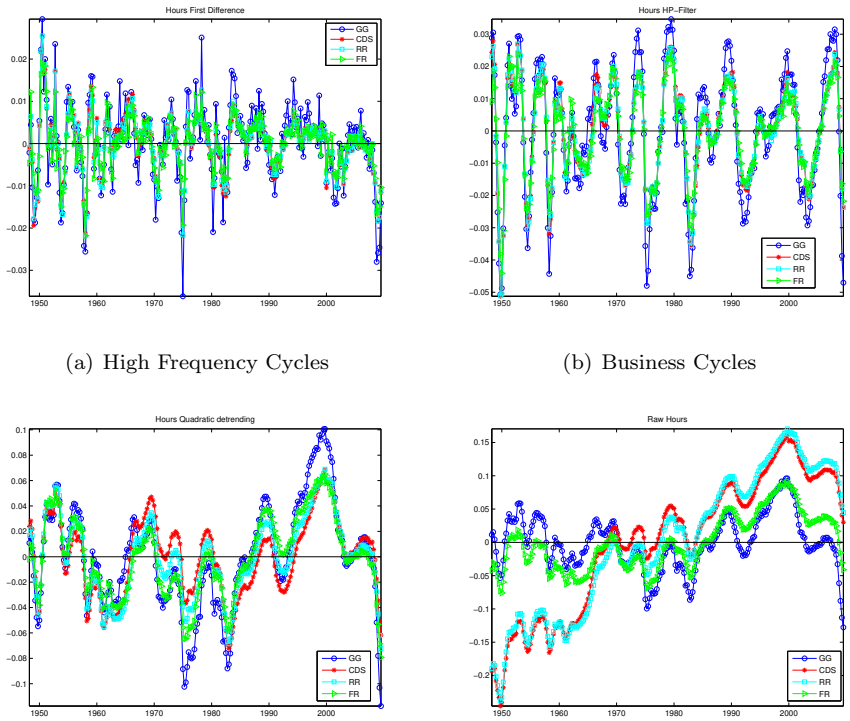
$$\Delta p_t^{CDS} = \Delta \left(\ln \frac{GDPC96_t}{CNP20OV_t} \right),$$
$$hobs_t^{CDS} = \ln \frac{PRS85006023_t * PAYEMS_t}{CNP20OV_t}.$$

The third data set (RR) follows Ríos-Rull, Schorfheide, Fuentes-Albero, Kryshko and Santaeulália-Llopis (2012), where the series are similar to CDS but normalized by a different population structure, i.e. the civilian non-institutional population of 16 years and over (CNP16OV):

$$\Delta p_t^{RR} = \Delta \left(\ln \frac{GDPC96_t}{CNP16OV_t} \right),$$
$$hobs_t^{RR} = \ln \frac{PRS85006023_t * PAYEMS_t}{CNP16OV_t}.$$

Finally, we also consider the measure of hours worked constructed by Francis and Ramey (2009), which takes into account the demographic structure of the population. The authors have kindly shared the data and are available at: http://weber.ucsd.edu/∼vramey. A similar database is used in Galí and Van Rens (2010).

Figure 1.1 reports the evolution of hours worked across different data sets and different filtering techniques. The picture uncovers sizeable differences along two dimensions, the proxy used to



(a) High Frequency Cycles

(b) Business Cycles

(c) Medium Cycles

(d) Raw (demeaned)

Figure 1.1: Hours worked across different databases and filters, form top left first difference, HP(1600) filter, quadratic detranded and raw.

measure hours worked and the properties of the cyclical component of hours worked. The figures present the portion of fluctuations of the times series of hours worked we wish to analyze in increasing order. In particular, with the first difference filter (FD) we emphasize high frequency movements and dampen medium run and business cycles fluctuations, with the HP(1600) filter we wipe out the fluctuations with periodicity larger then 32 quarters and leave unchanged fluctuations with shorter horizons and with the quadratic detrending (QD) we leave in the spectrum of hours a large portion of medium term fluctuations [1].

There are two important things we would like to mention. First, emphasizing a specific portion of fluctuations of hours worked might have important consequences for the estimated conditional and unconditional moments and their variations over time. Second, structural changes in the second moments of hours, output and productivity need not be necessarily located at at the typical business cycles frequencies, and it can well be the case that secular variations are located at medium term fluctuations. Hence, the evidence produced by using only high pass filters might be misleading.

[1] A similar exercise could be carried by using a band pass filter with a pre specified range. Since differences in the conclusions are unappreciable, we prefer to use the transformations typically used in the literature.

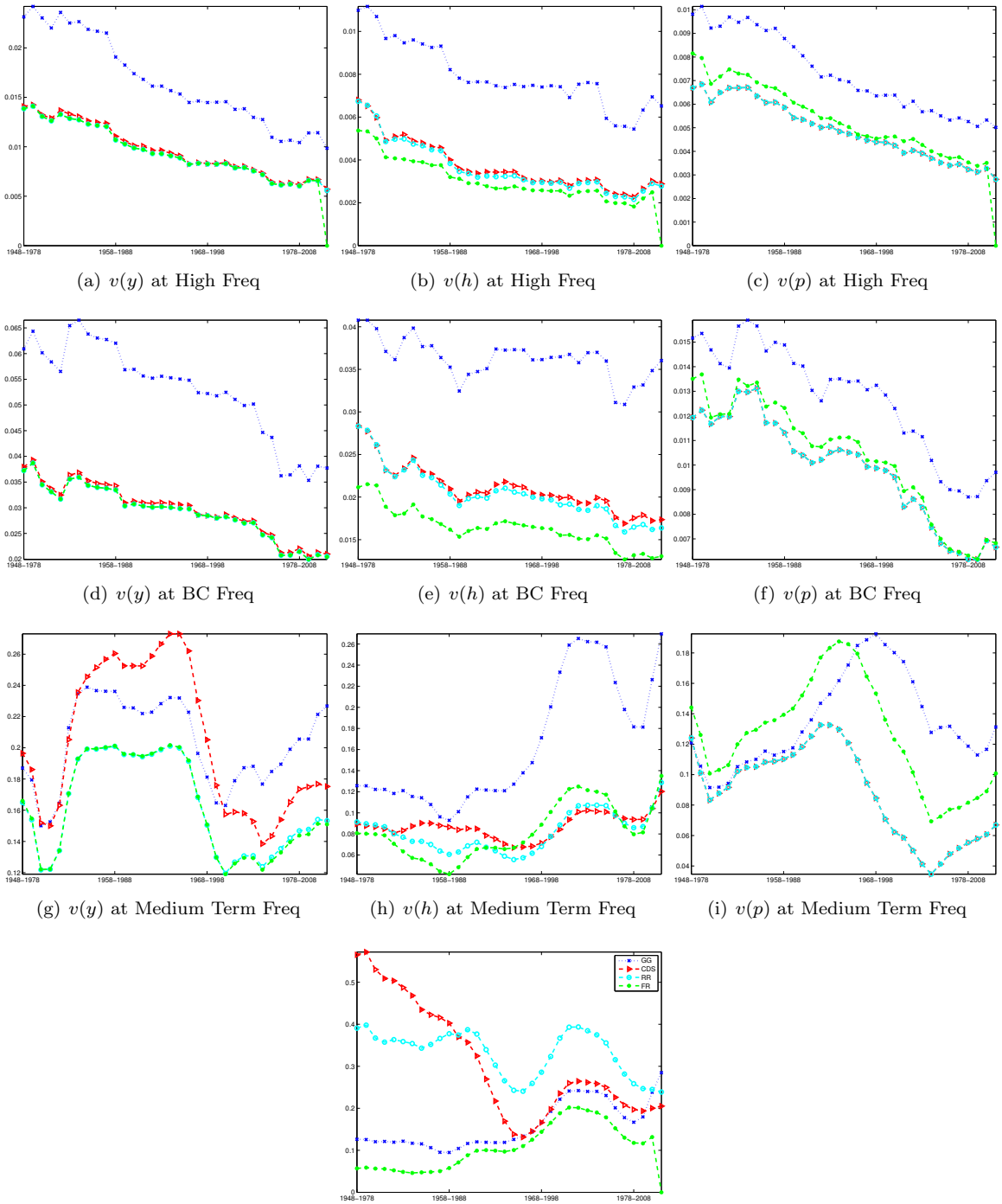
2 Sample Statistics over Time: Robustness

In what follows we study a number of sample statistics over time using the four databases presented and using different portions of cyclical fluctuations. It is important to stress that we do not look for an ideal filter nor for the best measurement of hours worked. Rather, we wish to study the robustness of the conditional and unconditional moments over time to changes in the specification of hours worked and of their cyclical component. Besides the response of hours to a technology shock, we try to pay particular attention to three pieces of evidence discussed in the literature: (a) a sensible reduction in the volatility of output, labor productivity and hours, and (b) an increase in the volatility of hours and labor productivity relative to output over time, and (c) a considerable decline in the cyclical behavior of labor productivity, measured by its comovement with either output or hours.

In order to study the time variation in hours, output and productivity, we split the sample into overlapping sub samples of fixed length. The choice of the window length is not trivial and there are evident trade-offs in the selection of the amplitude of the sample. Short samples make it easier to detect time variations but, with short windows, small sample biases could be important. In larger samples, this bias is alleviated but time variations are more difficult to detect. Moreover, each window should contain an adequate number of fluctuations for all filtered proxies. On the one hand, we cannot consider too short sub samples (say 8 years) otherwise some fluctuations of QD hours will not be considered since they exceed the sample length. On the other hand, too large windows could cancel out time variations since FD hours might contain too many fluctuations. Since we lack a formal discipline to select jointly cyclical fluctuations and sub sample amplitude, we adopt a rule of thumb and chose a sample size of 30 years in order to ideally include six fluctuations of five years in each window. Such range of fluctuations should be present in all the filtered proxies, form FD to QD hours. Finally, while 120 data points can be considered a large sample to estimate unconditional correlations, it is an acceptable sample size for conducting inference with a VAR with three lags (a total of 15 parameters to estimate). Hence, as in the main body of the text, we compute statistics of interest starting from the sample [1948:Q2,1978:Q1] and moving the window by one year until [1979:Q2,2009:Q1].

We also study the changes of sample statistics using a pre-specified break date. The choice of the break date is motivated by previous studies and coincides with 1984 (see for example Galí and Van Rens (2010) and Galí and Gambetti (2009)).

Figure 2.1 reports the volatilities of productivity (first column), hours (second column) and output (third column) over time when different portions of fluctuations are emphasized, i.e. form top to bottom we carve out high frequency fluctuations, business cycle fluctuations, medium cycles fluctuations and we leave unchanged all the fluctuations in the spectrum. The pictures show that at



(a) $v(y)$ at High Freq (b) $v(h)$ at High Freq (c) $v(p)$ at High Freq

(d) $v(y)$ at BC Freq (e) $v(h)$ at BC Freq (f) $v(p)$ at BC Freq

(g) $v(y)$ at Medium Term Freq (h) $v(h)$ at Medium Term Freq (i) $v(p)$ at Medium Term Freq

(j) $v(h)$ Raw Hours

Figure 2.1: Time variation of volatility emphasizing different frequencies of productivity, hours and output. Top bottom, FD, HP, QD and RAW hours.

high and business cycle frequency the reduction in volatility is evident and consistent across datasets. However, at medium term cycles such volatility reduction is difficult to spot for any proxy of hour

worked, a result that echoes the findings of Pancrazi (2012). Hence, while we confirm the findings in (a), we note that the reduction in volatility over time is a pattern mainly occurring at business cycles frequencies and at medium term cycles we detect no common monotonic behavior.

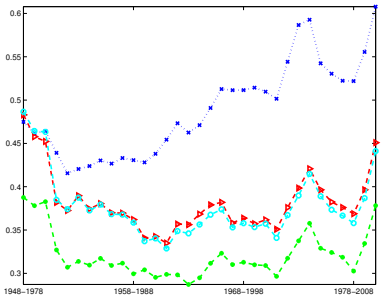
Figure 2.2 reports the volatilities of hours (first column) and productivity (second column) relative to that of output over time. The pictures show mixed results and we notice the following outcomes. First, at business and medium term cycles fluctuations hours worked volatility has increased relative to that of output for all the proxies considered. Second, the series of hours worked constructed in GG features a steady increase of its relative volatility at any the portion of the spectrum, both at high and low frequencies. Third, the increase in the relative volatility of productivity is difficult to detect. Hence, relative to the evidence (b), while we register an increase in the volatility of hours relative to output over time at medium run and BC frequencies, we do not detect a clear time varying pattern for the volatility of labor productivity relative to output.

Figure 2.3 reports the unconditional correlation of hours (right) and output (left) with productivity over time. In this case, again, it is difficult to find a pattern that is consistent across different definitions of hours worked and across different portions of fluctuations of interest. The reading of the various panels uncovers three main findings. First, the steady decline of the unconditional correlation of labor productivity is present at high frequency, business cycles and medium term frequencies using the definition of hours worked used in GG. Second, for any datasets different form GG it is difficult to recognize a monotone time varying pattern. For example, using the FR measure of hours such correlation is roughly constant at any frequency of the spectrum. Third, using raw data and the growth rate of productivity the unconditional correlation is increasing over time, a result which is not at odds with the time variations of the conditional correlations. It is worth mentioning that using rolling samples with shorter amplitudes -say windows of 60 quarters[2]- we obtain a similar picture across proxies of hours worked at high and business cycles frequencies; however, at medium terms cycles we find a flat pattern and we still detect an increase in the unconditional correlation of labor productivity growth with raw hours worked.

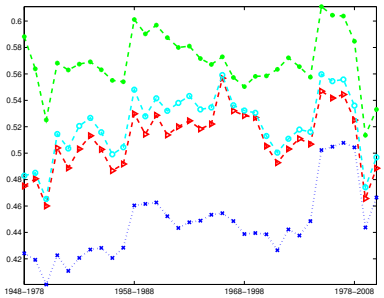
In all, by looking at sample statistics on overlapping subsamples, it is difficult to find results that are consistent across datasets and across transformations. Our results point at (1) a sensible reduction in the volatility of hours, output and labor productivity over time when a large portion of long and medium run fluctuations are removed (i.e. with an HP filter or taking first difference) and (2) a decline in the comovement between labor productivity and the hours worked time series constructed following GG at business and medium term cycles, and (3) increase in the correlation of labor productivity growth and any measure of raw hours worked.

We turn now to analyze the same statistics splitting the sample before and after 1984. Table 2.1

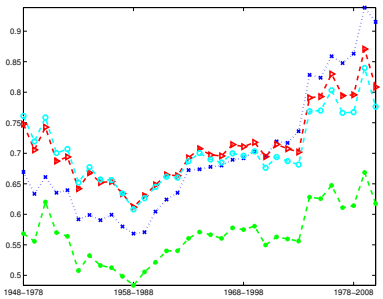
[2]Graphs are available upon request.



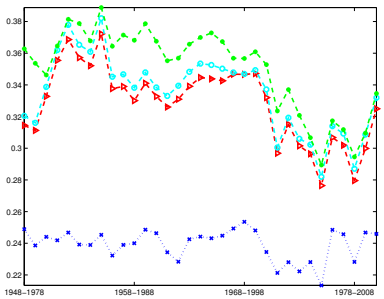
(a) $v(h)/v(y)$ at High Freq



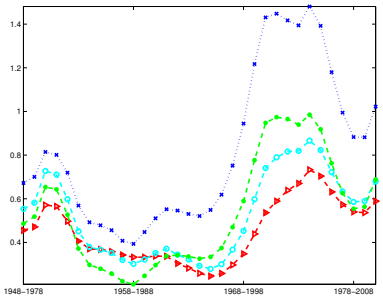
(b) $v(p)/v(y)$ at High Freq



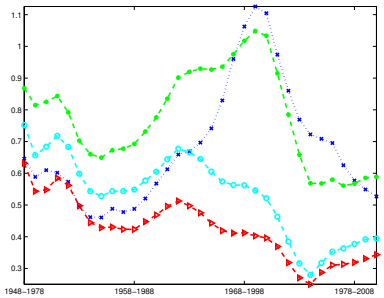
(c) $v(h)/v(y)$ at BC Freq



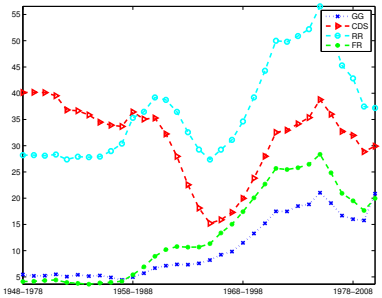
(d) $v(p)/v(y)$ at BC Freq



(e) $v(h)/v(y)$ at Medium Term Freq



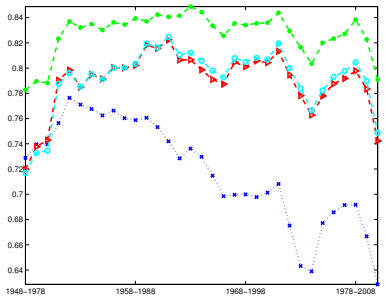
(f) $v(p)/v(y)$ at Medium Term Freq



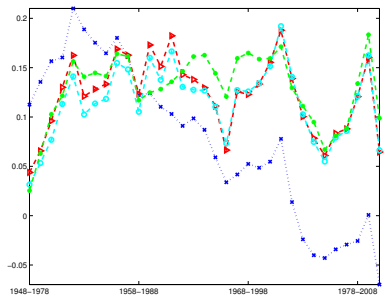
(g) $v(h)/v(y)$ Raw Hours

Figure 2.2: Time variation of the volatility of productivity and hours **relative** to output emphasizing different frequencies. Top bottom, FD, HP, QD and RAW hours.

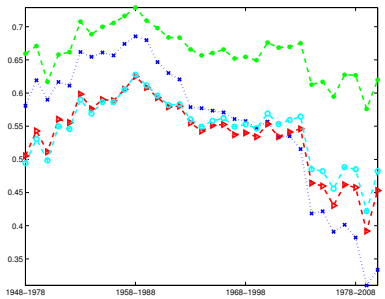
presents the ratios of post-1984 over pre-1984 standard deviations and relative standard deviations with respect to output of the three variables of interest in the four databases extracting different



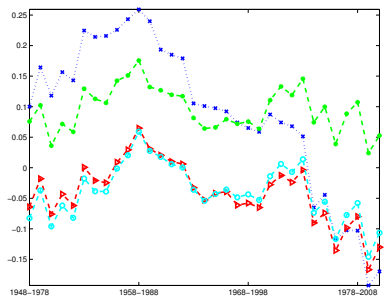
(a) $corr(y, p)$ at High Freq



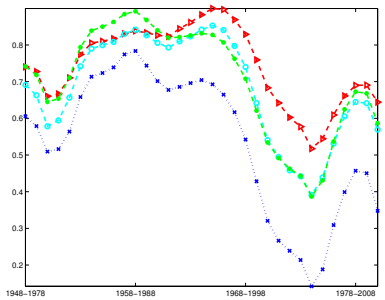
(b) $corr(h, p)$ at High Freq



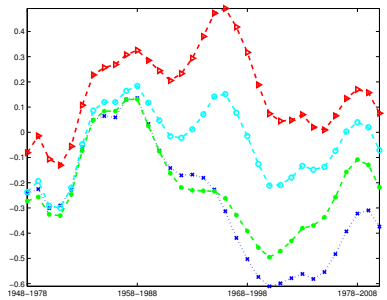
(c) $corr(y, p)$ at BC Freq



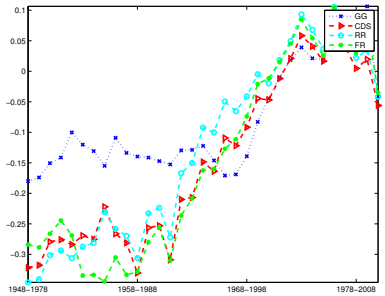
(d) $corr(h, p)$ at BC Freq



(e) $corr(y, p)$ at Medium Freq



(f) $corr(h, p)$ at Medium Freq



(g) $corr(h, p)$ Raw Hours

Figure 2.3: Time variation of the correlation between hours (right) and output(left) with productivity emphasizing different frequencies. From top to bottom, FD, HP, QD and RAW.

cyclical fluctuations as discussed above. If we focus on the absolute standard deviations, we can notice that at high and business cycles frequencies the ratio between pre and post 1984 is typically

smaller than one, with values that range form 0.5 to 0.7 for all proxies. If we focus instead on the quadratic detrended data or raw hours, we find mixed evidence with some ratios larger than one and some smaller. This result echoes what we find with the rolling window exercise, i.e. that the reduction of volatility is only located at high or business cycles frequencies. The ratio of the volatility of hours and productivity relative to GDP post 1984 over pre 1984 is greater than one with GG or FD data.

	Standard deviation $\frac{Post-1984}{Pre-1984}$				Relative STD with output $\frac{Post-1984}{Pre-1984}$			
	GG	**CDS**	**RR**	**FR**	**GG**	**CDS**	**RR**	**FR**
				First difference				
Output	0.56	0.55	0.56	0.56	1	1	1	1
Hours	0.75	0.63	0.63	0.67	1.35	1.13	1.13	1.2
Productivity	0.67	0.57	0.57	0.55	1.21	1.03	1.03	0.99
				HP-filter				
Output	0.61	0.59	0.58	0.58	1	1	1	1
Hours	0.83	0.65	0.63	0.67	1.36	1.12	1.08	1.15
Productivity	0.7	0.67	0.67	0.63	1.15	1.15	1.16	1.09
				Quadratic detrending				
Output	0.8	0.75	0.7	0.69	1	1	1	1
Hours	1.13	0.94	0.92	1.01	1.42	1.25	1.32	1.47
Productivity	1.03	0.66	0.66	0.77	1.28	0.88	0.95	1.12
				RAW Hours				
Hours - FDY	1.15	0.46	0.56	1.22	2.06	0.83	1	2.2
Hours - QDY	”	”	”	”	6.34	3.32	3.72	8.16
Hours - HPY	”	”	”	”	1.88	0.79	0.96	2.1

Table 2.1: Changes in volatility

Table 2.2 reports the unconditional correlations pre and post-1984. We applied the same filters as before as well as the combination of raw hours with filtered output and labor productivity. It shows cross correlations between the three variables of interest pre and post 1984 and their net change. While the correlation of labor productivity tends to decline after 1984 for the GG database, the quantitative picture is different for different datasets and filtering techniques. In particular using the database of GG, we would conclude that the procyclicality of labor productivity with output has declined considerably: a change of -0.27 or -0.51 depending on the filter used. However, if we consider - say - the database of FR and take first difference on hours the vanishing prociclycality of labor productivity with output is more modest, i.e. its correlation with output falls form 0.81 to

0.71.

	GG			CDS			RR			FR		
	Pre-1984	**Post-1984**	**change**	**Pre-1984**	**Post-1984**	**change**	**Pre-1984**	**Post-1984**	**change**	**Pre-1984**	**Post-1984**	**change**
First difference												
Output-Hours	0.78	0.68	-0.1	0.73	0.71	-0.02	0.73	0.71	-0.02	0.66	0.67	0.01
Hours-Productivity	0.18	-0.28	-0.47	0.1	-0.06	-0.16	0.09	-0.06	-0.15	0.1	-0.05	-0.15
Output-Productivity	0.75	0.51	-0.25	0.75	0.66	-0.09	0.75	0.66	-0.09	0.81	0.71	-0.1
HP-Filter												
Output-Hours	0.88	0.87	-0.02	0.84	0.8	-0.04	0.84	0.79	-0.05	0.82	0.78	-0.04
Hours-Productivity	0.19	-0.4	-0.59	-0.01	-0.24	-0.23	-0.02	-0.21	-0.19	0.15	-0.11	-0.26
Output-Productivity	0.62	0.11	-0.51	0.53	0.39	-0.14	0.52	0.43	-0.09	0.68	0.53	-0.15
Quadratic detrending												
Output-Hours	0.7	0.6	-0.1	0.68	0.76	0.08	0.6	0.68	0.08	0.51	0.49	-0.02
Hours-Productivity	-0.06	-0.49	-0.43	0.06	-0.05	-0.1	-0.09	-0.28	-0.19	-0.12	-0.43	-0.31
Output-Productivity	0.67	0.4	-0.27	0.77	0.61	-0.16	0.74	0.51	-0.23	0.79	0.58	-0.22
RAW Hours - First difference Y and Pr												
Output-Hours	0.17	0.32	0.14	-0.14	0	0.14	-0.13	-0.05	0.08	0.05	0.13	0.08
Hours-Productivity	-0.07	-0.01	0.07	-0.27	0.06	0.32	-0.27	0.06	0.33	-0.2	0.05	0.25
RAW Hours - QD Y and Pr												
Output-Hours	0.71	0.55	-0.16	0.34	0.83	0.49	0.2	0.86	0.65	0.54	0.68	0.14
Hours-Productivity	-0.04	-0.54	-0.5	0.28	0.1	-0.18	0.21	0.13	-0.09	0.01	-0.18	-0.2
RAW Hours - HP Y and Pr												
Output-Hours	0.65	0.46	-0.19	0.2	0.23	0.04	0.21	0.16	-0.05	0.66	0.27	-0.4
Hours-Productivity	0.17	-0.18	-0.34	-0.04	-0.2	-0.17	-0.05	-0.21	-0.16	0.12	-0.1	-0.22

Table 2.2: Changes in Cross Correlations

3 Structural Vector Autoregression

In this section we first describe the SVAR representation and then verify the robustness of the SVAR findings along three dimensions, measure of hours worked, portion of fluctuations considered and window size.

A reduced form Vector Autoregression (VAR) can be represented as

$$x_t = A_0 + A_1 x_{t-1} + ... + A_p x_{t-p} + u_t$$

where u_t are i.i.d. zero mean normal shocks with covariance matrix Σ. We assume that $u_t = \Omega\epsilon_t$ where $\epsilon_t = [\epsilon_t^s, \epsilon_t^d]$ is a normal i.i.d. shock with $E(\epsilon_t\epsilon_t') = I$, and where ϵ_t^s is the technology shock and ϵ_t^d a non technology shock. It follows from the assumptions that $\Sigma = \Omega\Omega'$. We consider $x_t = [\Delta p_t, h_t]$ in estimation, where $h_t = \ln H_t$. For exposition purposes it is more convenient to rewrite the system in a companion form

$$z_t = \mu + Bz_{t-1} + e_t$$

where $z_t = [x_t', x_{t-1}', ..., x_{t-p+1}']'$, $e_t = [u_t', 0, ..., 0]'$, $\mu = [A_0', 0, ..., 0]'$, and B is the companion form matrix. The long run restriction implies that the impact matrix of cumulative effects of the shock on labor productivity has a Cholesky factor, i.e. the matrix $F = \sum_{k=0}^{\infty} S_{2,2}(B^k)\Omega$ has a lower triangular structure where $S_{2,2}(.)$ is a selection matrix that picks the first two rows and columns of matrix B^k.

3.1 Transmission of technology shocks with SVAR: Robustness

We estimate the structural VAR (SVAR) model on rolling windows of fixed length, starting from the sample [1948Q2,1978Q1] in the baseline exercises, and repeating the estimation moving the starting date by one year. Posterior coefficients and the posterior covariance matrix are derived assuming uninformative priors. This section is divided into three parts. In the first part, we consider raw hours worked in estimation and compare different transmission mechanisms across datasets. In the second part, we focus on the response of hours worked to a technology shock and study the sensitivity of the response to different transformation of hours worked in estimation and to different rolling window amplitudes. In the third part, we show that the results are not sensitive to the measure of productivity used.

While there are small differences in selected sub samples and data series used, the broad picture that the response of hours worked following a technology shock was negative in early samples and has increased over time is consistent across different measures of hours. Moreover, the 68% confidence sets constructed around the median estimates (solid blue lines) reveal that in the early samples the response of hours is negative, in the middle samples it is zero, and in the late samples positive. This finding appears to be consistent also across different filters with the only exception of the first

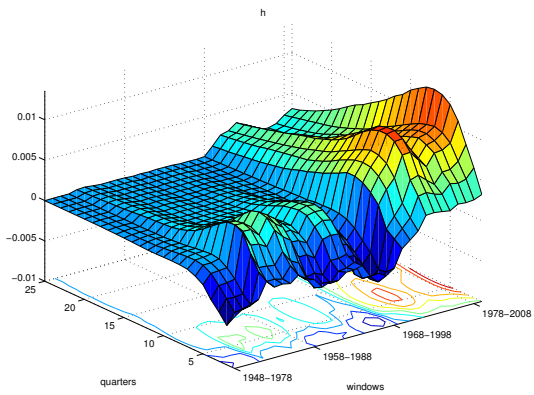
difference on hours worked. However, this is not surprising. A first difference filter dampens both long run and business cycles frequencies and tends to overemphasize high frequencies fluctuations. The secular change in the conditional correlation of hours and technology has occurred more likely at medium run or business cycles frequencies of the spectrum rather then at noisy frequencies. Hence, by taking first differences we downsize the impact of long run and BC fluctuations making difficult to spot time variations. This argument is reinforced if we consider the change in the response using HP filtered hours or QD hours, where an increasing portion of cyclical fluctuations are included in the estimation and the response of hours tend to be more sensitive to time variations. Moreover, the choice of the window amplitude does not seem to be a concern.

Finally, we find a time varying behavior in the response of productivity to "non-technology" shocks robust across datasets. Note that, as discussed at length in the paper, this shock cannot be directly and uniquely mapped into a non-technology shock in the structural model.

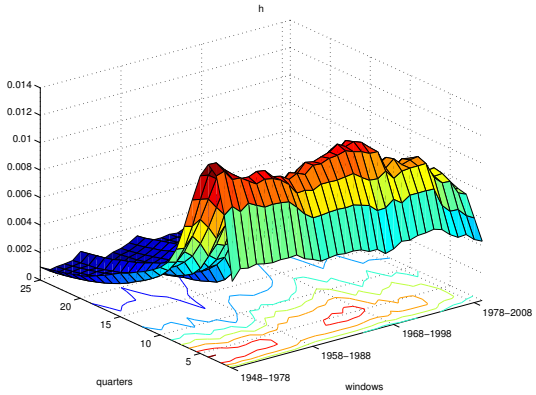
3.2 Transmission of Shocks across Datasets

In this section we consider the growth rate of productivity and raw hours worked in estimation and compare transmission mechanisms of various shocks across datasets. We also provide estimates of the 68% confidence sets for four selected sub samples. There are minor differences across datasets and we do find a robust increase in the response of hours worked to technology shock identified with long run restrictions.

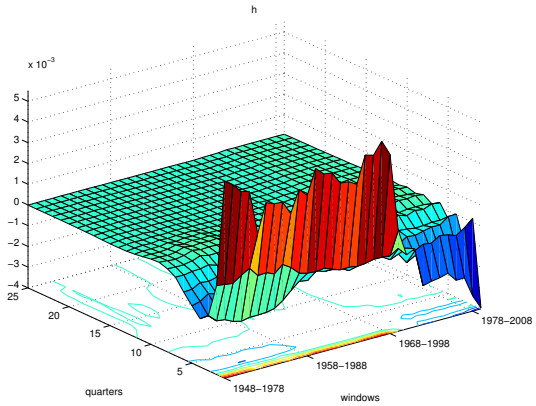
3.2.1 GG database



(a) Hours to tech

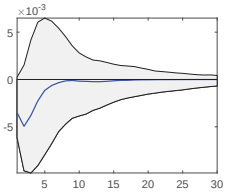


(b) Hours to non-tech

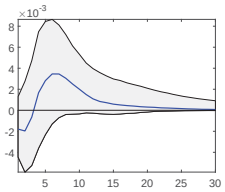


(c) Prod to non-tech

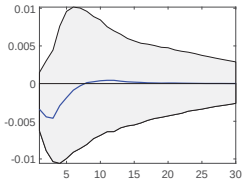
Figure 3.1: Median response of hours to a technology shock (top left) and to a non technology (top right) shock. Median response of productivity growth to a non technology shock (bottom).



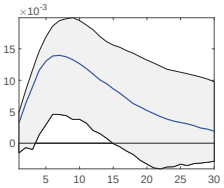
(a) 1948:Q2,1978:Q1



(b) 1958:Q2,1988:Q1



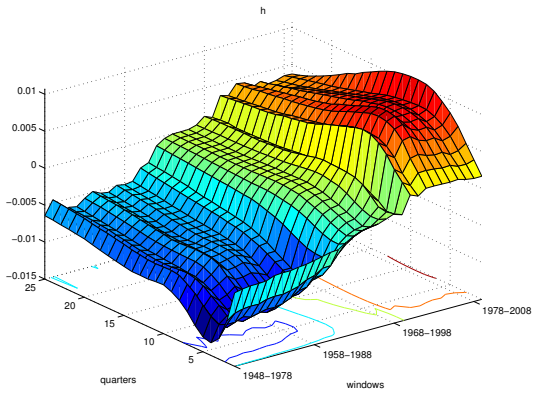
(c) 1968:Q2,1978:Q1



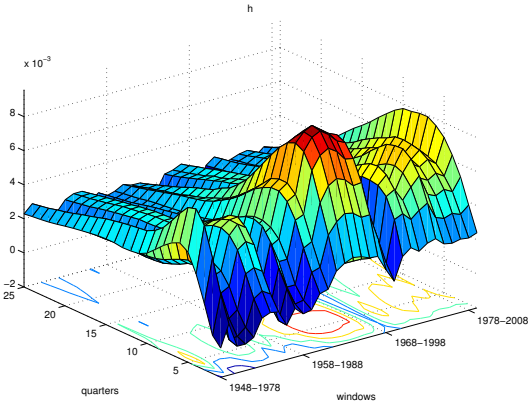
(d) 1979:Q2,2009:Q1

Figure 3.2: Confidence sets around selected subsamples.

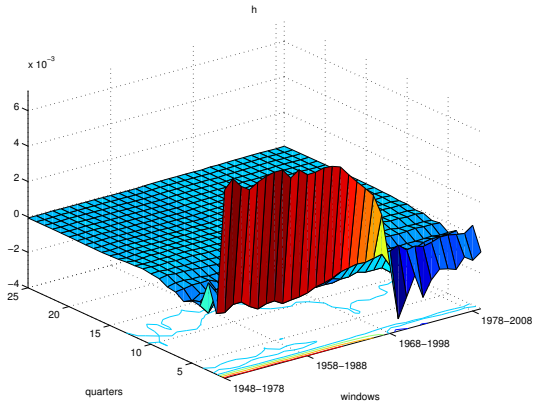
3.2.2 CDS database



(a) Hours to tech

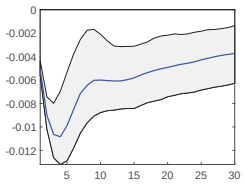


(b) Hour to non-tech

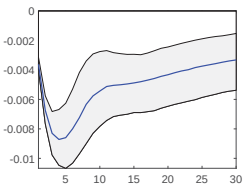


(c) Prod to non-tech

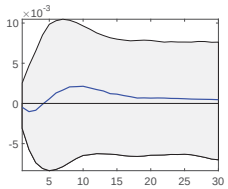
Figure 3.3: Median response of hours to a technology shock (top left) and to a non technology (top right) shock. Median response of productivity growth to a non technology shock (bottom).



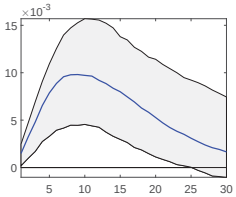
(a) 1948:Q2,1978:Q1



(b) 1958:Q2,1988:Q1



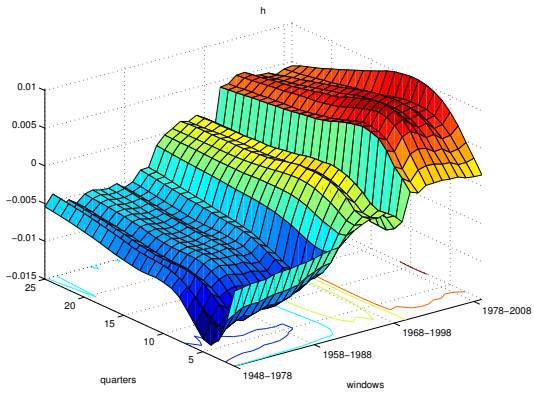
(c) 1968:Q2,1978:Q1



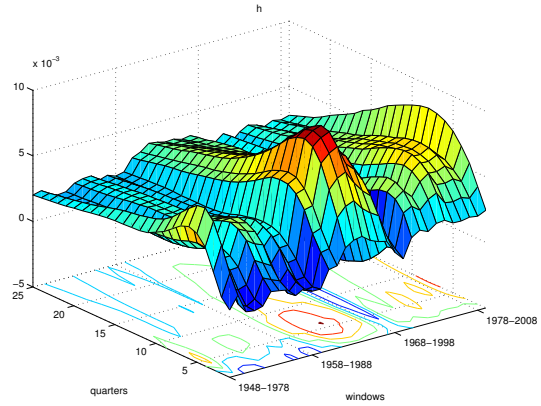
(d) 1979:Q2,2009:Q1

Figure 3.4: Selected subsamples.

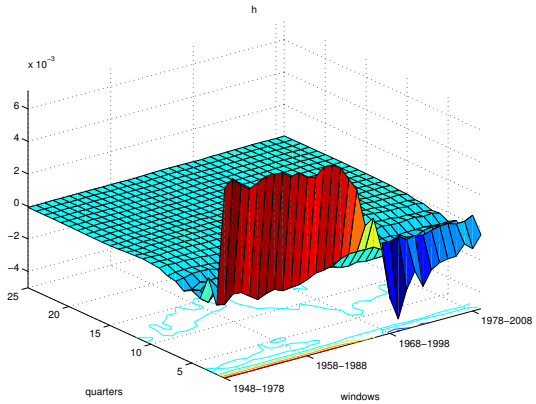
3.2.3 RR database



(a) Hours to tech

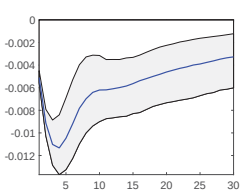


(b) Hour to non-tech

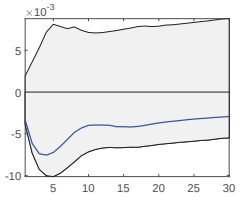


(c) Prod to non-tech

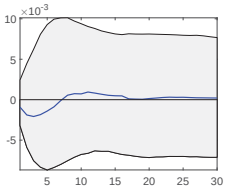
Figure 3.5: Median response of hours to a technology shock (top left) and to a non technology (top right) shock. Median response of productivity growth to a non technology shock (bottom).



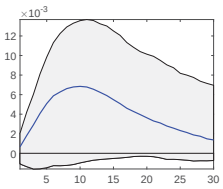
(a) 1948:Q2,1978:Q1



(b) 1958:Q2,1988:Q1



(c) 1968:Q2,1978:Q1



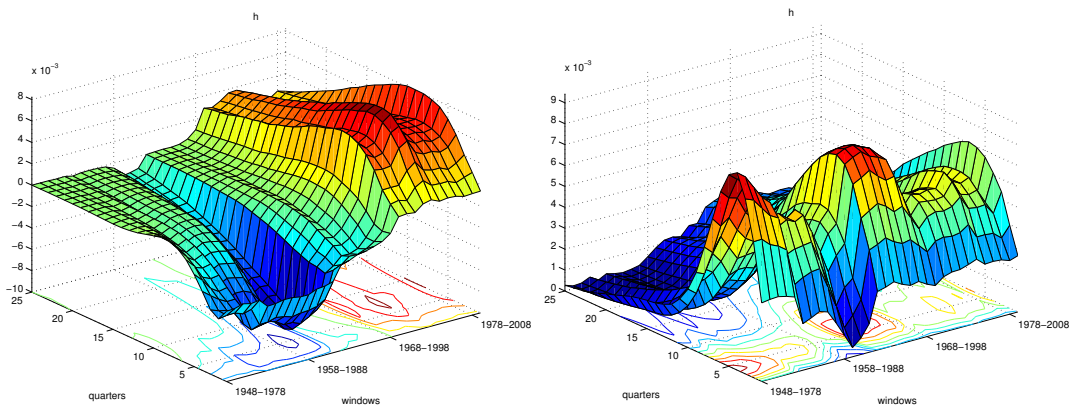
(d) 1979:Q2,2009:Q1

Figure 3.6: Selected subsamples.

3.2.4 FR database

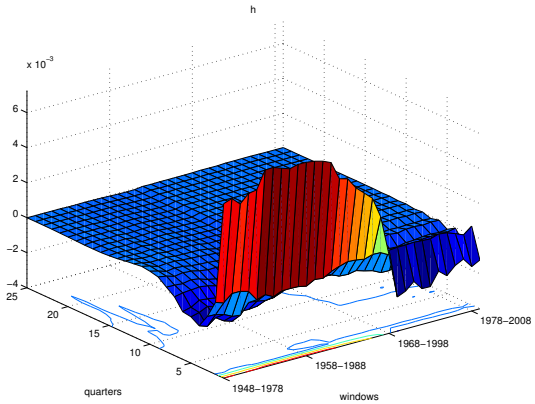
3.3 Transmission of technology shocks on filtered hours and different window lengths

Figure 3.9 reports the response of hours worked to a technology shock using different measures and different portions of fluctuations of hours worked. If we remove only long run fluctuations (i.e.



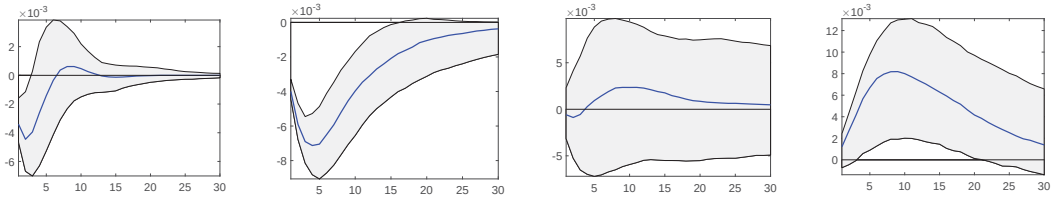
(a) Hours to tech

(b) Hour to non-tech



(c) Prod to non-tech

Figure 3.7: Median response of hours to a technology shock (top left) and to a non technology (top right) shock. Median response of productivity growth to a non technology shock (bottom).

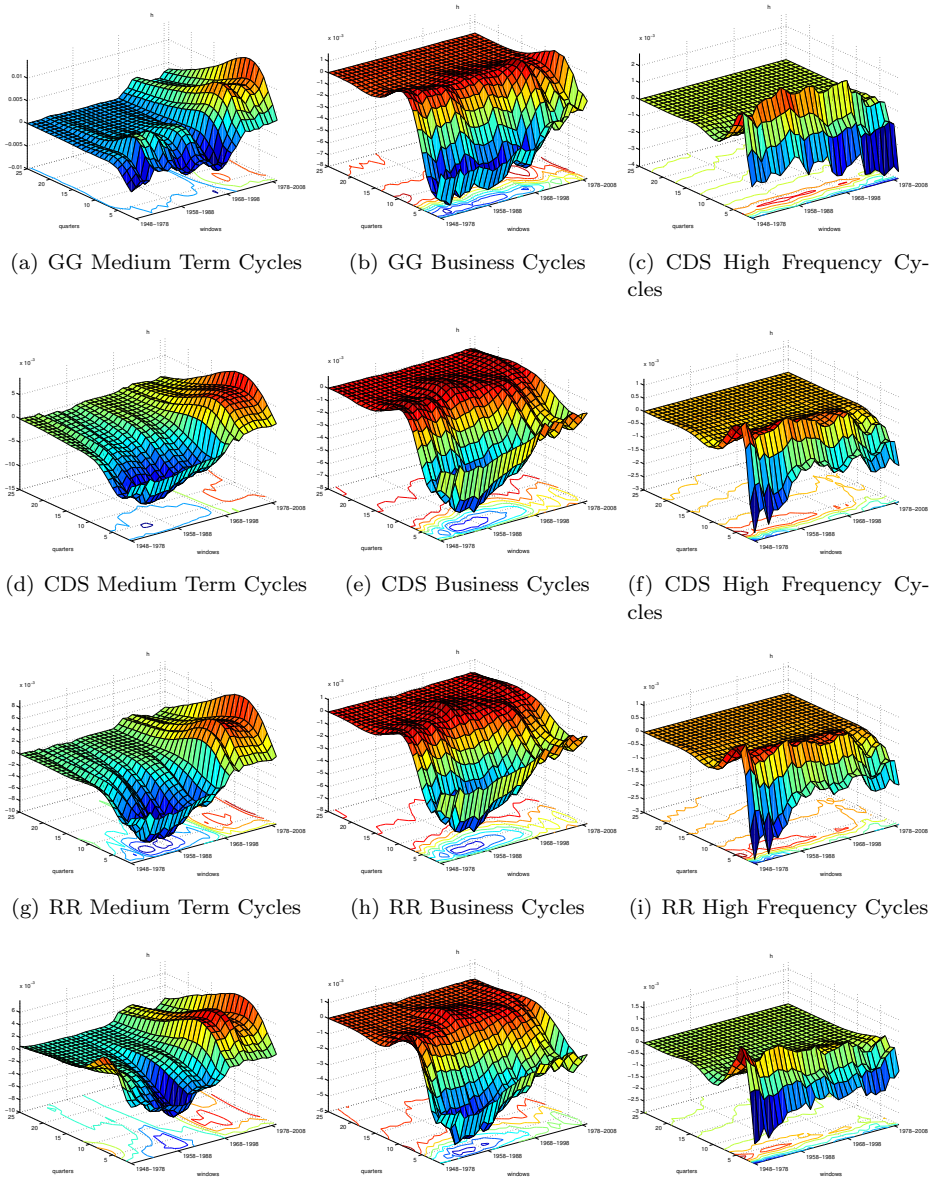


(a) 1948:Q2,1978:Q1 (b) 1958:Q2,1988:Q1 (c) 1968:Q2,1978:Q1 (d) 1979:Q2,2009:Q1

Figure 3.8: Selected subsamples.

QD hours), we obtain a very similar pattern of responses to those using raw hours in estimation. If we remove both long run and medium run fluctuations in hours worked (i.e. HP hours), while we still get an increasing pattern over time, the change in the response of hours is milder. If we remove long, medium run and part of the business cycles fluctuations, the time variation vanishes. This suggests an important finding, which is that the structural change in the response of hours worked is located mostly at medium run and partly at business cycles frequencies. Hence, any filter

emphasizing too much high frequency fluctuation is prone to wash out the time variations of the conditional correlations of hours.



(a) GG Medium Term Cycles (b) GG Business Cycles (c) CDS High Frequency Cycles

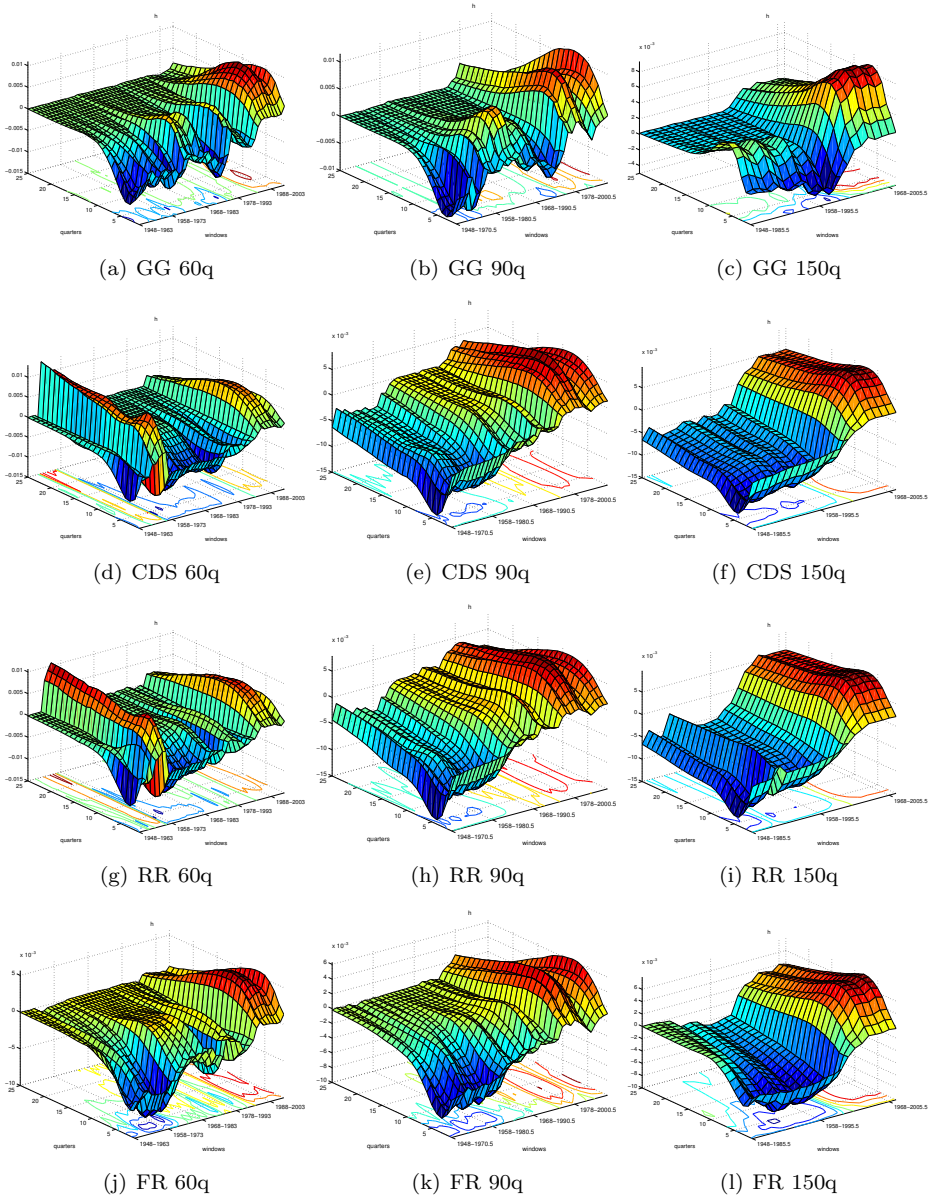
(d) CDS Medium Term Cycles (e) CDS Business Cycles (f) CDS High Frequency Cycles

(g) RR Medium Term Cycles (h) RR Business Cycles (i) RR High Frequency Cycles

(j) FR Medium Term Cycles (k) FR Business Cycles (l) FR High Frequency Cycles

Figure 3.9: Impulse Response of hours worked to a technology shock using different portions of fluctuations in hours worked. From top to bottom, GG, CDS, RR and FR database. From left to right QD, HP(1600) and FD hours worked.

Figure 3.10 reports the response of raw hours worked to a technology shock using different window sizes. The pictures show that the choice of the amplitude of the sample length does not affect dramatically our preferred empirical regularity. It is important to stress that smaller windows contain a larger share of high frequency components (noise) relative to the lower frequency one; this noise is typically absorbed by the parameters estimates. This, in turn, makes the time variation of the impulse responses not very smooth, more unstable and more prone to small sample bias.



(a) GG 60q (b) GG 90q (c) GG 150q

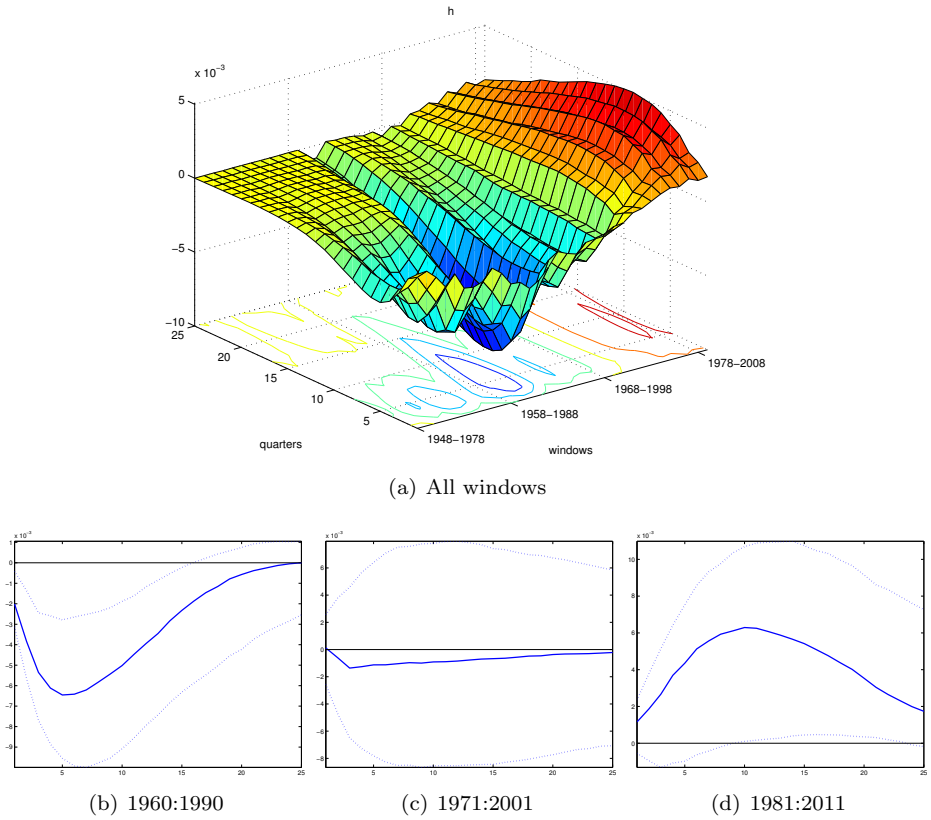
(d) CDS 60q (e) CDS 90q (f) CDS 150q

(g) RR 60q (h) RR 90q (i) RR 150q

(j) FR 60q (k) FR 90q (l) FR 150q

Figure 3.10: Impulse Response of hours worked to a technology shock using windows size (raw hours worked). From top to bottom, GG, CDS, RR and FR database.

The dynamic response of hours worked over time is not affected by the measure of technology process. To this aim, we replaced in the VAR the labor productivity with the utilization adjusted quarterly TFP growth proposed by Fernald (2014) and based on Basu, Fernald and Kimball (2006) as proxy for technology. Figure 3.11 displays the response of hours using the baseline specification of the paper (i.e. raw hours worked measured as in Francis and Ramey over rolling windows of 30 years) along with 3 selected subsamples with the bands. Figure 3.12 reports dynamic response of hours

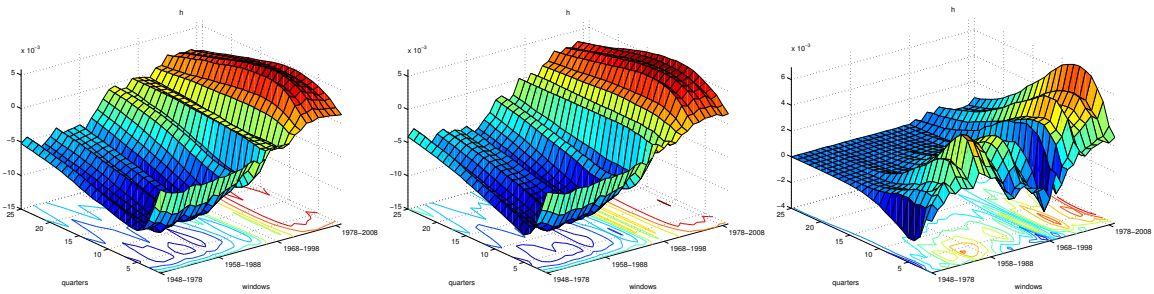


(a) All windows

(b) 1960:1990 (c) 1971:2001 (d) 1981:2011

Figure 3.11: Impulse Response of Hours worked to a technology shock with the utilization adjusted quarterly TFP. Upper panel all windows, bottom panels 68% confidence sets for selected subsamples.

worked over time using different proxies of hours worked.



(a) CDS (b) RR (c) GG

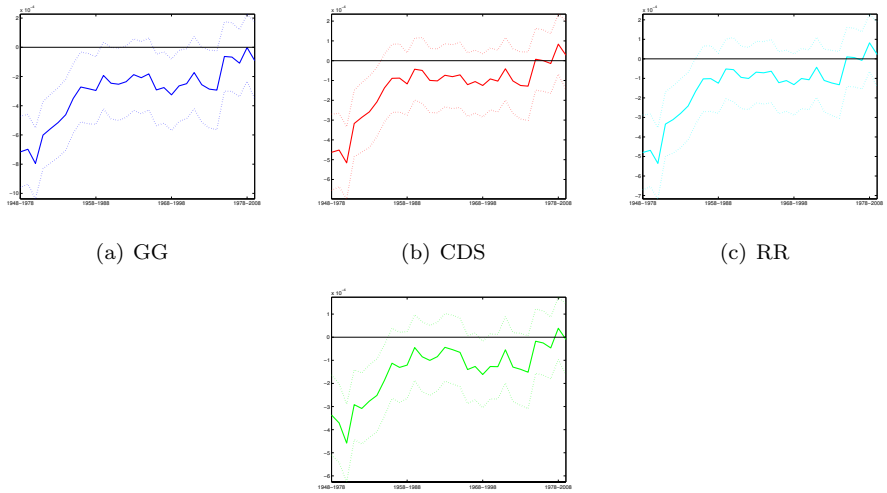
Figure 3.12: Impulse Response of Hours worked to a technology shock with the utilization adjusted quarterly TFP and different measures of hours.

4 A Complementary Empirical Analysis: Robustness

In this section we provide robustness of the results presented in section 2.2 of the paper to the alternative datasets. We consider the following specification

$$h_t = \alpha_0 + \alpha_1 t + \beta(L) h_t + \delta \, TFP_t + \epsilon_t$$

where $\beta(L)$ is a polynomial in the lag operator and TFP_t is a measure of utilization adjusted TFP growth proposed by Fernald (2014). We are interested on the estimates of δ over overlapping subsamples. Figure 4.1 reports the estimates of $\widehat{\delta}$ with the 68% confidence sets (dotted lines) across overlapping windows. Regardless of the number of instruments (number of lags), the estimated response of hours tend to increase over time, moving from negative to positive/zeros values.



(a) GG (b) CDS (c) RR

(d) FR

Figure 4.1: Estimates of $\widehat{\delta}$ with the 68% confidence sets (dotted lines) across overlapping windows. We assume one lag in estimation.

5 Estimates of the structural parameters of the RBC-CES model.

We consider a Real Business Cycles (RBC) model with Constant Elasticity of Substitution (CES) production function. The model description follows the one presented in the text of the paper.

The system of equilibrium condition is given by

$$
\begin{aligned}
V_t h_t^{\gamma} &= \frac{W_t}{C_t} \\
1 &= \beta E_t \left(\frac{C_t}{C_{t+1}} \left(r_{t+1} + 1 - \delta \right) \right) \\
Y_t &= y \left[\alpha \left(\frac{Z_t^k K_{t-1}}{k} \right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \left(\frac{Z_t^h h_t}{h} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\
W_t &= (1-\alpha) \left(Z_t^h \frac{y}{h} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{h_t} \right)^{\frac{1}{\sigma}} \\
r_t &= \alpha \left(Z_t^k \frac{y}{k} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{K_{t-1}} \right)^{\frac{1}{\sigma}} \\
K_t &= (1-\delta) K_{t-1} + I_t \\
Y_t &= C_t + I_t \\
z_t^h - z_{t-1}^h &= \rho_h (z_{t-1}^h - z_{t-2}^h) + \eta_t^h \\
z_t^k &= \rho_k z_{t-1}^k + \eta_t^k \\
v_t &= \rho_v v_{t-1} + \eta_t^v
\end{aligned}
$$

with $z_t^j = \ln Z_t^j$ and $v_t = \ln V_t$. In order to have a well defined steady state, we need to re-scale the real variables by the non stationary process. At the non stochastic steady state we have $h^{\gamma} = \frac{w}{c}$, $1 = \beta\,(r + 1 - \delta)$, $y = y$, $w = (1-\alpha)\frac{y}{h}$, $r = \alpha \frac{y}{k}$, $i = \delta k$, $y = c + i$. The log linearized equilibrium conditions, around the non-stochastic steady-state, of the variables rescaled by the non stationary process are (for simplicity, we indicate with small case letters the log deviation of a variable from its steady state)

$$
\begin{aligned}
y_t &= i/y \; i_t + c/y \; c_t \\
k_t &= (1-\delta)(k_{t-1} - z_t^h + z_{t-1}^h) + \delta i_t \\
y_t &= \alpha k_{t-1} + \alpha z_t^k + (1-\alpha) h_t - \alpha (z_t^h - z_{t-1}^h) \\
c_t &= E_t (c_{t+1} + (z_{t+1}^h - z_t^h) - \beta \; r \; r_{t+1}) \\
w_t &= v_t + \gamma h_t + c_t \\
w_t &= 1/\sigma (y_t - h_t) \\
r_t &= (\sigma - 1)/\sigma z_t^k + 1/\sigma (y_t - k_{t-1}) + 1/\sigma (z_t^h - z_{t-1}^h)
\end{aligned}
$$

Given our information set, the measurement equations are

$$\Delta p_t = y_t - y_{t-1} + (z_t^h - z_{t-1}^h) - (h_t - h_{t-1})$$
$$hobs_t = h_t$$

All the estimations are performed with Dynare version 4.1.3 (see Adjemian, Bastani, Karamï¿½, Juillard, Maih, Mihoubi, Perendia, Ratto and Villemot (2011)).

5.1 Identification of σ

This section verifies whether data can carry enough information to pin down σ in estimation.[3] We simulate 100 observations for hours and productivity assuming that $\alpha = 0.4$ and $\sigma = 0.2$ in one case (Case A) and that $\alpha = 0.4$ and $\sigma = 0.99$ in the other case (Case B). For the capital-labor elasticity of substitution, σ, we assume a uniform prior with 0 and 1.5 as boundaries. Posterior medians and credible sets are reported in Table 5.1. Data on productivity and hours worked appear informative

	true	Case A	Case B
α	0.40	0.39[0.31,0.47]	0.41 [0.35,0.48]
σ	0.20/0.99	0.27 [0.18,0.37]	1.13 [0.86,1.48]
γ	1.00	1.01 [0.85,1.18]	1.00 [0.85,1.15]
ρ_v	0.60	0.61 [0.43,0.77]	0.52 [0.42,0.62]
ρ_k	0.60	0.49 [0.34,0.63]	0.60 [0.36,0.83]
ρ_h	0.60	0.65 [0.56,0.75]	0.61 [0.46,0.76]
σ_v	0.01	0.0110 [0.0095,0.0125]	0.0093 [0.0064,0.012]
σ_k	0.01	0.0090 [0.0066,0.0102]	0.0108 [0.066,0.0149]
σ_h	0.01	0.0096 [0.0061,0.0128]	0.0094 [0.008,0.0108]
$corr(p_t, h_t)$	-0.15/0.15	-0.30 [-0.06,-0.49]	0.14 [-0.04,0.29]

Table 5.1: Prior and Posterior estimates with simulated data. Median and the credible sets in parenthesis.

about the parameters and shocks of interest. Typically, posterior credible sets include the parameter value used to simulate data. Even for σ, where we postulate a flat prior, the likelihood peaks very close to the true population value meaning that, if the model is correctly specified, we are able to pin down in estimation the parameters governing the CES production function.

5.2 Rolling windows estimation

We now analyze the behavior of the model when confronted with observed data on US productivity and hours worked. The solution of the RBC-CES model delivers time invariant policy functions

[3] The estimation of σ presents some econometric challenges, especially when combined with estimates of factor-augmenting technical change. See León-Ledesma, McAdam and Willman (2010).

and hence time invariant impulse response function. However, our empirical evidence suggests the existence of important time instabilities. Therefore, we wonder if the structural model is able to replicate such evidence if fitted to the same overlapping windows of the VAR. This leads us to compute a time-varying (non-parametric) posterior distribution of the parameters, θ. More precisely, let Y be set containing the entire sample information, $Y = \{y_1, ..., y_T\}$, and let Y_τ be subset containing the τ-th window information of width W, i.e. $Y_\tau = \{y_{n(\tau-1)+1}, ..., y_{n(\tau-1)+W}\}$ and n is the jump form one window to the following one. In our baseline settings we have $n = 4$ and $W = 120$. By estimating the structural model on overlapping windows we obtained a number of posterior distribution

$$p(\theta|Y_\tau) \propto f(Y_\tau|\theta)p(\theta)$$

for $\tau = 1, ..., (T - W)/n + 1$ where $f(Y_\tau|\theta)$ is the likelihood of the sample considered and $p(\theta)$ is the prior information of the parameters. Focusing on point estimates, we are interested in the $\tau = 1, .., 32$

$$\theta_\tau = E(\theta|Y_\tau) = \int \theta \; p(\theta \mid Y_\tau) \; d\theta$$

which gives us the time profile of the evolution of the estimates of θ.

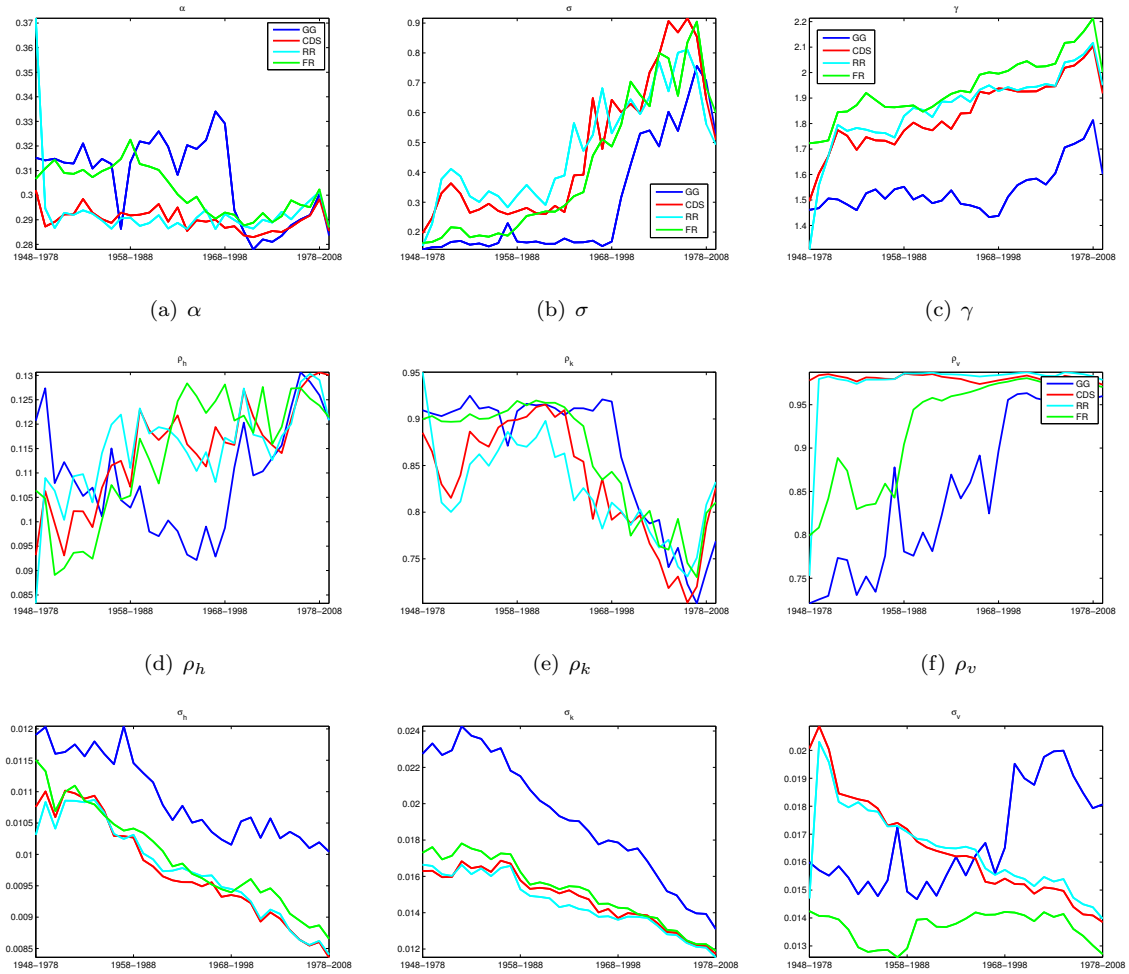
The choice of the priors is standard; beta distribution for the autoregressive parameters, inverse gamma for standard deviations and normals for α and γ, as it is customary in the literature. For σ we assumed a Gamma centered in in 0.5 with a relative loose prior, 0.5. We consider the measure of hours worked constructed by Francis and Ramey (2009) and consider the growth rate of productivity and hours worked in estimation. We estimate the model on rolling windows of fixed length, starting from the sample [1948Q2,1978Q1], and repeating the estimation moving the starting date by one year until [1979:Q2,2009:Q1]. In each subsample the growth rate of productivity and hours worked are demeaned. Table 5.2 reports prior and posteriors statistics for some selected subsamples.

Concerning the parameters of interest, the posterior mean of the degree of factor substitution is moves over the sample and suggests that the estimates of the elasticity of substitution has increased over time. The capital share is estimated around the standard value in the RBC literature, i.e. 0.30, and it is pretty stable over the sample period. This implies that, assuming no time-variation along the full sample, the point estimate of the correlation between hours worked and productivity is negative conditional on a labor augmenting technology shock in early samples and negative towards the end.

Similar conclusions apply if we study the estimated pattern of the structural parameters using different proxies of hours worked. Figure 5.1 reports the median estimates of the structural parameters and of standard deviations using the four datasets, GG, CDS, RR and FR.

	Prior			Posterior							
				1948-1978		1958-1988		1968-1998		1978-2008	
	Distr	mean	sd	mean	ci	mean	ci	mean	ci	mean	ci
α	Normal	0.3	0.05	0.307	[0.26,0.35]	0.322	[0.27,0.37]	0.293	[0.24,0.34]	0.287	[0.24,0.34]
γ	Normal	1	0.1	1.735	[1.35,2.11]	1.882	[1.52,2.23]	2.005	[1.65,2.35]	2.013	1.66,2.36]
σ	Gamma	0.5	0.5	0.193	[0.15,0.23]	0.237	[0.18,0.28]	0.596	[0.51,0.68]	0.700	[0.60,0.80]
ρ_h	Beta	0.5	0.2	0.115	[0.06,0.17]	0.115	[0.06,0.17]	0.141	[0.06,0.21]	0.136	[0.05,0.22]
ρ_k	Beta	0.5	0.14	0.890	[0.86,0.92]	0.911	[0.88,0.93]	0.809	[0.77,0.84]	0.776	[0.74,0.81]
ρ_v	Beta	0.5	0.14	0.770	[0.62,0.92]	0.863	[0.79,0.94]	0.974	[0.96,0.98]	0.970	[0.96,0.98]
σ_h	Igamma	0.05	4	0.012	[0.011,0.012]	0.011	[0.010,0.011]	0.009	[0.008,0.009]	0.008	[0.007,0.008]
σ_k	Igamma	0.05	4	0.018	[0.016,0.019]	0.016	[0.014,0.018]	0.015	[0.012,0.017]	0.013	[0.011,0.014]
σ_v	Igamma	0.05	4	0.015	[0.012,0.017]	0.013	[0.010,0.015]	0.014	[0.012,0.016]	0.013	[0.011,0.014]

Table 5.2: Prior and posterior statistics for some selected sub-sample. Igamma stands for the inverse gamma distribution, ci for 68% credible sets.



(a) α (b) σ (c) γ

(d) ρ_h (e) ρ_k (f) ρ_v

(g) σ_h (h) σ_k (i) σ_v

Figure 5.1: Median estimates of structural parameters over rolling windows for each dataset.

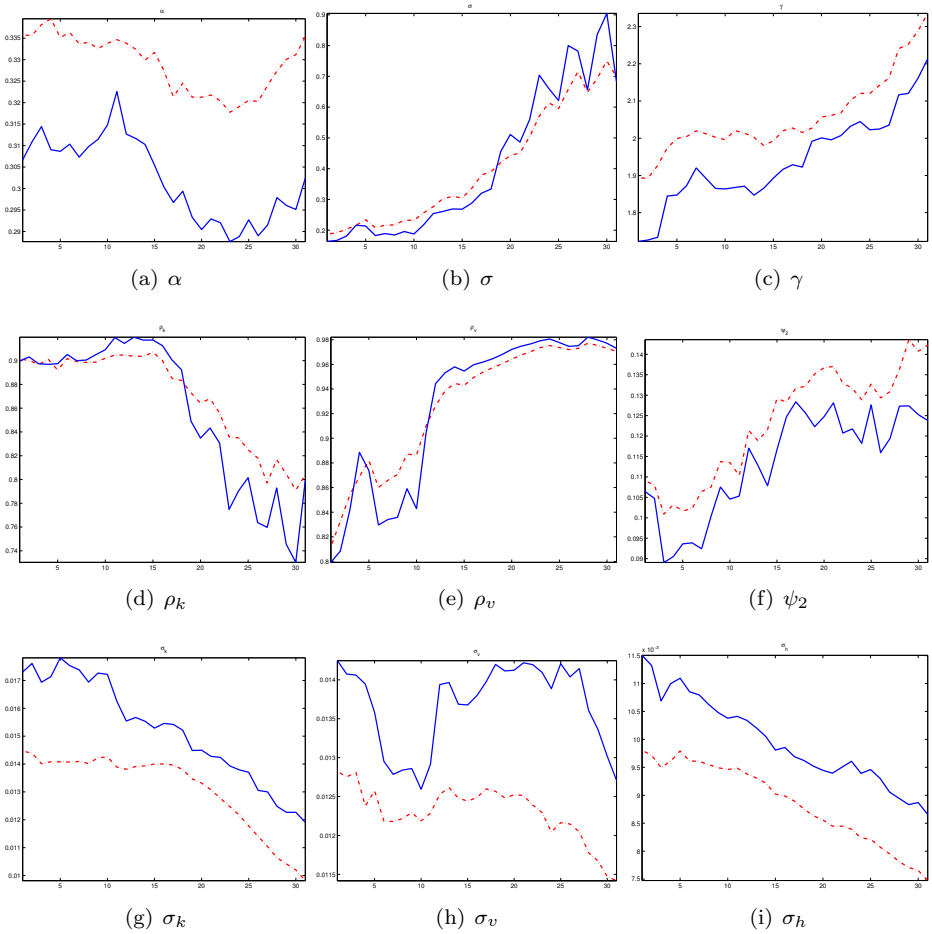
5.3 Rolling windows estimation with non uniform weighting scheme.

In the paper we argue that the large variation in the estimates of the elasticity is partly due to the uniform weighting scheme we impose on each window. Moreover, we claim that one way to smooth the estimates of σ is to downsize the impact of sub-sample endpoints. In the kernel estimation literature this is typically done by applying a bell-shaped weighting scheme on each bandwidth. In this section we try to convey this intuition and adopt this practice for our structural inference.

In the non-parametric estimation (i.e. kernel density estimation, kernel regressions or in the estimation of the sample spectrum), it is standard practice to use kernels, i.e. to assign non-uniform weights to the points belonging to a specific bandwidth and de-emphasize the importance of the beginning- and end-of-sample observations. Popular kernels are triangular, quadratic, Epanechnikov or normal. The use of kernels permits to estimate continuous and differentiable empirical density functions (as opposed to stepwise histograms), smooth sample spectrums or smooth time evolving linear regression parameters (as opposed to abrupt and noisy approximation) without specifying the parametric representation of the distribution function, of the spectral representation, or of the law of motion of the time variation in the parameters. We would like to bridge these ideas in our setup which shares with those setting the non-parametric evolution of the structural parameters. To this aim, we consider the following operator

$$\begin{aligned}
\theta_\tau^h &= E(\theta \mid K(Y_\tau)) = E(\theta \mid k_1\ y_{\tau_1}, ..., k_W\ y_{\tau_W}) = \\
&= \int \theta\ p(\theta \mid k_1\ y_{\tau_1}, ..., k_W\ y_{\tau_W})\ d\theta \\
&= \int \theta\ \left(\prod_{j=1}^{W} f(k_j\ y_{\tau_j} | \theta) \right) p(\theta)\ d\theta \\
\text{where}\ \ k_j &= \phi\left(\frac{2j - W}{2W}; 0, h \right) / \phi(0; 0, h)
\end{aligned}$$

and $\phi(x; \mu, \sigma)$ is the probability value of x of a normal distribution with mean μ and standard deviation σ. One can verify that if $h \to \infty$, then $k_j \to 1$ for all j and we are back to the uniform weighting scheme of the baseline exercise. h is a shrinking parameter that distribute the information content of the data; the smaller this value, the more we deemphasize the importance to the tails of the sample windows. We apply the same bell shaped weighting scheme to each window. We considered $h = 1.9$ which generates a distribution of weights that ranges from 0.57 to 1. In figure 5.2, we plot the median of the rolling windows parameter estimates in the baseline exercise and with the kernel function. We observe an upward increase in the σ estimates, however time variations are smoother and the range of the σ variation goes from 0.2 to 0.7. This smoothness in the estimated parameter is somehow reflected in the impulse response of hours over time, which turns out to be more unruffled. The smooth pattern is more evident for the VAR than for the RBC since the kernel



(a) α (b) σ (c) γ

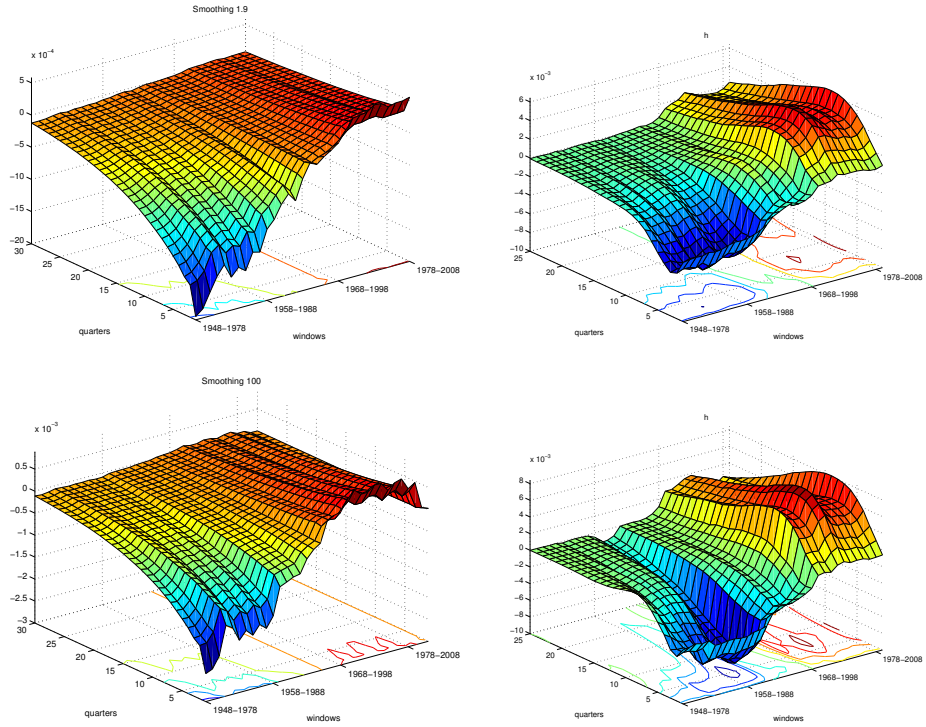
(d) ρ_k (e) ρ_v (f) ψ_2

(g) σ_k (h) σ_v (i) σ_h

Figure 5.2: Blue solid line baseline estimation, red dash dotted line kernel estimation with $h = 1.9$

weights impact directly in the reduced form coefficients in the latter and only indirectly through the structural parameter of the former.

However, as we argued in the paper we prefer to be agnostic and to give priority to the observables without imposing any ad hoc weighting scheme.

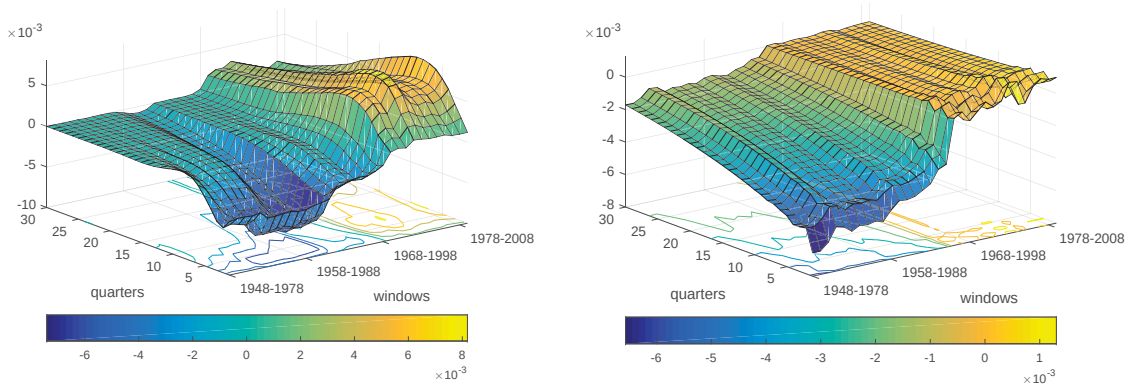


(c) RBC (d) SVAR

Figure 5.3: Bottom row line baseline estimation with RBC model (left) and SVAR (right). Top row line kernel estimation with $h = 1.9$ with the RBC model (left) and SVAR (right).

6 Can changes in capital-labor elasticity reproduce the SVAR evidence?

The time-varying relationship between hours and technology identified by a SVAR with long-run restrictions is similar to the one obtained from our RBC model with CES production function. However, Erceg, Guerrieri and Gust (2005) and Chari, Kehoe and McGrattan (2008), amongst others, express concerns about the ability of SVARs with long-run restrictions to identify model shocks. This may then cast doubts about whether comparisons of model-based and SVAR-based impulse-responses constitute a reliable way to evaluate our model. To address this issue, we simulate 50 sets of data of 120 observations from the RBC-CES model using the mean estimates in each window. With each simulated dataset we estimate a SVAR with 3 lags and compute the impulse response. We then compare the data-based SVAR with the SVAR with model-simulated data. Now even if we believed that the SVAR was unable to identify technology shocks, both models would be compared on the basis of the same (potentially misspecified) metric. Figure 6.1 reports the median



(a) SVAR actual data

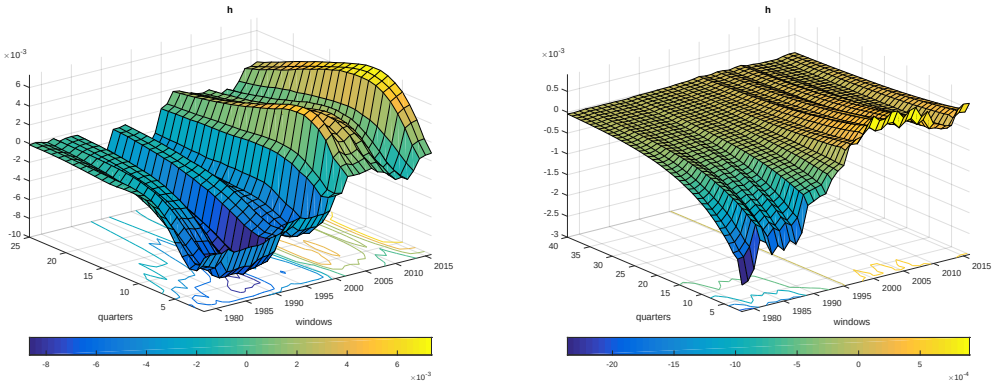
(b) SVAR simulated data

Figure 6.1: Impulse responses of hours to a positive labor augmenting technology shock.

impulse responses of hours for the SVAR (on the right panel) with simulated data, and those obtained by a SVAR with actual data. A visual inspection reveals that the instantaneous response of hours obtained with a SVAR on simulated data is similar to the one obtained with SVAR using actual data. Overall, we conclude that changes in the elasticity of capital-labor substitution are able to generate the observed time varying path of a SVAR with long-run restrictions. We note at this point that our model has two shocks that do not affect productivity in the long run. Hence, a standard bi-variate SVAR would be capturing both shocks under the "non-technology" label. It is in this sense that we believe that the response to the non-technology shock is not an appropriate metric to focus on because there is no one to one mapping between the theory and the SVAR shocks.

7 Estimation Robustness: Adding the Great Recession.

In this section we check if our results are robust if we extend the dataset to include the Great Recession years. We estimate both the SVAR and RBC model until the 2016Q4. The main take over from this extension is that the Great Recession temporarily blurred the correlation of hours and technology both in the VAR and in the RBC (figure 7.1). In particular it occurs in the following windows: 1981Q1-2010Q4 (33), 1982Q1-2011Q4 (34), 1983Q1-2012Q4 (35), 1984Q1-2013Q4 (36). In these windows, the response diminishes and becomes statistically non significant, see figure 7.3. These are the windows were the Great Recession years are at the end of the sample and create instability in the rolling windows estimations. Nevertheless the overall pattern of σ does not revert to early sample estimates as showed by the last 3 points estimates in figure 7.2.



(a) VAR (b) RBC

Figure 7.1: FR database, Response of hours worked to a technology shock.

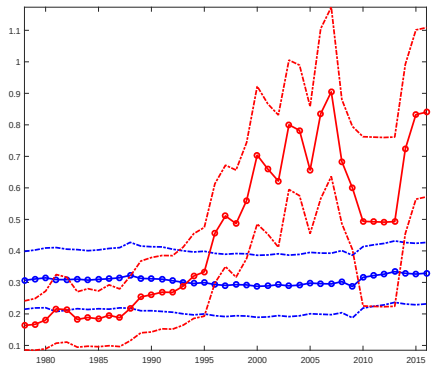
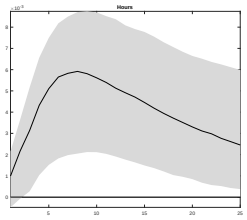
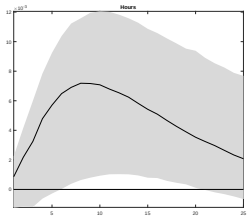


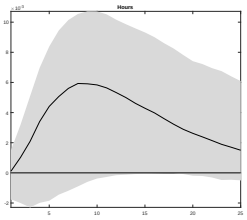
Figure 7.2: FR database, estimates of α (blue) and σ (red).



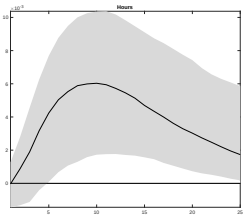
(a) 1979-2008



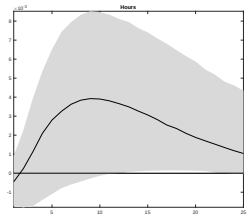
(b) 1980-2009



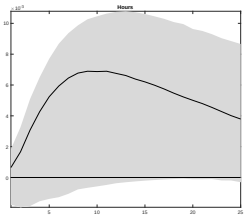
(c) 1981-2010



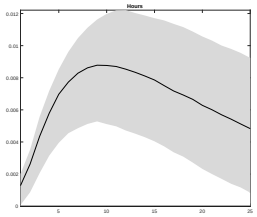
(d) 1982-2011



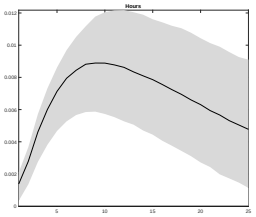
(e) 1983-2012



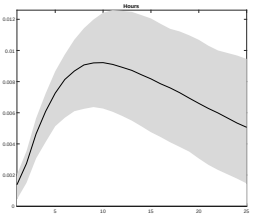
(f) 1984-2013



(g) 1985-2014



(h) 1986-2015



(i) 1987-2016

Figure 7.3: FR database, estimates of the response of hours to a technology shock in selected subsamples. Gray areas credible sets.

8 Competing Structural Interpretation I: the role of Monetary Policy.

We first provide a general discussion and concise results and, in the subsequent sections, details about model and estimations for the interested reader.

8.1 General results

Since the sign switch of hours roughly coincides with the onset of the 'Great Moderation' period, a popular view attributes time variations to the change of the Fed's monetary policy at the beginning of the 1980s.[4] In the 70s the monetary authority believed that there was an exploitable trade-off between inflation and output. Since output was low following the oil shocks of 70s, the temptation to inflate was strong. However, the option of keeping inflation temporarily high was unfeasible: in the medium run, inflation reached a higher level with output settling at its potential. Since the 1980s, the Fed learned that the output-inflation trade-off was not exploitable and concentrated on the objective of stabilizing inflation. A low inflation regime ensued and the better predictability of monetary policy made the macroeconomic environment less volatile, see Clarida, Galí and Gertler (2000).

Galí, López-Salido and Vallés (2003) argue that the change in monetary policy stance has contributed to shape not only the second moments of inflation and the output gap but moments of other variables, such as the correlation between hours and technology shocks. Their empirical evidence is restricted to two arbitrarily chosen subsamples and the structural interpretation is based on a calibrated New Keynesian model. While informative, their analysis lacks a formal statistical exercise to test whether data supports their conjecture. We therefore verify how our explanation of the observed changes in the response of hours to technology shocks, which hinges on changes in aggregate production technology, relates with their competing explanation based on the monetary policy regime switch. To this end, we ask the question: could our results driven by a change in monetary policy? To answer this question, we simulate data from the two models in Galí et al. (2003): a simple NK model without capital with either a Taylor-type rule (hours respond positively to a technology shock) or a constant money growth rule (hours responds negatively). The data are simulated using the same calibration values as in the original paper. We then use the two simulated datasets to estimate our RBC-CES model.[5] The key results of this exercise are reported in Table 8.1, and the full setup and results are reported in the sub-sections below. At first glance, it appears that our model interprets the variation in the correlation between hours and productivity (generated

[4] This points towards the importance of a detailed analysis of the timing of these changes.

[5] The only difference with the original set up in Galí et al. (2003) regards the introduction of a preference shock in their basic NK model. This is due to two reasons. First, the model is very stylized and has a linear production function, generating a perfect correlation between productivity and hours worked. Thus, the covariance matrix is singular, hence not invertible, therefore no likelihood-based estimation can be performed. Second, we also have a preference shock in our model and introducing it in the NK set-up of Galí et al. (2003) aids comparability.

	Taylor rule	Money rule
	Parameter Estimate	
α	0.51 (0.45, 0.56)	0.07 (0.07, 0.08)
σ	0.75 (0.68, 0.82)	0.008 (0.007,0.009)
ρ^h	0.45 (0.33, 0.57)	0.041 (0.01,0.07)
	Correlation of hours and productivity	
NK model	0.85	-0.78
	Standard Deviation of Hours	
NK model	0.24	1.20
RBC-CES model	0.73 ($\sigma = 0.60$)	0.50 ($\sigma = 0.30$)

Table 8.1: Statistics for simulated data. (95% CI in parenthesis)

by a monetary policy switch) as a variation in the relative estimates of the elasticity of substitution and of the capital share. This result could be interpreted in the sense that the two alternative explanations cannot be distinguished from data on productivity and hours. However, this is not entirely true and the observational equivalence of the two theoretical structures comes at some cost. First, the estimation exercise delivers implausible estimates of α, σ and ρ^h. For instance, α, which is to be interpreted as the capital share at the steady state normalization point, changes from almost 0.08 to 0.51. Similar caveats apply to other parameters. Moreover and most importantly, the change in monetary policy stance has very strong implications for the volatility of hours worked. In particular, a switch from a money-growth rule to a Taylor-type rule generates a very drastic decrease in the volatility of hours, see Table 8.1. However, our empirical evidence using different datasets does not detect this pattern.[6] By contrast, in a comparable calibration of our model, the standard deviation of hours when $\sigma = 0.3$ (roughly the average estimate in the first half sub-samples) is 0.5 and it increases to 0.73 if we set $\sigma = 0.6$ (roughly the average estimate in the second half sub-sample). Secondly, the estimates of α for both monetary rules and σ for the money growth rule are very far from theoretical priors.

These results are in line with the structural VAR exercise of Canova and Gambetti (2009) who find little support for the role of monetary policy changes in driving output and inflation dynamics and point towards the potential importance of changes in the behavior of the private sector. In accordance, Nucci and Riggi (2013), for instance, attribute changes in the response of hours to an increase in performance-related pay schemes during the 1980s. Their results explain a reduction in the negative response of hours to a technology shock and also the change in the reaction of productivity to a non-technology shock. However, their model cannot account for a *sign* switch

[6] These numbers do not change significantly, as shown below, if the simulated data are obtained without the preference shock as in the original paper.

in the response of hours to technology shocks. Furthermore, as explained before, changes in the responses to non-technology shocks cannot be mapped to specific model shocks and may capture in the best of cases a combination of shocks.

8.2 Model setup

Here we show the derivation of the Galí et al. (2003) model augmented with a preference shock. As discussed in the paper we add this exogenous demand shock for two reasons. First of all because the original model with a Taylor rule generates simulated data for productivity and hours which are perfectly correlated, as showed in table 8.2, and because of this cannot be used to estimate our original model. The second reason is that in our original model we also have a preference shock, hence we feel that this ensure more homogeneity across models. The rest of the model follows straight from Galí et al. (2003).[7]

The model is simple version of the Calvo (1983) model with staggered price setting.

They assume a continuum of firms, indexed by subscript $i \in [0, 1]$, each producing a differentiated good with a technology

$$Y_t(i) = A_t N_t(i), \tag{8.1}$$

where (log) productivity $a_t = log(A_t)$ follows the exogenous process:

$$\Delta a_t = \rho \Delta a_{t-1} + \epsilon_t^a \tag{8.2}$$

with $\rho \in [0, 1)$.

The representative household is infinitely lived and seeks to maximize

$$E_0 \Sigma_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - V_t \frac{N_t^{1+\varphi}}{1+\varphi} \right) \tag{8.3}$$

subject to a (standard) sequence of budget constraints and a solvency condition, and where $C_t = (\int_0^1 C_t(i)^{\frac{\varepsilon-1}{\varepsilon}} di)^{\frac{\varepsilon}{\varepsilon-1}}$ is a consumption index, N_t is hours worked and the (log) preference shock $v_t = log(V_t)$ follows an AR(1) process:

$$v_t = \rho_v v_{t-1} + \epsilon_t^v \tag{8.4}$$

with $\rho_v \in [0, 1)$.

The log-linearized Euler equation associated with the consumer's problem, combined with the market clearing condition $Y_t = C_t$, yields

[7] In what follows we borrow their description of the model here for completeness of exposition.

$$y_t = -\frac{1}{\sigma}(r_t - E_t\pi_{t+1} - rr) + E_t y_{t+1} \tag{8.5}$$

where y_t denotes (log) aggregate output, r_t is the nominal interest rate, π_{t+1} is the rate of inflation between t and t+1; and $rr = -log(\beta)$ represents the steady state real interest rate.

The labor market is perfectly competitive, with the labor supply schedule associated with the solution to the consumer's problem being given by

$$\frac{N_t^{\varphi}}{C_t^{-\sigma}} V_t = \frac{W_t}{P_t} \tag{8.6}$$

where W_t is the nominal wage and P_t the price level. Given the production function and the assumption of perfect competition in the labor market $\frac{W_t}{P_t} = A_t$ and recall that $C_t = Y_t = A_t N_t(i)$ hence from 8.6 they have:

$$N_t^{\varphi+\sigma} = \frac{A_t^{1-\sigma}}{V_t} \tag{8.7}$$

in logs

$$log(N_t) = n_t = \frac{1-\sigma}{\varphi+\sigma} a_t - \frac{v_t}{\varphi+\sigma} \tag{8.8}$$

and

$$w_t - p_t = \sigma c_t + \varphi n_t + v_t. \tag{8.9}$$

Hence, all firms face a common real marginal cost $mc_t = w_t - p_t - a_t$. Clearing of goods and labor markets implies

$$\begin{aligned} mc_t = w_t - p_t - a_t &= \sigma c_t + n_t\varphi + v_t - a_t \\ &= \sigma y_t + (y_t - a_t)\varphi + v_t - a_t \\ &= (\sigma+\varphi) y_t - (1+\varphi) a_t + v_t. \end{aligned} \tag{8.10}$$

Each firm faces an isoelastic demand for its product (generated by the solution to the consumer's problem), and takes the path of aggregate variables as given. If all firms adjust prices optimally each period (flexible prices), the price-marginal cost markup is common across firms, constant over time, and equal to $\frac{\varepsilon}{\varepsilon-1}$. Accordingly, $mc_t = -log(\frac{\varepsilon}{\varepsilon-1}) = mc$, for all t.

Now, the equilibrium processes for output, hours and the expected real rate, under flexible prices, are independent of monetary policy. The process for output can be derived by substituting in 8.10 actual with *natural* levels for y and mc:

$$y_t^* = \gamma + \psi a_t - \chi v_t \tag{8.11}$$

where $\gamma = \frac{mc}{\varphi+\sigma}$, $\psi = \frac{1+\varphi}{\varphi+\sigma}$ and $\chi = \frac{1}{\varphi+\sigma}$.

The natural level of hours follows from the production function

$$n_t^* = \gamma + (\psi - 1)a_t - \chi v_t. \tag{8.12}$$

Using 8.5 and 8.11 the natural real interest rate is

$$\begin{aligned} rr_t^* &= rr + \sigma\psi\Delta a_{t+1} - \sigma\chi\Delta t_{t+1} \\ rr_t^* &= rr + \sigma\psi\rho\Delta a_t - \sigma\chi\Delta t_{t+1}. \end{aligned} \tag{8.13}$$

If, on the other hand, firms can adjust prices only infrequently, the markup (and, hence, the real marginal cost) will no longer be constant. As a result a gap between actual output and its natural level may emerge. They denote that gap by $x_t = y_t - y_t^*$ and refer to it as the output gap. It follows from 8.10, together with the previous definition, that the output gap will be proportional to the deviation of real marginal cost from its frictionless level, i.e., its level under flexible prices. Formally they have $\hat{mc}_t = (\sigma + \varphi)x_t$, where $\hat{mc}_t = mc_t - mc$.

The exact form of the equation describing aggregate inflation dynamics depends on the way sticky prices are modelled. They follow Calvo (1983), and assume that each firm resets its price in any given period only with probability $1 - \theta$, independently of other firms and of the time elapsed since the last adjustment. Thus, each period a measure $1 - \theta$ of producers reset their prices, while a fraction θ keep their prices unchanged. In that case, the aggregation of optimal price-setting decisions can be shown to yield the familiar new Phillips curve:

$$\pi_t = \beta E_t \pi_{t+1} + k x_t, \tag{8.14}$$

where $k = (1 - \theta)(1 - \beta\theta)(\sigma + \varphi)/\theta$.

Finally, they can rewrite equilibrium condition 8.5 in terms of the output gap and the natural rate of interest:

$$x_t = -\frac{1}{\sigma}(r_t - E_t\pi_{t+1} - rr_t^*) + E_t x_{t+1}. \tag{8.15}$$

Equations 8.14 and 8.15, together with a specification of monetary policy (i.e., of how the interest rate is determined), describe the equilibrium dynamics of the model economy in the presence of exogenous variations in aggregate technology. At this stage they analyze the economy's response to such disturbances under alternative specifications of monetary policy.

8.2.1 Model with a Taylor rule

Suppose that the central bank follows the rule

$$r_t = rr + \phi_\pi \pi_t + \phi_x x_t \tag{8.16}$$

i.e., the nominal rate responds systematically to the contemporaneous values of inflation and the output gap. This is a version of the rule put forward by John Taylor as a good characterization of U.S. monetary policy.

Substituting 8.16 into the equilibrium conditions 8.14 and 8.15 they obtain a state space representation of the equilibrium dynamics that reduces to a 2x2 system with x_t and π_t as endogenous variables and a_t and v_t as exogenous processes.

8.2.2 Model with a constant money growth rule

Suppose instead that the monetary authority targets the rate of growth of the money supply. Formally,

$$m_t - m_{t-1} = \gamma_m = 0 \tag{8.17}$$

where m denotes the quantity of money in circulation, expressed in logs. The assumption of 0 growth of money is consistent with a 0 inflation steady state. The demand for money holdings is assumed to take a conventional form:

$$m_t - p_t = y_t - \eta r_t. \tag{8.18}$$

Letting $m_t^* = m_t - p_t - \gamma - \psi a_t + \chi v_t$ they can rewrite the money demand in terms of stationary variables only:

$$m_t^* = x_t - \eta r_t. \tag{8.19}$$

Furthermore, it follows from the definition of m_t^* and 8.17 that

$$m_{t-1}^* = m_t^* + \pi_t + \psi \Delta a_t + \chi(v_{t-1} - v_t). \tag{8.20}$$

The equilibrium conditions are now represented by a 3x2 system in x_t, π_t and m_t^* as endogenous variables and a_t and v_t as exogenous variables.

8.3 Calibration, theoretical IRFs, simulated data and RBC-CES estimation

We calibrate the model(s) using the same parameters value as in (Galí et al. 2003): $\phi_\pi = 1.5$, $\phi_x = 0$, $\sigma = \varphi = 1$, $\beta = 0.99$, $\theta = 0.75$, $\rho = \rho_v = 0.2$. The standard deviation of the shocks is assumed to be equal to 1%.

Table 8.2 shows the standard deviations and cross-correlations of the simulated variables if we only allow for the presence of the permanent technology shock and we shout down the preference shock (as they originally did in Galí et al. (2003)). Results clearly show how those data cannot be used for the estimation of our model given the perfect positive correlation between hours and productivity under the Taylor rule case.

moments	Δ Productivity	Hours (Taylor)	Hours (Money Growth)
STD	1.0446	0.1938	1.2228
corr(x, Δ pr)	1	1	-0.7921

Table 8.2: Statistics for simulated data, only technology shock.

Figures 8.1 to 8.3 reproduce the IRFs in Galí et al. (2003) for the permanent technology shock and, in addition, plot the responses of endogenous variables in the two model economies to a preference shock.

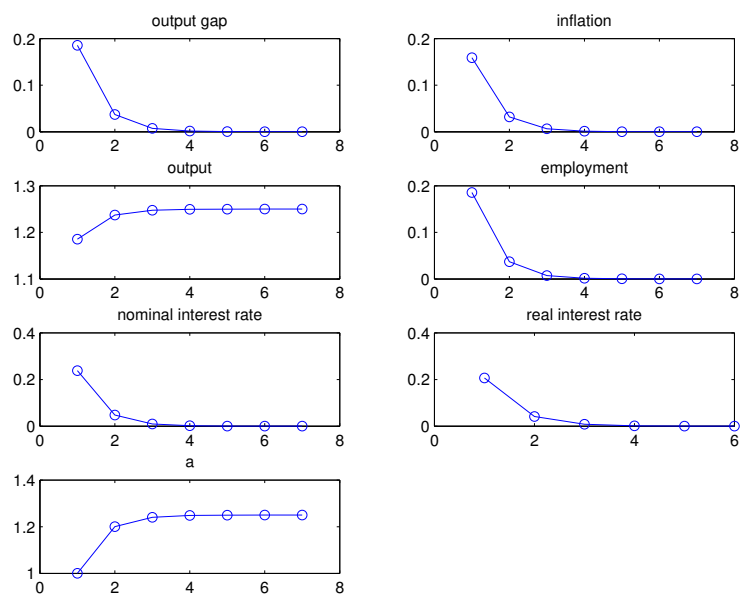


Figure 8.1: IRFs in the 'Taylor' economy to a technology shock

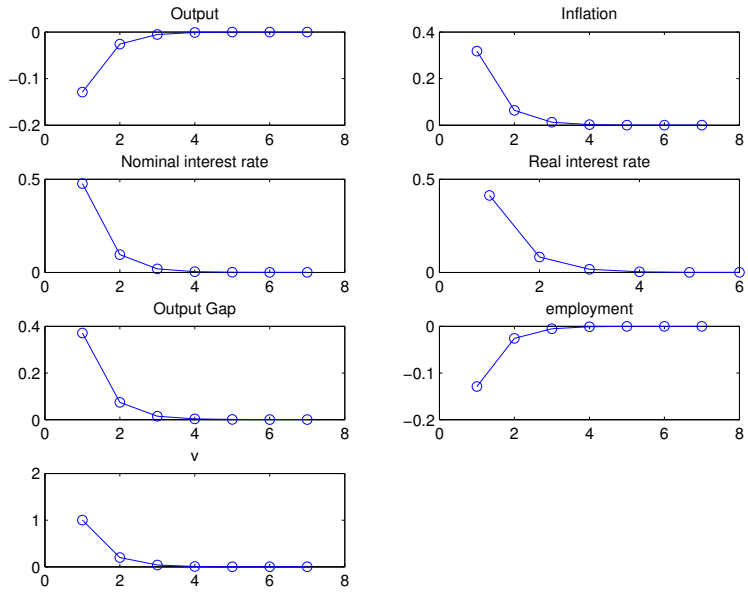


Figure 8.2: IRFs in the 'Taylor' economy to a preference shock

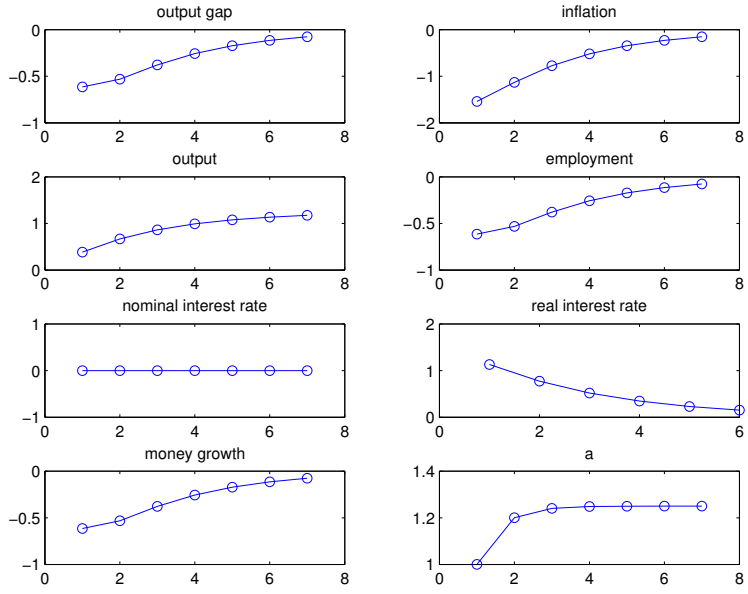


Figure 8.3: IRFs in the 'Constant Money Growth' economy to a technology shock

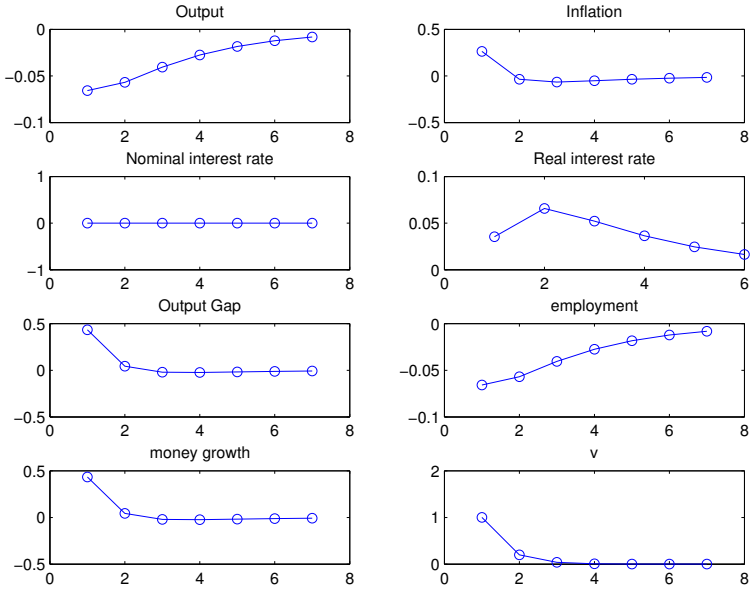


Figure 8.4: IRFs in the 'Constant Money Growth' economy to a preference shock

Figure 8.5 plots simulated data for productivity and hours from the two economies. We simulate 650 periods, we drop the first 500, and we retain the remaining 150 observations. Clearly the simulated productivity series is the same in the two economies.[8]

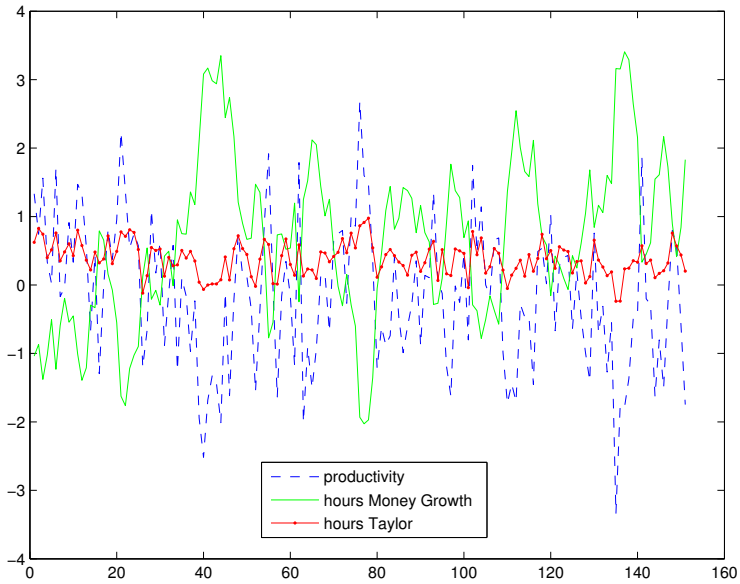


Figure 8.5: Simulated data

Table 8.3 presents the standard deviations and cross-correlations of the simulated variables. We can see how the economy where the monetary policy is conducted using a taylor rule produces data for hours which are far less volatile compared with the economy with a constant money growth rule. Cross correlations with the first difference of productivity mirrors the IRFs showed above.

moments	Δ Productivity	Hours (Taylor)	Hours (Money Growth)
STD	1.0446	0.2410	1.2026
corr(h, Δ pr)	1	0.8497	-0.7893

Table 8.3: Statistics for simulated data, technology and preference shock.

We now use the simulated data showed in the previous section to estimate our RBC model with a CES production function. We use the same priors as in the estimation with real data with the only difference that this time we do not estimate the inverse of the frisch elasticity as we experience convergence problems when we do so and because we have already showed with real and simulated data that with the information set used it is difficult to pin down this parameter. The results are obtained by running 2 MCMC chains of 150000 draws each, of which we drop 20% and we end up

[8]Starting with the same random seed.

with 120000 draws per chain.

As expected we can see that our model is matching the different correlation between the two observables in the two data sets by changing the threshold and the wedge between α and σ.

Parameter	Priors			Posteriors					
					Taylor			Money Growth	
	mean	std	distribution	mean	CI lb	CI ub	mean	CI lb	CI ub
α	0.3	0.05	normal	0.5097	0.4561	0.5624	0.0784	0.0754	0.0813
σ	0.5	0.4	gamma	0.7531	0.6877	0.822	0.0081	0.0075	0.0088
ρ_v	0.5	0.14	beta	0.4568	0.2445	0.687	0.506	0.2756	0.7427
ρ_k	0.5	0.14	beta	0.3344	0.1456	0.5626	0.6602	0.5377	0.8022
ρ_h	0.5	0.2	beta	0.4582	0.3361	0.5779	0.041	0.0046	0.0763
η^h	0.05	4	inv gamma	2.5927	2.1565	3.0422	1.0774	0.9718	1.1811
η^k	0.05	4	inv gamma	0.3417	0.0155	0.4896	0.0786	0.07	0.0944
η^v	0.05	4	inv gamma	0.0913	0.0131	0.2313	0.0848	0.0095	0.1938

Table 8.4: Estimation results

9 Competing Structural Interpretation II: the role of investment adjustment costs

In this section we want to verify if a variation in the degree of investment adjustment cost could generate positive and negative responses of hours worked.

Our investigation suggests that with large (small) enough investment adjustment costs it is possible to generate positive (negative) responses of hours to a technology shock on impact in a standard RBC model. However, regardless of the value of the adjustment costs, such model would be unable to generate fully negative dynamics of hours. It is then inconsistent with the observed evidence in the VAR, for which the response of hours appears persistently negative (positive) in early (late) samples.

9.1 RBC model with investment adjustment costs

We consider a Real Business Cycles (RBC) model with Constant Elasticity of Substitution (CES) production function and with investment adjustment costs. We model those cost so that

$$K_t = (1-\delta)K_{t-1} + (1 - s(X_t))I_t$$

where $s(1) = s'(1) = 0$ and $s''(1) \neq 0$ and $X_t = I_t/I_{t-1}$; K_t is capital and I_t is investment. The rest of the model follows the one presented in the text.

The system of equilibrium condition is given by

$$
\begin{aligned}
V_t h_t^{\gamma} &= \frac{W_t}{C_t} \\
1 &= q_t \left(1 - s(X_t) - s'(X_t)X_t\right) + \beta E_t \left(q_{t+1} \frac{C_t}{C_{t+1}} s'(X_{t+1}) X_{t+1}^2\right) \\
q_t &= E_t \beta \frac{C_t}{C_{t+1}} \left(r_{t+1} + q_{t+1}(1-\delta)\right) \\
Y_t &= y \left[\alpha \left(\frac{Z_t^k K_{t-1}}{k}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(\frac{Z_t^h h_t}{h}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
W_t &= (1-\alpha)\left(Z_t^h \frac{y}{h}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{h_t}\right)^{\frac{1}{\sigma}} \\
r_t &= \alpha \left(Z_t^k \frac{y}{k}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{K_{t-1}}\right)^{\frac{1}{\sigma}} \\
K_t &= (1-\delta)K_{t-1} + (1 - s(X_t))I_t \\
Y_t &= C_t + I_t \\
X_t &= I_t / I_{t-1}
\end{aligned}
$$

where q_t is Tobin q, or equivalently the ratio between the multipliers of the household constraints. Assuming $\psi_1 = 1$, Z_t^h is not stationary and the dynamics of the model are explosive. In order to have a well defined steady state, we need to re-scale the real variables by the non stationary process.

At the non stochastic steady state we have $h^{\gamma} = \frac{w}{c}$, $1 = q$, $1 = \beta\left(r + 1 - \delta\right)$, $y = y$, $w = (1-\alpha)\frac{y}{h}$, $r = \alpha \frac{y}{k}$, $i = \delta k$, $y = c + i$, $x = 1$. The log linearized equilibrium conditions, around the non-stochastic steady-state, of the variables rescaled by the non stationary process are (for simplicity, we indicate with small case letters the log deviation of a variable from its steady state)

$$y_t = i/y \; i_t + c/y \; c_t \tag{9.1}$$

$$k_t = (1-\delta)(k_{t-1} - z_t^h + z_{t-1}^h) + \delta i_t \tag{9.2}$$

$$y_t = \alpha k_{t-1} + \alpha z_t^k + (1-\alpha)h_t - \alpha(z_t^h - z_{t-1}^h) \tag{9.3}$$

$$q_t = c_t - c_{t+1} - z_{t+1}^h + z_t^h + \beta r r_{t+1} + \beta(1-\delta)q_{t+1} \tag{9.4}$$

$$q_t = s''(1)(x_t + (z_t^h - z_{t-1}^h)) - \beta s''(1)(x_{t+1} + (z_{t+1}^h - z_t^h)) \tag{9.5}$$

$$w_t = v_t + \gamma h_t + c_t \tag{9.6}$$

$$w_t = 1/\sigma(y_t - h_t) \tag{9.7}$$

$$r_t = (\sigma - 1)/\sigma z_t^k + 1/\sigma(y_t - k_{t-1}) + 1/\sigma(z_t^h - z_{t-1}^h) \tag{9.8}$$

$$x_t = i_t - i_{t-1} \tag{9.9}$$

By means of a sensible calibration exercise, we can study the impact of a labor augmenting technology shock on hours worked for different values of the elasticity of capital-labor substitution

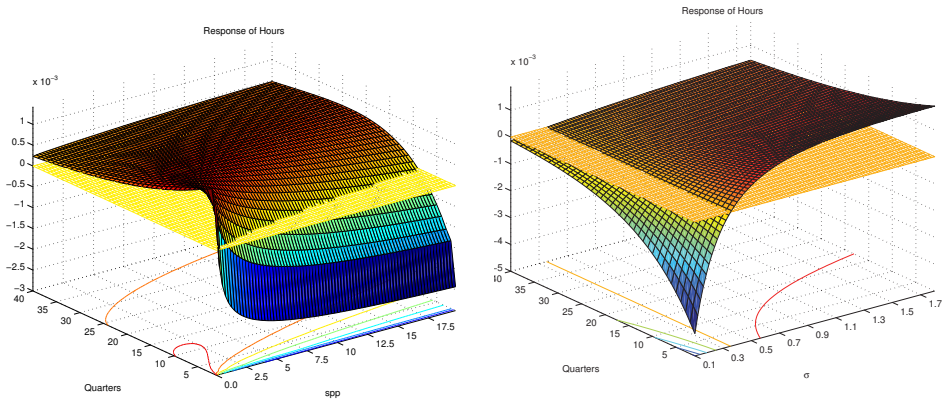


Figure 9.1: Impulse response of hours worked to a labor-augmenting technology shock for different values of s'' with $\sigma \to 1$ and $\alpha = 0.33$ (Left panel). Instantaneous response of hours worked to a labor-augmenting technology shock for different values of σ and $s'' = 2$ and $\alpha = 0.33$ (Right Panel).

and investment adjustment costs, the parameters of interest. Without loss of generality, we assume that the labor augmenting technology process is non stationary, i.e. $\psi_{1,h} = 1$. The rest of the parameters are calibrated as in the main body of the text. We considered first the case where the production function is Cobb-Douglas ($\sigma \to 1$) and the capital adjustment cost varies from 0 to 20 (Figure 9.1 left panel). We then fix the adjustment cost parameter to a value of 2 and vary σ between 0.1 and 2 (Figure 9.1 right panel). A few things are worth noting. First, there is a sign switch in the response of hours due to a change in investment adjustment cost. However, this change in sign occurs only on impact. Indeed, regardless of the value of the investment adjustment cost, the response of hours turns positive after few quarters. Hence, while investment adjustment costs are able to generate negative hours responses on impact, they are unable to produce a long-lasting negative response of hours worked to a technology shock.[9] Second, with positive adjustment costs the elasticity of substitution is the crucial parameter which generates a long lasting positive or negative response of hours. However, the threshold is no longer uniquely determined by value of α. Third, the support of σ able to generate positive and negative response of hours has opened.

10 Competing Structural Interpretation III: habit formation

In this section we want to verify if a variation in the degree of internal habit formation, with and without the presence of investment adjustment costs, could generate positive and negative response of hours worked.

This exercise is motivated by Rebei (2014) who estimates several competing small scale DSGE

[9] This result is insensitive to different calibration of the remaining structural parameters and also introducing endogenous persistence with habits in consumption. We obtain similar results for $\gamma = \{0.5, 1.0, 1.5, 2, 2.5, 3.0\}$ and for different parameterizations of the exogenous processes.

models that extend the basic RBC model and are able to reproduce the observed, over the full sample, negative response of hours following a positive technology shock. He hows that, over the full sample 1960:Q1-2008:Q4, an RBC model with habits in consumption and investment adjustment costs is the preferred model in terms of model posterior probabilities.

Our investigation suggests that the presence of habit formation alone can generate a sign switch in the response of hours to a TFP shock but in order to generate a negative response one needs an implausible value of the habit parameter (close to 1). When we allow for both habits in consumption and investment adjustment costs we show how the response of hours will turn always negative unless the value of both the investment adjustment costs and the habit parameter are very low. It is then clear that the presence of habit formation, Cobb-Douglas production, and investment adjustment costs as in Rebei (2014) is able to generate, for different combinations of the parameters of the model, a priori, both positive and negative responses of hours to technology shock. Even if the switch in the sign of the impulse response of interest happens for implausible values of habits and adjustment cost to investment, this model then constitutes a competing model to our proposed RBC-CES. We then proceed and estimate this model over rolling subsamples as we did for our RBC-CES model. The results however do not present any interesting time variation in the parameters of interest and in the impulse responses of hours. We can then conclude that an RBC model with investment adjustment costs and habits in consumption, while capable, in principle, to produce both positive and negative responses of hours to technology shocks, is not able to capture the time variation in the conditional correlation of hours and productivity observed in the data.

10.1 RBC model with habit formation and investment adjustment costs

We consider a variation of the Real Business Cycles (RBC) presented in section 9.1 with a Cobb-Douglas production instead of a CES and with internal habit formation. Follwing Rebei (2014) we assume a utility function $U = \left(log(C_t - \chi C_{t-1}) - V_t \frac{N_t^{1+\gamma}}{1+\gamma}\right)$ hence the first order condition of the household problem with respect to consumption becomes:

$$\lambda_t = \frac{1}{C_t - \chi C_{t-1}} - E_t \frac{\beta\chi}{C_{t+1} - \chi C_t}$$

where λ_t is the lagrange multiplier associated with the consumer budget constraint. The only other difference with respect to the model in 9.1 is the Cobb-Douglas production instead of a CES.

The log linearized equilibrium conditions, around the non-stochastic steady-state, of the variables rescaled by the non stationary process are (for simplicity, we indicate with small case letters the log

deviation of a variable from its steady state)

$$\lambda = \frac{1}{1-\beta\chi}(\frac{-1}{1-\chi}c_t + \frac{\chi}{1-\chi}(c_{t-1} + z_t^h - z_{t-1}^h)) - \frac{\beta\chi}{1-\beta\chi}(\frac{-1}{1-\chi}(c_{t+1} + z_{t+1}^h - z_t^h) + \frac{\chi}{1-\chi}c_t) \tag{10.1}$$

$$y_t = i/y\ i_t + c/y\ c_t \tag{10.2}$$

$$k_t = (1-\delta)(k_{t-1} - z_t^h + z_{t-1}^h) + \delta i_t \tag{10.3}$$

$$y_t = \alpha k_{t-1} + (1-\alpha)h_t - \alpha(z_t^h - z_{t-1}^h) \tag{10.4}$$

$$q_t = c_t - c_{t+1} - z_{t+1}^h + z_t^h + \beta r r_{t+1} + \beta(1-\delta)q_{t+1} \tag{10.5}$$

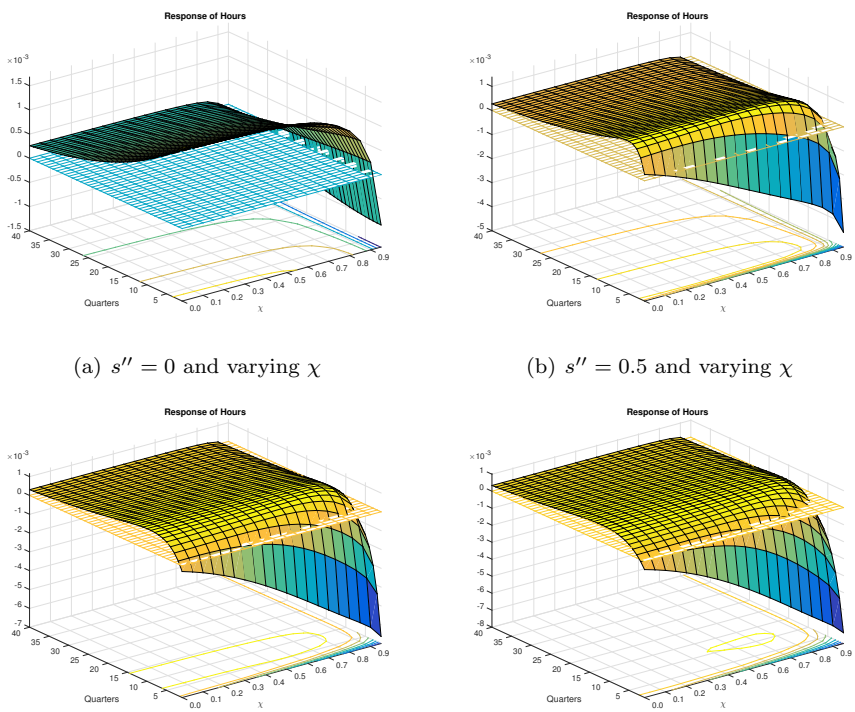
$$q_t = s''(1)(x_t + (z_t^h - z_{t-1}^h)) - \beta s''(1)(x_{t+1} + (z_{t+1}^h - z_t^h)) \tag{10.6}$$

$$w_t = v_t + \gamma h_t + c_t \tag{10.7}$$

$$w_t = y_t - h_t \tag{10.8}$$

$$r_t = y_t - k_{t-1} + z_t^h - z_{t-1}^h \tag{10.9}$$

$$x_t = i_t - i_{t-1} \tag{10.10}$$



(a) $s'' = 0$ and varying χ

(b) $s'' = 0.5$ and varying χ

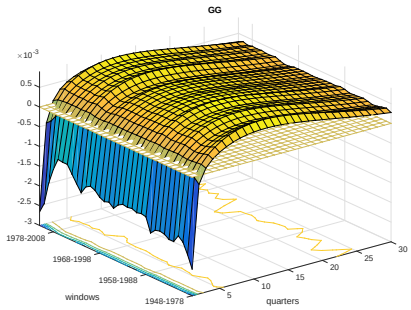
(c) $s'' = 2.5$ and varying χ

(d) $s'' = 5$ and varying χ

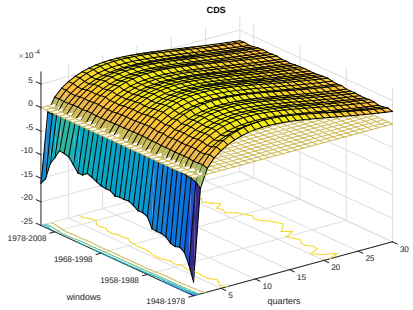
Figure 10.1: Impulse response of hours worked to a labor-augmenting technology shock for different values of χ and s''.

Panel (a) of figure 10.1 shows how the presence of habit formation alone can generate a sign switch in the response of hours to a TFP shock but in order to generate a negative response one needs a value of the habit parameter close to 1.[10] When we add investment adjustment costs together with habits (panels (b)-(d)) we show how the response of hours will turn always negative unless the value of both the investment adjustment costs and the habit parameter is very low. Also, as in the case with only investment adjustment costs, while the impact of the technology shock on hours is negative the IRF turns positive after few quarters unless the habit parameter is very close to unity. It is then clear that this model, for different combinations of the parameters of interest, is then able a priori to generate both positive and negative responses of hours to technology shock. We then proceed and estimate this model over rolling subsamples as we did for our RBC-CES model. We use the same priors as in our baseline model for common parameters and we use a beta distribution centered around 0.5 with 0.2 standard deviation for χ and a normal distribution centered around 5 with 0.5 standard deviation for s''. Figure 10.2 shows the results using the four different datasets used to estimate our baseline model and figure 10.3 shows the evolution of the parameters. It is clear how the results do not present any interesting time variation in the parameters of interest and in the impulse responses of hours. The adjustment costs parameter is estimated consistently around 4.9 in all windows/datasets while the habit parameter shows a bit more variation, especially at the end of the sample. Its estimate varies between 0.15 and 0.4 and, if anything, moves in the direction of a more negative response towards the end of the sample. Hence the estimated impulse responses of hours to technology shocks in this model do not seem to change much over time and clearly do not resemble the ones estimated in our rolling SVAR. We can then conclude that an RBC model with investment adjustment costs and habit in consumption is not able to capture the time variation in the conditional correlation of hours and productivity observed in the data.

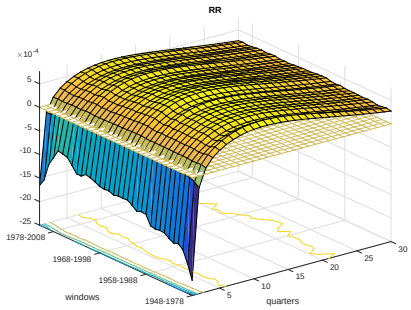
[10] Rebei (2014) estimate a value around 0.99 but most of the literature estimate it around 0.7. Christiano, Eichenbaum and Evans (2005) find a value of 0.63 while Smets and Wouters (2007) find a value of 0.71.



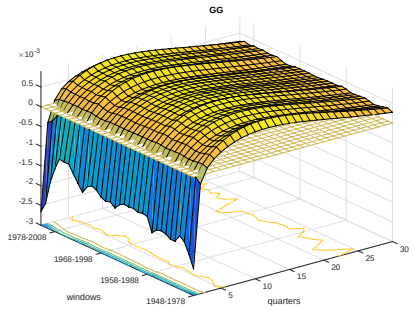
(a) GG data



(b) CDS data

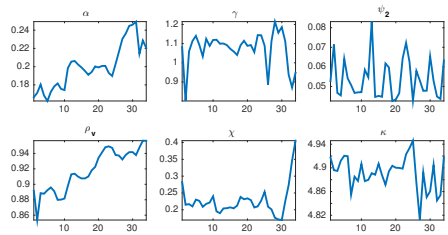


(c) RR data

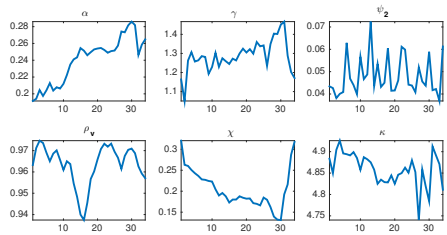


(d) FR data

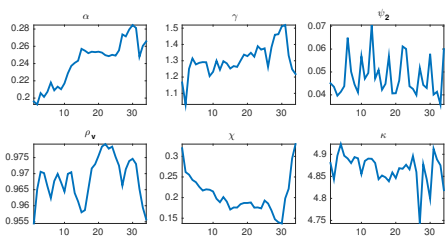
Figure 10.2: Rolling window estimation of the impulse response of hours to a positive technology shock in the model with habits, Cobb-Douglas and investment adjustment costs.



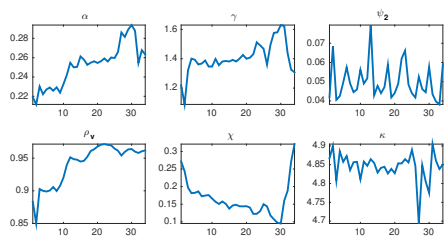
(a) GG data



(b) CDS data



(c) RR data



(d) FR data

Figure 10.3: Rolling window estimation of key parameters of the model for different datasets.

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