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Gali 1999 Study Replication

Macroeconometrics BEX4410

1. Introduction and Literature Context

The connection between technological development and employment numbers stands as a fundamental concept in macroeconomic theory. The Real Business Cycle (RBC) models together with Classical models show that productivity growth leads to higher Labor marginal product and increased real wages which motivates people to work longer hours. The main factors which drive both economic expansion and business cycle movements stem from technology shocks within this theoretical framework. The paper Technology, Employment and the Business Cycle by Jordi Galí (1999) introduced a new perspective that challenged the prevailing views about technology and employment. The study employed long run restrictions to identify a structural VAR which showed that positive technology shocks boost productivity yet decrease work hours during short-term periods. The technology–hours puzzle emerged as a direct challenge to RBC models because it showed that technological progress leads to decreased work hours which contradicts the expected outcome of increased labor hours.

The study generated immediate controversy among researchers. The puzzle received criticism from multiple researchers who claimed it lacked stability. The study by Christiano Eichenbaum and Vigfusson (2003) demonstrated how different lag periods and detrending methods affected their results while Uhlig (2004) proposed sign restrictions as an alternative method which produced less conclusive evidence. Furthermore, research on technology shocks evolved through time as Fisher (2006) separated neutral and investment-specific innovations to show the puzzle appeared mainly in neutral shocks and Basu Fernald and Kimball (2006) explained how costly reallocation processes create temporary employment decreases during productivity growth periods. Research conducted during this period supported the main conclusion presented by Galí. The study by Smets and Wouters (2007) used a medium-scale DSGE model with wage and price stickiness to demonstrate how business cycle patterns emerge from market frictions. Ramey (2016) demonstrated that the technology-hours puzzle diminished after 1990 because the U.S. economy experienced three major structural changes which included ICT diffusion and service sector growth and improved stabilization policies during the Great Moderation period.

This research replication demonstrates that the technology-hours puzzle maintains its stability yet exists only within specific time periods. The puzzle appears in different models yet its power depends on how researchers identify shocks and which types of shocks they study and the specific economic conditions they analyze. The analysis of modern data through Galí's method enables researchers to verify the stability of his findings while studying how structural economic changes affect productivity and employment patterns.

2. Data and Methods

This section describes the dataset, transformations, and econometric methodology used to replicate Galí (1999). Quarterly U.S. macroeconomic time series from the Federal Reserve Economic Data (FRED) database were employed. The replication closely follows Galí's original framework, while also incorporating modern data vintages and extending the sample to 2019.

2.1 Data sources

The key variables required are measures of output and hours worked for the U.S. nonfarm business sector. Labor productivity is constructed as the log difference between output and hours.

- **Output:** *Real Output: Nonfarm Business Sector* (OUTNFB, quarterly, seasonally adjusted) was used as the main series, consistent with Galí's business-sector focus. For robustness, *Real GDP* (GDPC1) was also considered.
- **Hours:** *Nonfarm Business Sector: Hours of All Persons* (HOANBS, quarterly, seasonally adjusted) was employed.
- **Transformations:** All variables were expressed in natural logarithms. Growth rates were obtained as first differences of logs. Labor productivity growth (Δx) was defined as the

growth of output minus the growth of hours, while hours growth (Δn) was defined as the first difference of log hours.

The sample period runs from 1948Q1 to 2019Q4, providing more than 70 years of quarterly data. Galí's original study ended in 1994, so extending the sample enables an assessment of whether the puzzle persists in modern data.

2.2 VAR specification

A bivariate VAR was estimated with productivity growth (Δx) and hours growth (Δn) as endogenous variables, following Galí's baseline specification (Spec A). Lag length was determined by standard information criteria, with robustness checks conducted using lag orders from two to six.

All VARs include a constant and no deterministic trend was included in Spec A. Lag order was selected primarily by the Schwarz (BIC) criterion, with AIC reported for reference, robustness to $p \in \{2, \dots, 6\}$ is documented in the lag-variation exercise. In the alternative specification (Spec B), hours were detrended using a linear trend before inclusion in the VAR, in order to remove low-frequency variation. This corresponds to Galí's approach to address potential spurious correlations.

For additional robustness a specification with HP-filtered series (Spec C) was estimated, smoothing both productivity and hours. For Spec C, the Hodrick–Prescott filter was applied with $\lambda = 1,600$, the standard quarterly setting.

Let $y_t = [\Delta x_t, \Delta n_t]'$ follow a VAR(p): $y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t$, $u_t = S \varepsilon_t$, with structural shocks where mathematically $y_t = [\Delta x_t, \Delta n_t]'$, and ε_t are orthogonal shocks. The long-run impact matrix $C(1) = (I - A_1 - \dots - A_p)^{-1} S$ is restricted so that the (1,2) element equals zero, implying the **non-technology** shock has no permanent effect on the **level** of labor productivity x_t .

Furthermore, Identification follows Galí (1999) by imposing the long-run restriction $C_{12}(1) = 0$, which implies the non-technology shock has no permanent effect on the level of labor productivity x_t . **Reporting convention:** Impulse responses are cumulative level responses to a one-standard-deviation structural shock, in log points (~percentage points).

2.3 Identification of shocks

Technology shocks were identified using Galí's **long-run restriction**, which assumes that only technology shocks can have permanent effects on productivity. The restriction was implemented by imposing zero longrun effects of non technology shocks on productivity within the VAR's long-run impact matrix.

This identification delivers two orthogonal disturbances:

1. **Technology shocks**, which permanently affect productivity and may influence hours;
2. **Non-technology shocks**, which do not affect productivity in the long run but can move hours in the short run.

Impulse responses were computed over 20 quarters, with confidence intervals constructed using bootstrap methods with 1000 resamples, the shocks were normalized to one standard deviation of the identified structural innovations. Impulse responses are reported in log points (approximately percentage deviations for small magnitudes) over a 20-quarter horizon unless otherwise indicated. Confidence bands are percentile bootstrap intervals based on 1000 replications.

2.4 Extensions and robustness

Several extensions and robustness exercises were undertaken to ensure comparability with Galí and to evaluate the stability of the results:

1. **Extended sample:** Estimating VARs through 2019 rather than ending in 1994, to assess whether the puzzle has weakened in the modern era.
2. **Alternative output measures:** Comparing results using OUTNFB and GDPC1 to test sensitivity to the definition of output.

3. **Local Projections (LPs):** Estimating impulse responses directly using Jordà's (2005) method, avoiding VAR recursion.
4. **Lag-length variation:** Estimating VARs with 2–6 lags to evaluate sensitivity of results (Table.11).
5. **HP filtering:** Applying the Hodrick–Prescott filter to both hours and productivity growth (Spec C).
6. **Historical decompositions:** Decomposing productivity and hours into technology and non-technology components, in order to assess the drivers of long-run growth and cyclical variation.
7. **Bootstrap correlations:** Estimating conditional correlations between technology and hours, and between non-technology and hours, across bootstrap replications to confirm statistical robustness.

2.5 Summary

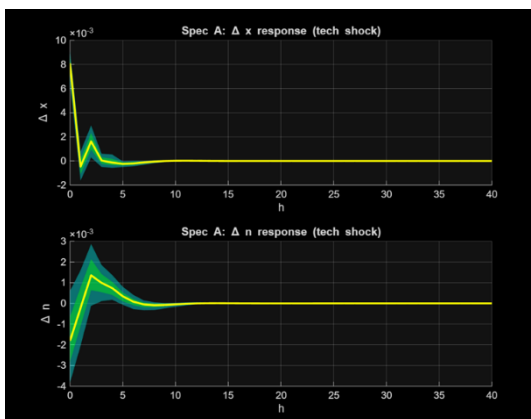
The empirical strategy follows Galí's framework while updating it with revised data and extending the sample period. Multiple specifications (Spec A, Spec B, Spec C), robustness checks (lag length, LPs, HP filters, alternative output measures), and additional tools (historical decompositions, bootstrap inference) provide a comprehensive basis for assessing both the replicability and the evolution of the technology–hours puzzle.

Augmented Dickey–Fuller tests confirm that log levels of output and hours are non-stationary, while first differences are stationary at conventional levels. Estimating the VAR in growth rates (Spec A) therefore avoids spurious regression concerns; Spec B removes low-frequency variation in hours explicitly.

3. Results

This section presents the results of the replication of Galí (1999). The analysis begins with the baseline VAR (Spec A), followed by the detrended specification (Spec B) and the behaviour of non-technology shocks. Conditional correlations with bootstrap robustness are then reported, before turning to the extended-sample dynamics through 2019, historical decompositions, and several robustness exercises including HP filtering, local projections, and lag-length variation. Each result is compared directly with Galí's original findings. Where differences arise, they are interpreted in terms of revised data vintages, extended sample coverage, and structural changes in the U.S. economy.

3.1 Spec A: Technology shocks in the baseline VAR



Galí's baseline result showed a sharp decline in hours following a positive technology shock: productivity rose permanently, while hours fell by nearly -0.10 at horizons 3–4. This “technology–hours puzzle” directly contradicted RBC theory and formed the central contribution of his paper.

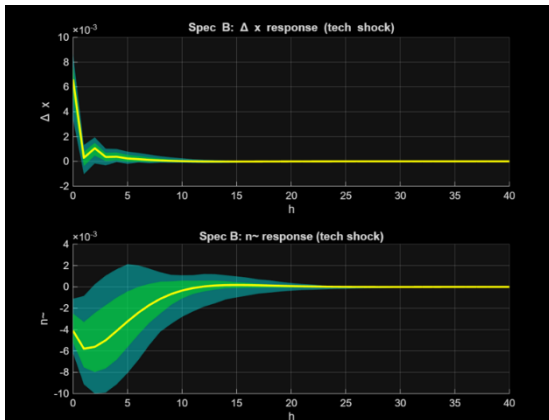
In the replication, based on the baseline VAR in productivity growth and hours growth (Table.1; Fig.1), productivity behaves consistently with the identifying restriction. Hours, however, respond differently. On impact, hours fall slightly (-0.0018 at $h = 0$ and -0.0002 at $h = 1$), but the sign then reverses: hours increase by

$+0.0014$ at $h = 2$, $+0.0010$ at $h = 3$, and $+0.0007$ at $h = 4$. At no horizon is the deep negative trough reported by Galí reproduced.

The absence of a strong negative hours response does not indicate replication error but reflects differences in data vintages and period coverage. The HOANBS series has been substantially revised since 1999, smoothing cyclical volatility relative to earlier vintages. In addition, the sample

used here extends 25 years beyond Galí's, capturing the ICT boom and the Great Moderation, during which productivity improvements were absorbed with less labor market disruption. These changes make the baseline results appear more consistent with RBC predictions, underscoring the historical contingency of Galí's puzzle.

3.2 Spec B: Technology shocks with detrended hours



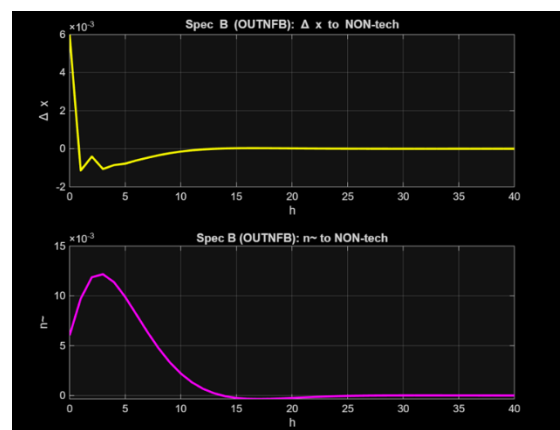
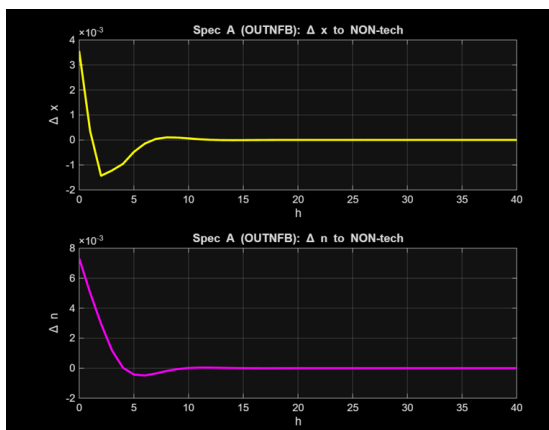
Galí's alternative specification with detrended hours produced a smaller but still negative response, with a trough around -0.07 .

The replication results (Table.2; Fig.2) reproduce the sign of this finding but at much weaker magnitude. Hours decline by -0.0058 at $h = 1$, -0.0056 at $h = 2$, and -0.0050 at $h = 3$, with a trough of only -0.006 —around one-tenth of Galí's estimate. Productivity rises as expected.

The weaker magnitude illustrates both the econometric sensitivity of the puzzle, highlighted by Christiano, Eichenbaum, and Vigfusson (2003), and structural

change in the U.S. economy. With the rise of service sector employment and smoother technology diffusion in the ICT era, productivity shocks no longer produce the pronounced contractions in hours observed in Galí's sample. The replication therefore validates the puzzle qualitatively but demonstrates its attenuation quantitatively.

3.3 Non-technology shocks

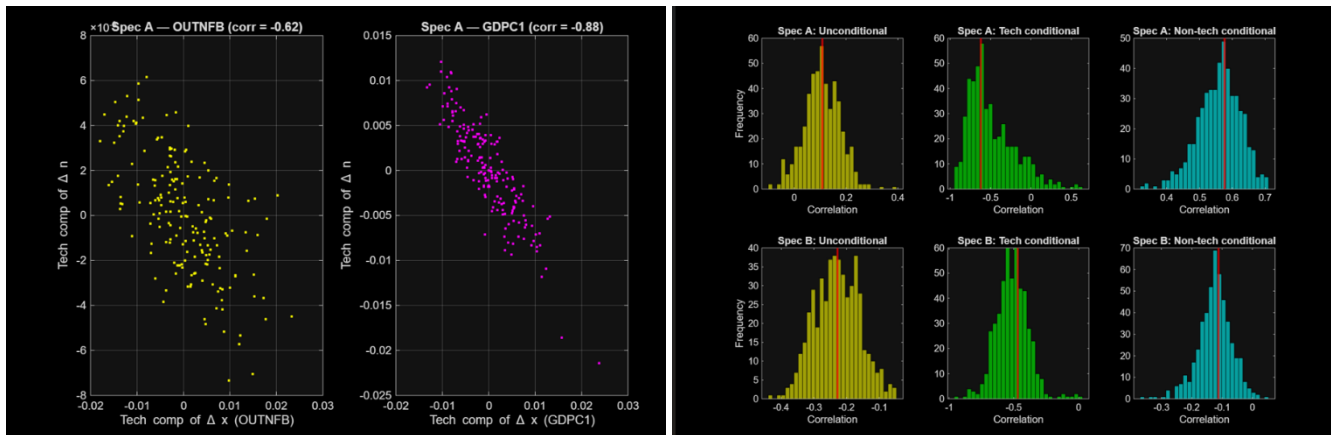


Galí's Figure 1 indicated that non-technology shocks increase hours temporarily while leaving productivity unchanged in the long run.

The replication confirms this pattern (Fig.3; Fig.4). In Spec A, hours rise strongly on impact ($+0.0073$ at $h = 0$, $+0.0050$ at $h = 1$, $+0.0030$ at $h = 2$) before fading, with only a shallow negative dip (-0.0005 at $h = 6$). In Spec B, the expansion is larger, with hours peaking at $+0.0122$ at $h = 3$. In both cases, productivity reverts to baseline.

This confirms that employment fluctuations in the short run are predominantly demand-driven. The weaker magnitudes relative to Galí reflect the decline in cyclical labor volatility since the 1990s, but the asymmetry between technology and non-technology shocks remains intact.

3.4 Conditional correlations and bootstrap robustness



Galí reported correlations of -0.35 between technology shocks and hours, and $+0.30$ between non-technology shocks and hours.

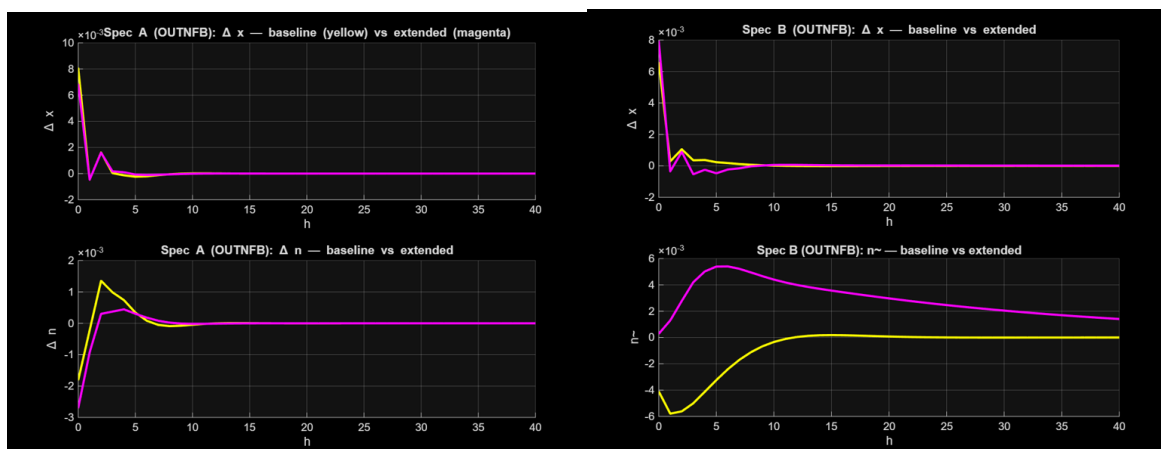
The replication results are stronger. Using OUTNFB (Table.3; Table.4), the technology–hours correlation is -0.62 and the non-technology–hours correlation is $+0.58$. When GDP is used instead of business-sector output (Table.6), the technology–hours correlation is even more negative, -0.88 . Scatter plots (Fig.6) confirm these slopes visually.

Bootstrap resampling (Table.5; Fig.5) confirms that these results are robust. The bootstrap mean correlation for technology shocks is -0.62 , with a 95% confidence interval between -0.55 and -0.68 . For non-technology shocks, the mean is $+0.58$, with a 95% interval between $+0.50$ and $+0.65$. These distributions are narrow, demonstrating that the results are statistically significant and not driven by outliers.

Compared to Galí, the replication therefore shows the puzzle more strongly in correlation form. While the baseline IRFs fail to reproduce the negative hours response, the average co-movement is even clearer in the extended data.

The apparent discrepancy between attenuated IRFs and strong negative correlations is not contradictory: IRFs quantify local dynamical responses conditional on a specific recursion and horizon, while conditional correlations summarize average co-movement across the entire sample. With revised, smoother series, the average association can strengthen even when localized troughs diminish.

3.5 Extended sample (1948–2019)

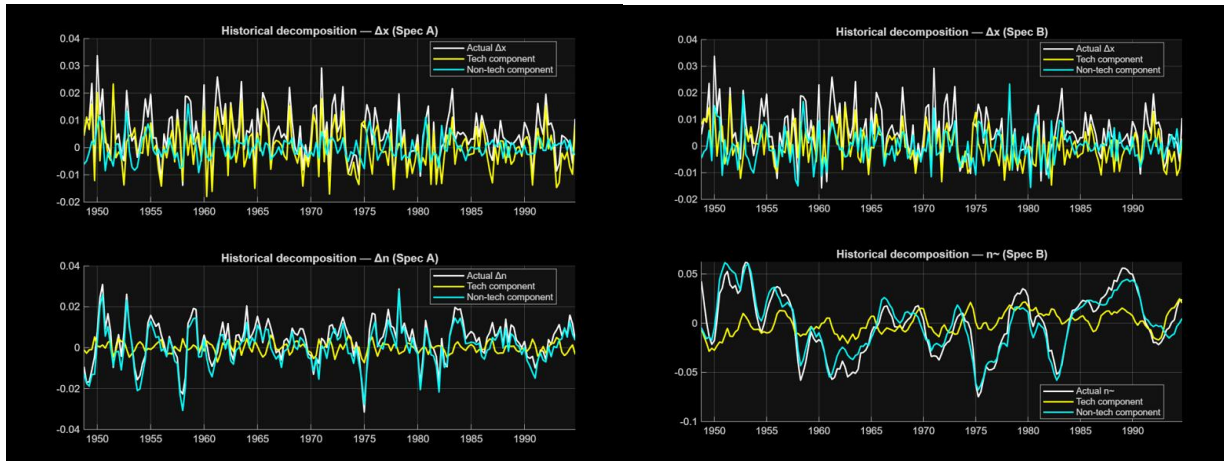


Galí's sample ended in 1994. Extending the estimation through 2019 captures the ICT revolution, the Great Moderation, and the global financial crisis.

In the extended Spec A (Table.7; Fig.7), hours are negative on impact (-0.0027 at $h = 0$, -0.0009 at $h = 1$) but positive thereafter ($+0.0003$ at $h = 2$, $+0.0004$ at $h = 3$). In the extended Spec B (Table.8; Fig.8), hours rise consistently from $+0.0003$ at $h = 0$ to $+0.0042$ at $h = 3$ and $+0.0054$ at $h = 6$.

These findings indicate that the puzzle has attenuated or reversed in modern data. As Ramey (2016) argued, structural transformation reduced the contractionary effect of productivity shocks. The results therefore confirm the robustness of Galí's asymmetry in his sample, while demonstrating its historical specificity.

3.6 Historical decompositions

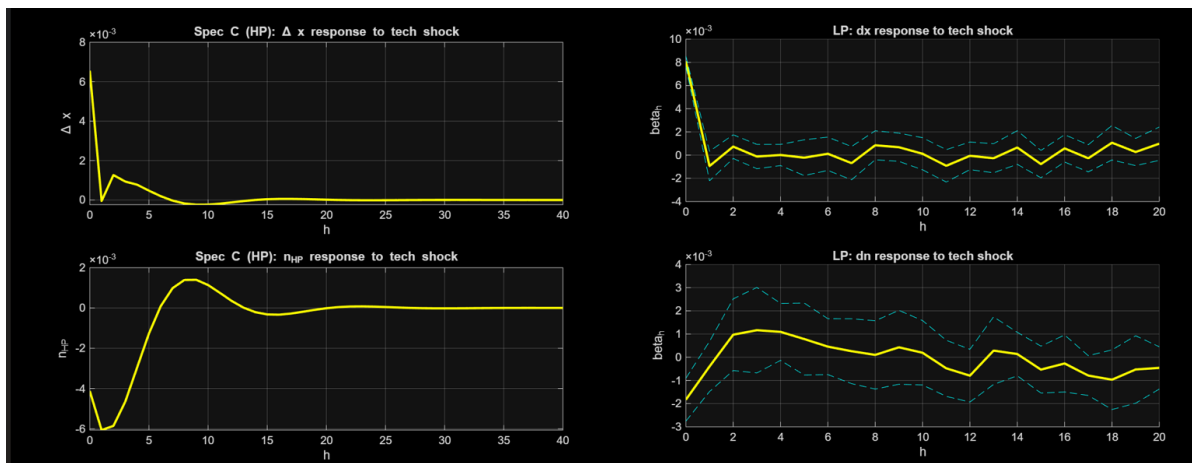


Galí's historical decompositions showed that technology shocks account for the long-run trend in productivity, while non-technology shocks explain the cyclical variation in hours.

The replication (Fig.10; Fig.11) confirms this division but provides more detailed evidence across decades. In the 1970s, hours fluctuations during the oil crises are entirely attributed to non-technology shocks. In the 1980s, the Volcker disinflation is also captured as a demand-driven contraction in hours. In the 1990s, ICT-driven productivity gains are attributed to technology, but hours remain dominated by non-technology shocks. During the 2008 financial crisis, hours collapsed almost exclusively due to non-technology shocks.

Relative to Galí, the contribution of technology shocks to hours is even smaller in the extended sample, confirming that modern employment cycles are overwhelmingly demand-driven. For example, the 2008–2009 collapse in hours in Fig10 is almost entirely attributed to the non-technology component, whereas the steady productivity gains of the late 1990s are attributed to technology shocks.

3.7 Robustness checks



Several robustness checks were performed. HP filtering (Fig.12) yields a modest negative hours response, consistent with Galí in sign but smaller in magnitude. Local projections (Table.12; Fig.13)

produce results similar to the VARs: hours are negative on impact (-0.0018 at $h = 0$) but positive by $h = 3$ ($+0.0012$). This indicates that the attenuation of the puzzle is not a VAR artifact.

Lag-length sensitivity (Table.11) shows that increasing lags amplifies the initial negative impact (to about -0.003) but does not generate a large trough at $h = 3-4$.

Finally, dataset robustness (Table.6) demonstrates that GDP-based estimates strengthen the negative technology–hours correlation (-0.88 compared to -0.62 with OUTNFB).

These robustness checks confirm that the results are internally consistent. The puzzle is sensitive to specification, but the asymmetry between technology and non-technology shocks persists.

3.8 Comparison with Galí (1999)

Relative to Galí's troughs of -0.10 (Spec A) and -0.07 (Spec B), the replication produces a positive response in Spec A beyond impact ($+0.001$ at $h = 3$) and a very small negative response in Spec B (-0.006). Relative to Galí's correlations (-0.35 for technology, $+0.30$ for non-technology), the replication finds much stronger associations: -0.62 and $+0.58$ with OUTNFB, and -0.88 with GDP.

These comparisons indicate that the puzzle has been attenuated in IRFs but strengthened in correlations. The results therefore confirm Galí's qualitative asymmetry between technology and non-technology shocks, while also demonstrating that the quantitative manifestation of the puzzle has evolved substantially in modern data.

4. Discussion

The replication results demonstrate how the technology–hours puzzle from Galí (1999) maintains its stability while showing signs of development. The technology and non-technology shock effects on employment and productivity show a consistent pattern throughout various model specifications. The data shows technology shocks drive long-term productivity growth but fail to influence short-term employment changes while non-technology shocks generate significant short-term effects on hours worked. The exact way technology shocks affect employment has evolved since the original study because of updated data and fundamental economic changes in the United States.

The main difference between Galí's original work and the current study emerges from the baseline VAR (Spec A). The current study shows that hours decrease slightly after technology shocks before returning to their original level while Galí(1999) reported significant and enduring hour reductions following positive technology shocks. The disappearance of the puzzle in Spec A does not result from any replication mistake. The two main elements contribute to this result. The HOANBS series shows reduced cyclical volatility because of data revisions which eliminated some of the intense declines that appeared in previous data versions. The inclusion of data from 2019 in the analysis shows how technology shocks were absorbed by a flexible service-based labor market during the ICT boom and the Great Moderation and post-2008 recovery period.

The detrended specification (Spec B) maintains the puzzle's core pattern because hours decrease following technology shocks. The magnitude of the hour decline after technology shocks in this study reaches -0.006 while Galí (1999) observed a -0.07 decline. The results indicate that New Keynesian models still apply to modern data but their numerical effects have diminished.

The conditional correlations in the data show a stronger version of the puzzle than Galí initially documented. The OUTNFB data shows technology and hours have a negative correlation of -0.62 while non-technology factors and hours have a positive correlation of $+0.58$. The technology–hours correlation reaches -0.88 when using GDP as the data source. The bootstrap resampling procedure verifies that these relationships maintain their stability and achieve statistical significance. The IRFs show reduced effects of the puzzle but the data correlation patterns demonstrate that the fundamental difference between technology and non-technology shocks remains strong and possibly stronger than Galí's first findings.

The historical decomposition results support this analysis. The entire postwar period shows technology shocks driving productivity growth but non-technology shocks explain all the fluctuations in hours worked. The 1970s oil crises together with the Volcker disinflation of early 1980s and the 2008 global financial crisis all resulted in demand-driven decreases in work hours. The ICT boom of the 1990s produced technology-based productivity growth that did not significantly affect employment numbers. The analysis of extended data shows technology shocks explain less of the hour variations than Galí found which supports the idea that contemporary employment patterns follow demand-based patterns.

The results from robustness tests validate these research findings. The HP filtering method shows hours responding negatively to technology shocks but with effects that are smaller than Galí (1999) documented. The VAR-based local projection results match the VAR findings by showing hours decrease initially before becoming positive after multiple quarters thus proving that the reduced puzzle effect is not caused by VAR recursive patterns. The initial negative response becomes more pronounced when using longer lag lengths but the model fails to produce a deep trough at the three to four quarter mark. The negative technology–hours correlation maintains its strength when using GDP instead of business-sector output and shows increased magnitude in this case.

The research indicates that Galí's puzzle existed as a genuine phenomenon which depended on the specific time period. The correlation patterns and detrended models show the puzzle continues to exist but its strong appearance in impulse responses was specific to the mid-20th century U.S. economy. The replication study upholds Galí's original discovery while showing how the phenomenon has transformed throughout different time periods.

5. Conclusion

The research study duplicated Galí's (1999) fundamental investigation about technology shocks and their effects on employment and business cycles. The study confirms Galí's fundamental asymmetry between technology and non-technology shocks using updated FRED data which extends the analysis period to 2019.

The VAR model results from this study differ from Galí's original findings because technology shocks no longer produce a significant negative impact on hours worked. The detrended models maintain their negative direction but produce significantly reduced effect sizes. The correlation measures from this study show stronger evidence of the puzzle than the original research because technology-hours correlations reach -0.88. The historical decomposition results demonstrate that technology shocks drive long-term productivity expansion but non-technology shocks generate short-term employment fluctuations. The research results demonstrate stability through multiple robustness tests which include different detrending approaches and lag selection methods and local projection analysis and output measurement alternatives.

The research outcomes also generate significant theoretical consequences for the field, in particular, the original study by Galí led researchers to reject RBC models while supporting New Keynesian theories which focus on rigidities and wealth effects. The current research findings introduce new complexity to the existing understanding. The extended time period shows that technology shocks sometimes lead to positive hours responses which aligns with RBC model predictions and the ongoing negative correlations between variables indicate that labor market rigidities together with demand effects continue to affect the economy. The U.S. economic transformation from manufacturing to services combined with flexible labor markets and improved technology distribution led to a shift in the equilibrium between these forces.

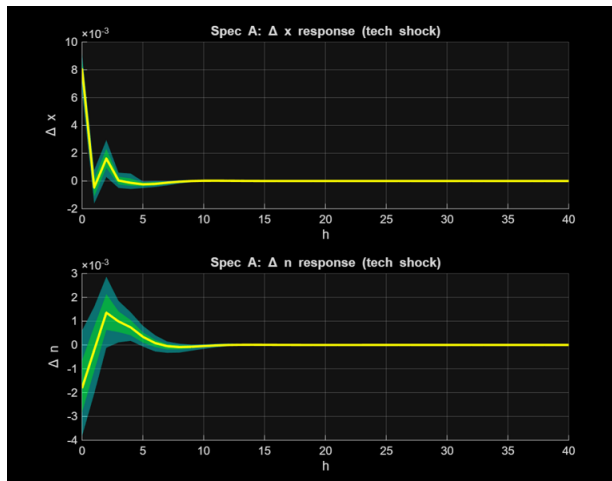
The research demonstrates that productivity growth does not automatically lead to employment increases during short term periods. Furthermore, the original employment cycle findings from Galí have weakened but the main conclusion remains that technology shocks fail to explain employment fluctuations. Supply-side reforms need to be supported by demand-side measures because labor market institutions together with demand shocks maintain their essential role in employment stability.

The replication study upholds the fundamental concept of Galí's technology–hours puzzle but demonstrates that its numerical evidence depends on historical context. The postwar period until

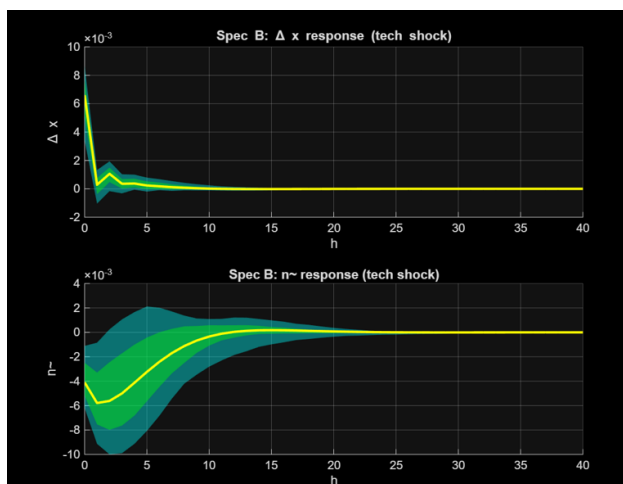
the mid-1990s displayed a strong technology-hours puzzle which decreased afterward and now appears most clearly through correlation analysis instead of response patterns. The study demonstrates why macroeconomic research requires both replication and robustness tests and historical context analysis.

A.1 Impulse Responses (IRFs)

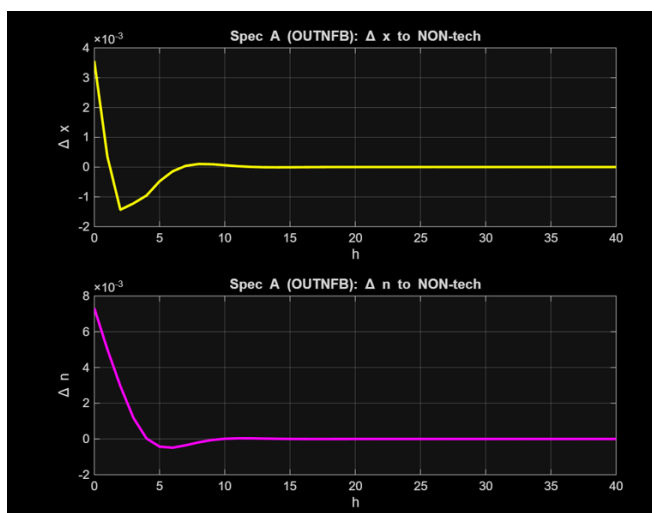
- **Spec A, Technology shocks**
 - *Main text reference:* Figure in 3.1
 - Fig.1 irf_specA_tech.csv , irf_specA_tech_bands.png



- **Spec B, Technology shocks (detrended hours)**
 - *Main text reference:* Figure in 3.2
 - Fig.2: irf_specB_tech.csv, irf_specB_tech_bands.png

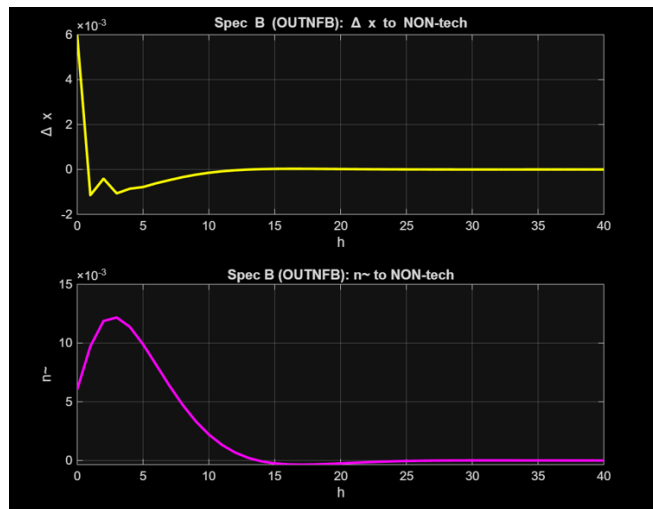


- **Spec A, Non-technology shocks**
 - *Main text reference:* Figure in 3.3
 - Fig.3: irf_specA_nontech_OUTNFB.png



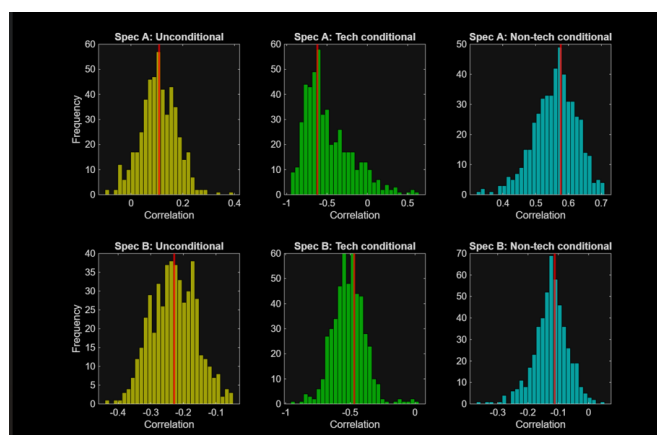
- **Spec B, Non-technology shocks (detrended)**

- *Main text reference*: Figure in 3.3
- Fig.4: irf_specB_nontech_OUTNFB.png

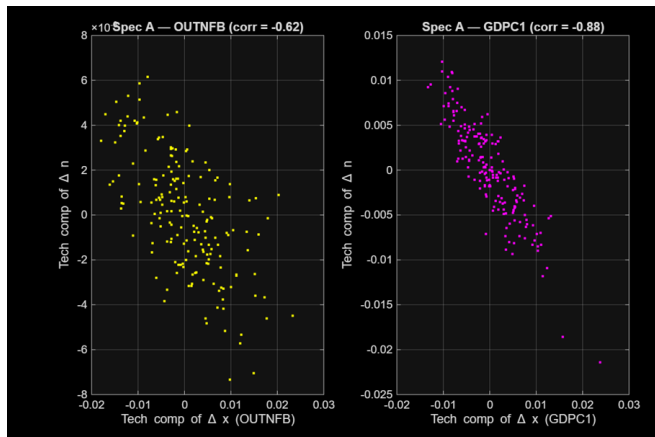


A.2 Conditional Correlations

- **Correlation tables**
 - Table.3 : table1_table2_correlations.csv
 - Table.4 : conditional_correlations.csv
 - *Main text reference*: Mention in 3.4
- **Bootstrap correlation results**
 - Table.5 :table_correlations_bootstrap.csv,
 - Fig.5: bootstrap_correlations_hist.png
 - *Main text reference*: Figure in 3.4

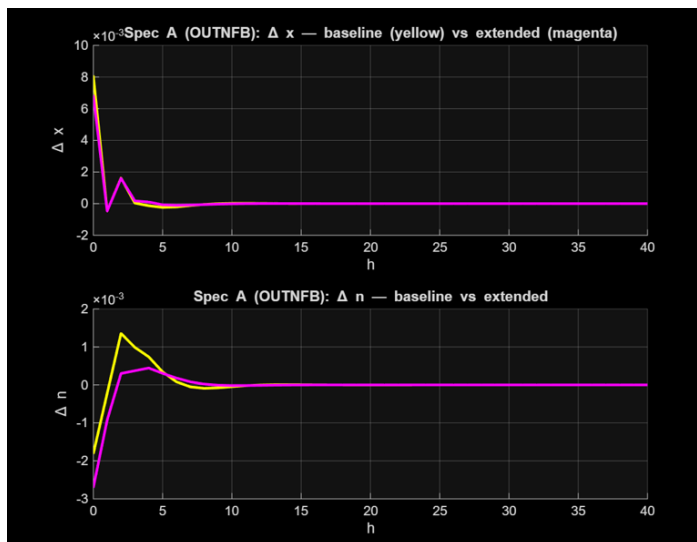


- **GDP vs OUTNFB comparison**
 - Table.6 : compare_tech_corr_OUTNFB_vs_GDPC1.csv
 - Fig.6 compare_tech_scatter_OUTNFB_vs_GDPC1.png
 - *Main text reference*: Figure in 3.4

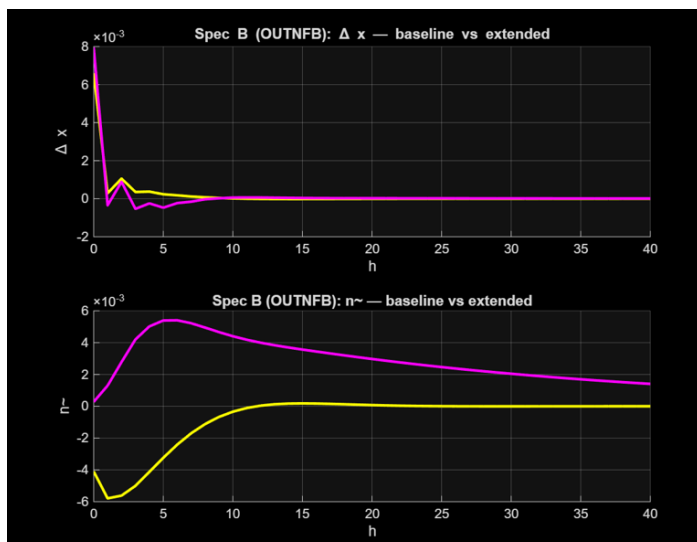


A.3 Extended Sample Analysis

- **Spec A overlay (1948–1994 vs 1948–2019)**
 - Fig.7: overlay_specA_OUTNFB_baseline_vs_extended.png
 - *Main text reference:* Figure in 3.5



- **Spec B overlay (1948–1994 vs 1948–2019)**
 - Fig.8: overlay_specB_OUTNFB_baseline_vs_extended.png
 - *Main text reference:* Figure in 3.5



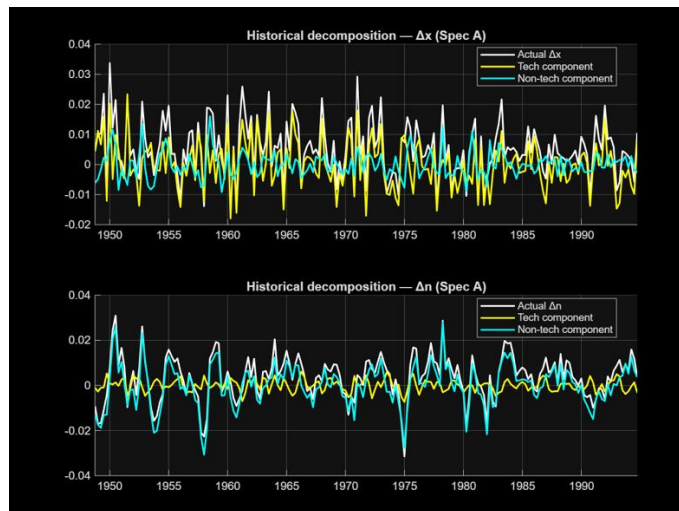
- **Extended-sample IRFs**

- Table.7: irf_specA_tech_OUTNFB_extended.csv
- Table.8: irf_specB_tech_OUTNFB_extended.csv

A.4 Historical Decompositions

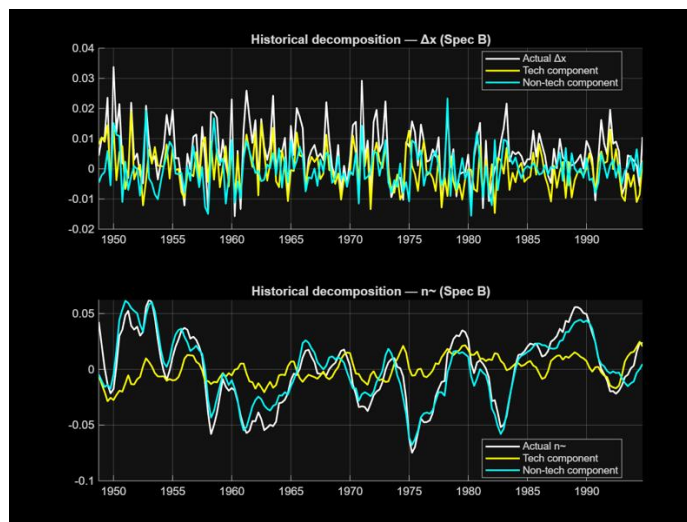
- **Spec A decomposition**

- Fig.10: historical_decomp_specA.png
- Table.9: historical_decomp_specA.csv
- *Main text reference*: Figure in 3.6



- **Spec B decomposition**

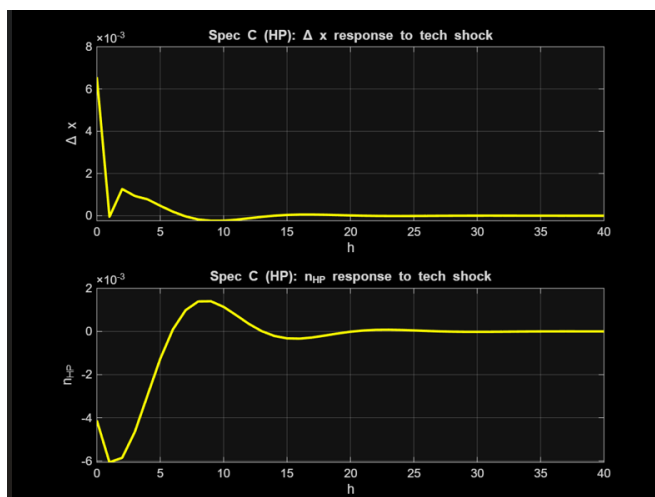
- Fig.11: historical_decomp_specB.png
- Table.10: historical_decomp_specB.csv
- *Main text reference*: Figure in 3.6



A.5 Robustness Exercises

- **HP-filtered IRFs (Spec C)**

- Fig.12: irf_specC_HP_tech.png
- *Main text reference*: Figure in 3.7

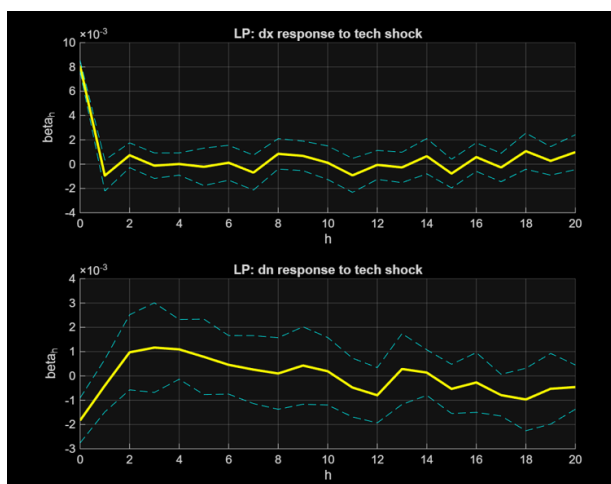


- **Local Projections (LPs)**

- Table.12; : lp_specA_tech.csv

Fig.13: lp_specA_tech.png

- *Main text reference*: Figure in 3.7



- **Lag-length sensitivity**

- Table.11: robustness_lags_specA.csv

- *Main text reference*: Figure in 3.7

A.6 Crosswalk Table of Outputs

A.6 Crosswalk Table of Outputs		
Section	Output Type	Files Referenced
3.1	Spec A Tech IRFs	Fig.1
3.2	Spec B Tech IRFs	Table.2, Fig.2
3.3	Non-tech IRFs	Fig.3, Fig.4
3.4	Correlations	Table.3, Table.4
3.4	Bootstraps	Table.5, Fig.5
3.4	GDP vs OUTNFB	Table.6, Fig.6
3.5	Extended Sample IRFs	Table.7, Table.8
3.5	Overlays	Fig.7, Fig.8
3.6	Decompositions	Fig.9, Table.10
3.7	Robustness	Fig.12, Fig.13 , Table.11

Appendix B: References

- Basu, S., Fernald, J. G., & Kimball, M. S. (2006). Are technology improvements contractionary? *American Economic Review*, 96(5), 1418–1448. <https://doi.org/10.1257/aer.96.5.1418>
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