Working Paper Series

The Changing Nature of Technology Shocks

WP 24-13

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September 2024

Abstract

We document changes to the pattern of technology shocks and their propagation in post-war U.S. data. Using an agnostic identification procedure, we show that the dominant shock driving total factor productivity (TFP) is akin to a diffusion or news shock and that shock transmission has changed over time. Specifically, the behavior of hours worked is notably different before and after the 1980s. In addition, the importance of technology shocks as a major driver of aggregate fluctuations has increased over time. They play a dominant role in the second subsample, but much less so in the first. We build a rich structural model to explain these new facts. Using impulse-response matching, we find that a change in the stance of monetary policy and the nature of intangible capital accumulation both played dominant roles in accounting for the differences in TFP shock propagation.

Keywords: Technology shocks, TFP, business cycles, shock transmission.

JEL Classification: E2, E3.

*We thank Christiane Baumeister, Christian Bayer, Benjamin Born, Efrem Castelnuovo, Neville Francis, Alok Johri, Giorgio Primiceri, Valerie Ramey, Frank Schorfheide, Felipe Schwartzman, Eric Sims, Hyunseung Oh, Michael Weber and Mirko Wiederholt for helpful comments and suggestions. We thank seminar participants at Durham University, Sheffield University, University of Reading, Dalhousie University, the Federal Reserve Board of Governors and conference participants at the 2023 Society for Economic Measurement Conference, the Workshop on Empirical and Theoretical Macroeconomics Lancaster University, 2023 Society for Computational Economics Conference, and the 2024 International Association for Applied Econometrics Conference. All remaining errors are our own. The views expressed in this paper are those of the authors and not necessarily those of the Federal Reserve Bank of Richmond or the Federal Reserve System. Görtz: University of Augsburg, Department of Economics, Email: christoph.goertz@uni-a.de. Gunn: Carleton University, Department of Economics, Email: chris.gunn@carleton.ca. Lubik: Federal Reserve Bank of Richmond, Research Department, Email: thomas.lubik@rich.frb.org

1 Introduction

The idea that stochastic shifts in the technological frontier of the economy are a main driver of business cycles plays a central role in modern macroeconomics. Yet, the nature of such "technology shocks" remains elusive. The question is still whether shifts in technology trigger a response that resembles business cycles. If so, how important are such disturbances for explaining aggregate fluctuations? Does it matter if these technological shifts are surprise shocks or anticipated in advance?

In this paper, we take a step back and explore the role of technological shocks in answering these questions. In the spirit of Francis et al. (2014) and Angeletos et al. (2020), we employ a VAR to identify a technology shock as the one, which maximizes the forecast error variance of TFP at a long, but finite horizon. We show that the nature of the technology shock, namely its incidence and propagation, differ markedly pre- and post-Great Moderation. Specifically, we document three general findings over these two subsamples: (i) the transmission of technology shocks has changed over time, (ii) the importance of technology shocks in terms of business cycles has increased over time, and (iii) the most relevant shock driving TFP is not necessarily a surprise shock as assumed in many models, but rather a diffusion or anticipated shock.

We identify technology shocks for two subsamples spanning the periods 1954Q2-1983Q4 and 1984Q1-2019Q4.[1] The change in the transmission of technology shocks is reflected in the striking difference in the response of hours worked across the two subsamples: in the first subsample hours falls on impact; in the second it rises. Yet consumption, GDP and other aggregates rise consistently in both samples. Moreover, although the hours response differs across samples, they co-move positively with investment, inventories, the real wage and negatively with interest spreads in both samples. As a group, these responses change sign over the two samples relative to the consistent rise in consumption, GDP and stock

[1] Splitting the sample in the early 1980s is consistent with the practice in the literature as it reflects a widely documented break in unconditional correlation patterns in the data (see e.g. Kim and Nelson (1999) and McConnell and Perez-Quiros (2000)). At the same time, we recognize that changes in the nature of shock propagation may occur more gradually and consequently present robustness of our results to methods capturing a more gradual change.

prices over both subsamples.[2] An important corollary to this finding is that evaluating the propagation of technology shocks using long samples that straddle the 1980s may be problematic in the context of standard linear VARs, as impulse response functions likely show a weighted average of rather different shock transmissions.

We identify the technology shocks using a max share approach. It seeks out the shock that "best explains" the variance in TFP at some long, but finite horizon. Identification is thus agnostic about the presence of surprise or news components in technology shocks. Forecast error variance decompositions show that while the identified shock explains a large and similar share of TFP over the two periods, it explains a substantially larger share of output variations in the second subsample than in the first. This observation is also consistent with the prior main finding about the response of hours and other aggregates to the identified shock and their unconditional changes in behavior. That is, the negative comovement of hours and consumption in the first subsample makes it difficult for the shock to account for a large proportion of business cycle activity when unconditionally hours and consumption co-move positively.

Finally, our third and perhaps most intriguing key result is the dynamic behavior of TFP. In each subsample TFP only rises after several periods, and then grows gradually beyond that. This pattern is consistent with the idea of an anticipated or news shocks as in Beaudry and Portier (2004). It is also consistent with the slow diffusion of innovation over time and its gradual effect in raising TFP as in Comin and Gertler (2006). We thus argue that an anticipated or a diffusion process is the dominant form of the technological shock over both samples. Our three findings have implications for the design of structural business cycle models to adequately resemble and analyze aggregate fluctuations for different eras.

Our key findings leave open the question whether the changing nature of technology shocks are largely due to changes in propagation or incidence, volatility and comovement of the shocks. In the spirit of Sims and Zha (2006), we perform the following counterfactual

[2]Interestingly, this connection between hours and inventories in particular is consistent with the literature that suggests a tight relationship between these two (and other variables, e.g. spreads) and argues for them to be assessed in conjunction.

analysis. We construct hypothetical technology shocks for the first subsample using the estimated VAR lag coefficients but the variance-covariance matrix estimated from the second sample. Similarly, we construct hypothetical shocks from the polynomial lag coefficients estimated from the second subsample, but variance-covariance matrix estimated from the first. We find that the impulse responses are essentially unchanged, which supports the idea that changes in the variance-covariance matrix are not driving the different results across periods. Rather, it is changes in the VAR coefficients and thus propagation.

In the next step, we build a structural DSGE model to replicate the empirical findings from the VAR and identify the underlying driver of the observed changes. We let our modeling choices be informed by the wide-ranging literature on structural changes in the early 1980s, which has advanced explanations such as changes in the stance of monetary policy, improved inventory management, financial innovations, and the IT revolution. Consequently, we augment a New Keynesian framework with a banking sector and financial frictions based on Gertler and Karadi (2011), inventory holding by firms as in Bils and Kahn (2000), intangible capital as an additional input into production, which we refer to as knowledge capital, as in Chang et al. (2002), as well as various other standard nominal and real rigidities.

We estimate the model using an impulse-response matching approach as in Christiano et al. (2005). The model is estimated separately for each sample period, conditional on an anticipated shock to the growth rate of non-stationary TFP designed to capture the model equivalent of our identified technology shock. We then evaluate various candidate hypotheses for the source of the change through the lens of the model. Our results suggest that the change in the response of technology over time was likely some combination of a change in the stance of monetary policy, a change in the nature of knowledge capital accumulation, and a change in the cost of utilizing capital.

With respect to the change in the stance of monetary policy, our results suggest a move towards tighter monetary policy in response to inflation in a Taylor-type rate-setting rule in line with the standard findings in the literature such as Lubik and Schorfheide (2004). This policy change affects transmission through real-interest rate effects on labor and inventory decisions, and a powerful channel discussed in Christiano et al. (2008) through which under nominal wage rigidities an inflation-targeting central bank influences the path of the real wage. With respect to the change in the nature of knowledge capital accumulation, our results suggest a decline in the depreciation of new knowledge capital over time, causing firms to increase labor demand as they seek to acquire valuable new knowledge capital in the face of expanding future technology. Taking this mechanism via knowledge capital literally, one interpretation is that firms changed the way to organize their production inputs and accessibility of institutional knowledge, as the processes of production changed rapidly due to the IT revolution in the last two decades of the twentieth century. Finally, we find that an increase in the cost of utilizing capital works through general equilibrium effects via the credit sector and affects the return to capital and thereby an associated increase in demand for new capital.

On the empirical side, our work links to an active literature that focuses on the importance of longer-run identification of technology shocks in VARs. Galí (1999) employs long-run restrictions on labor productivity to identify technology shocks and finds a decline in hours worked in response to a positive shock. Technology shocks account just for a very small part of total fluctuations in output and hours worked at business cycles frequencies, which is taken as evidence against the Real Business Cycle paradigm.[3] Others including Christiano et al. (2004), Uhlig (2004) and Dedola and Neri (2007) find the opposite result with regards to the response of hours worked and the importance of technology shocks for aggregate fluctuations, arguably attributable to differences in the specification of hours in the VAR. Francis et al. (2014) propose the so-called max share identification, which identifies a technology shock as the one that maximizes the forecast-error variance of labor productivity at some long but finite horizon. In particular, they show that the max share identification outperforms standard long-run restrictions by significantly reducing the bias in the short-run impulse responses and raising their estimation precision. Notably, they find a negative hours response.[4]

[3] See also Shea (1998), Ramey (2005), Pesavento and Rossi (2005) and Basu et al. (2006).

[4] Francis et al. (2014) derive their results from a single sample using 1948Q2-2009Q4. Cardi and Restout

We build on the insights of this debate by employing max share identification of technology shocks. In contrast to the existing literature, we focus on two distinct subsamples which are characterized by notable differences in unconditional time series behavior. While we use TFP instead of labor productivity for our core analysis, we also show that our split-sample result for hours worked holds using labor productivity instead of TFP.

Our work also connects with the news shock literature that studies anticipated shocks to technology. Similar to the debate following Galí (1999), the response of hours worked to identified news shocks has been a key feature of this literature. Key papers such as Barsky and Sims (2011) and Kurmann and Sims (2021) (both with sample period 1960Q1–2007Q3), find that hours worked do not co-move with output and consumption, but decline in response to favorable anticipated technology shocks. Others document a broad-based expansion of macroeconomic aggregates (e.g., Görtz et al. (2024) and Görtz et al. (2022)) who consider 1983Q1-2018Q2 and 1984:Q1–2017:Q1 samples, respectively.

We also speak to the large literature that documents differences in time series behavior across the Great Inflation/Great Moderation samples.[5] While this literature documents the data unconditionally, we point to important changes conditional on technology shocks. Garin et al. (2018) show that a change in the relative importance of aggregate and sectoral shocks over time alters business cycle moments. This literature and our work has implications for the estimation of structural models. It highlights the relevance of subsample estimation or estimation with time varying parameters.

The remainder of the paper proceeds as follows. In Section 2, we provide VAR-based evidence on the changing nature of macroeconomic aggregates across subsamples in response to the dominant technological shock. Section 3 introduces the structural model which is subsequently used to isolate the theoretical channels that drive differences in the response of hours worked to anticipated technology shocks across subsamples. In section 4, we employ

(2024) document that the contractionary effect of surprise technology shocks on hours worked has shrunk over time in OECD countries.

[5]We cannot do justice here to this extensive literature, see e.g. Stock and Watson (1999), Kahn et al. (2002), McCarthy and Zakrajsek (2007), Galí and Gambetti (2009), Sarte et al. (2015) and Foerster et al. (2022).

an IRF matching procedure to estimate key parameters and then investigate in section 5 the empirical relevance of these channels in light of the quantitative results. Section 6 concludes.

2 Changing Productivity Dynamics: Empirical Results

We provide VAR-based evidence on the differential behavior of macroeconomic aggregates in response to technology shocks. Our empirical strategy relies on a parsimonious VAR with an agnostic identification procedure over two different sub-samples. We discuss the implications of these results and provide an initial analysis of the source of the observed changes over each subsample.

2.1 Data and Empirical Methodology

We estimate a VAR with five variables as a baseline: TFP, GDP, consumption, hours worked and the S&P500 stock market index. The key variable for the identification of the shock that moves productivity is observable TFP. We use the TFP measure provided by Fernald (2014), which is based on the growth accounting methodology in Basu et al. (2006) and corrects for unobserved capacity utilization. GDP, consumption and hours worked serve as our measures of economic activity, while the S&P500 captures information available to economic agents about future macroeconomic developments. GDP, consumption and hours worked are all seasonally adjusted and in real per-capita terms (except for hours worked which are not deflated). All variables enter in levels, consistent with the practice in the empirical VAR literature (e.g. Barsky and Sims (2011), Francis et al. (2014)). We use three lags with a Minnesota prior and compute confidence bands by drawing from the posterior.[6]

The objective of our identification strategy is to isolate broadly-defined technology shocks as the main driver of aggregate fluctuations. We remain largely agnostic about whether such shocks have contemporaneous or delayed effects or whether they are anticipated or unanticipated. Instead, our identification rests on the assumption that a distinguishing

[6] Appendix C provides details on the data sources and all used time series. Further details about the VAR model, the max share identification and prior specifications are provided in Appendix A.

feature of a technology shock is its ability to influence the behavior of the macroeconomy at long-horizons. We implement this idea by using the max share methodology as suggested in Francis et al. (2014), who maximize the forecast error variance share of a productivity measure at a long but finite horizon.[7]

We consider a horizon h to be 10 years. We use TFP as the target variable for identifying this shock, namely the one that best-explains TFP at a long horizon. The identification allows us to remain agnostic about the type of technology shock being identified (anticipated vs. surprise), and does not require us to make the strong identification assumption that TFP is completely exogenous at all horizons and comprised of just surprise and news shocks.[8]

There is wide agreement in the literature that aggregate time series behavior in the US changed in the early 1980s, separating the Great Inflation from the Great Moderation. There is less agreement as to the underlying drivers of that change, whether it is due to structural changes of the US economy, a changed incidence of shocks, or better policymaking. Using these observations as background, we thus frame our investigation around the two subsamples on either side of the onset of the Great Moderation. We estimate the VAR separately for each of two subsamples spanning the periods 1954Q2–1983Q4 and 1984Q1–2019Q4. The specific dates are chosen based on cross-correlation patterns of several macro-aggregates in samples before and after the mid-1980s. In particular, McConnell and Perez-Quiros (2000) and Kim and Nelson (1999) document a structural break at the first quarter of 1984 (see also e.g. Galí and Gambetti (2009) and Stock and Watson (1999) for further evidence on this structural break).

[7]Francis et al. (2014) advance max share identification as an alternative to long-run identification such as Galí (1999) as it avoids small-sample bias inherent to these approaches. In addition our approach is consistent with suggestions in Uhlig (2003) and in the spirit of Angeletos et al. (2020)

[8]Similar to Kurmann and Sims (2021) we do not impose zero-impact restrictions to separate anticipated from surprise shocks to technology. Arguably, this helps avoid measurement issues that may arise with a variable like TFP in the short-run. We consider alternative specifications and identification as a robustness check.

2.2 New Empirical Facts: Evidence from Two Periods

Figure 1 shows impulse response functions (IRFs) to our identified technology shock with the red and blue lines corresponding to the first and second subsamples, respectively. There are several important points to note. First, while our agnostic shock identification does not exclude the possibility that TFP jumps on impact, in both subsamples, the dominant effect on TFP is one that grows over time. In particular, TFP only rises significantly with a lag of eleven quarters and after the other variables in the VAR. This is consistent with a diffusion-based or anticipated (news) technology shock.

Second, there is a striking difference in the comovement of the key aggregate variables between the two subsamples. Whereas in the latter subsample we observe a broad-based and positively co-moving expansion of GDP, consumption and hours worked, in the earlier subsample hours worked fall.[9] Consumption rises also in the first subsample, yet its short- and medium-run expansion is less pronounced than that in the second subsample. For GDP this disparity is even more apparent as output rises in the first subsample significantly only after seven quarters. Finally, stock prices rise in both subsamples. This rise in stock prices along with that of consumption over the two subsamples is generally consistent with a "good news" technological expansion, despite the differential response of hours worked between the subsamples.

Overall, we observe marked differences in the responses of the variables over the two episodes for almost identical TFP responses. We interpret these findings as broadly consistent with the view of changes in the structure of the US economy as propagation is different. In that sense our findings contrast with Sims and Zha (2006) who argue for differences in the shock processes between the two eras. [10]

[9]The qualitative differences across subsamples with respect to hours worked is reflected in the labor market overall. Consistent with the decline in hours during the first subsample, Appendix B documents a decline in the labor force participation rate and a rise in the unemployment rate using the same VAR specification. In contrast, for the second subsample, the labor force participation rate increases and the unemployment rate declines.

[10]These impulse response functions are robust to using labor productivity as an alternative measure for productivity. Details are documented in Appendix B. Our results are also robust to alternating the number of lags and to variations in the max share horizon h.

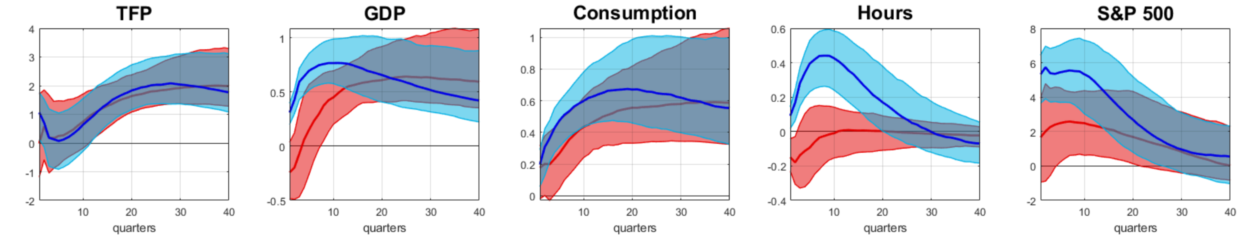


Figure 1: **IRF to TFP shock.** First subsample 1954Q2-1983Q4 (red), second subsample 1984Q1-2019Q4 (blue). The solid line is the median and the shaded colored areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure 2 shows the forecast error variance decompositions for the variables in the VAR over the two subsamples. The identified shock explains a substantial and very similar share of variation in TFP across the two episodes reaching a peak of 60% at horizon of 10 years. In the first subsample the shock is of substantially lower importance for fluctuations in GDP (red lines, ranging approximately between 10-55%) than in the second subsample (blue lines, approximately 70-85%). The increase in the shock's importance in the second subsample is consistent with the IRF evidence from Figure 1, where we observed stronger shock propagation and comovement across all macroeconomic aggregates, including hours worked. The opposite sign response of hours worked – relative to GDP and consumption – is consistent with the notion that the technology shock in the first subsample is of lesser importance although the range of uncertainty in the second subsample is considerable..

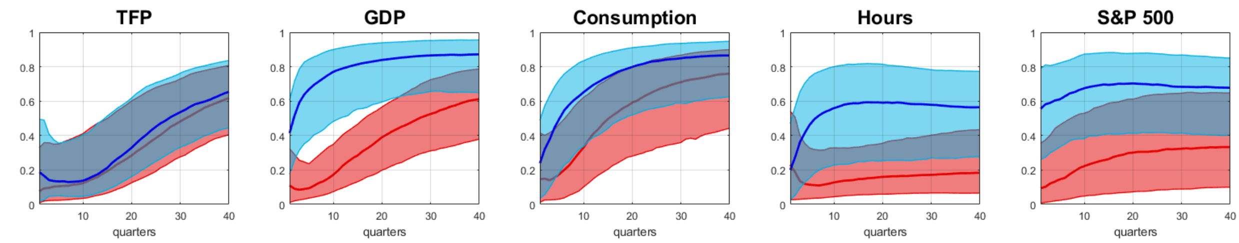


Figure 2: **Forecast Error Variance Decomposition — share explained by the TFP shock.** First subsample 1954Q2-1983Q4 (red), second subsample 1984Q1-2019Q4 (blue). The solid line is the median and the shaded colored areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters.

In summary, the above results suggest that: (1) The importance of technology shocks has increased over time — as a major driver of aggregate fluctuations they play a dominant role in the second subsample but less so in the first; (2) the transmission of technology shocks has changed over time, especially with regards to the qualitative response of hours worked; (3) the most relevant shock driving TFP is not necessarily a surprise shock as assumed in many models, but rather a news or diffusion shock. We will discuss the implications of these findings further in the next section which investigates the shock transmission in more detail.

2.3 Digging Deeper: Subsample Differences in Shock Transmission

We have documented differences in the transmission of TFP shocks over two subsamples. We now dig deeper into potential mechanisms by considering additional variables. Figure 3 shows responses of multiple variables of interest for the transmission of TFP shocks. Subplots in this figure are from a VAR with TFP, GDP, consumption, hours worked, the S&P 500 and one additional variable of interest at a time. The depicted response of hours is from the VAR that includes inventories. The variables not shown are very similar to those in Figure 1.

As the figure shows there are considerable differences across the two subsamples in their response to a TFP shock. In particular, inventories, investment and the real wage fall, and the BAA spread rises in the first subsample, whereas in the second subsample the pattern is reversed. In addition, there is a short-lived decline in inflation in both subsamples. The patterns of the remaining two variables are less clear: the federal funds rate does not respond significantly in either subsample, and capital utilization rises in the second subsample, but its response is insignificant in the first.

Taken together, the results from Figures 1 to 3 suggest the following with regards to the behaviour of the key variables in response to the technological shock. First, consumption and stock prices rise and inflation falls in both subsamples. This rise in consumption and stock prices in tandem with the delayed rise in TFP is consistent with the idea of "good news" associated with a rise in lifetime wealth due to expected TFP growth (see e.g. Beaudry and Portier (2006)). Moreover the short-lived decline in inflation is a widely reported response

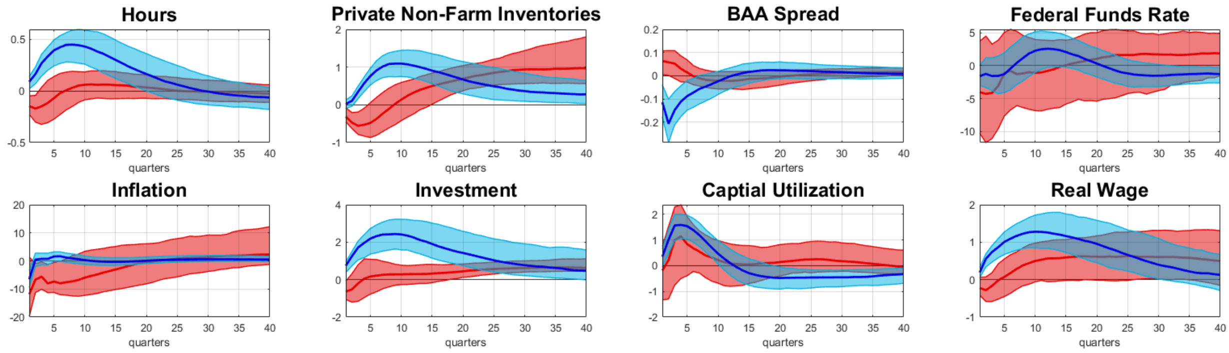


Figure 3: **IRF to TFP shock.** First subsample 1954Q2-1983Q4 (red), second subsample 1984Q1-2019Q4 (blue). The solid line is the median and the shaded colored areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations. Subplots are based on a VAR with TFP, GDP, consumption, hours worked, the S&P 500 and one of the plotted variables at a time.

to technology news shocks (see e.g. Barsky and Sims (2011) Kurmann and Sims (2021), Görtz et al. (2022)). Second, hours worked, investment, inventories, the real wage and the BAA spread co-move in a consistent way *with each other* over both samples – and indeed, consistent with their unconditional correlations in the data – however, as a group, their response flips between the two subsamples. In particular, as a group, these variables respond in the short run in a "contractionary" way in the first subsample, and "expansionary" in the second subsample. This is also consistent with the somewhat more muted response of output in the first subsample relative to that in the second subsample, reported in Figure 1. In fact, the responses in the first period are consistent with a news shock in a standard RBC model with standard preferences as in King and Rebelo (2000); whereas the responses in second period can be generated from the standard news shock specification of Jaimovich and Rebelo (2009), which use preferences that avoid the wealth effect on hours.

2.3.1 Grouping Comovement: Labor, Inventories, Investment and Credit Spreads

The second observation made in the paragraph above is suggestive of a potential connection between developments on the labor market, inventories, investment and credit spreads.

The close relationship between hours and inventories has been stressed for example by

Maccini and Rossana (1984) and Galeotti et al. (2005), who point out the need for a joint understanding of the dynamics of inventories and hours worked. Also Chang et al. (2009) emphasize this point and document the comovement of inventories and employment conditional on (unanticipated) technology shocks. They further stress the connection between the sign of the employment response to technology shocks and the cost of holding inventories. Their notion that a positive response of hours worked is more likely the less costly it is to hold inventories, is consistent with the patterns we document in Figure 3 on inventories, hours and credit spreads. Risk premia, such as credit spreads, have been recognised in the literature also as a measure for the opportunity cost of holding inventories. See for example Jones and Tuzel (2013) who document this relationship between risk premia and inventories unconditionally and Görtz et al. (2024) who stress the importance of credit spreads as opportunity cost for inventory holdings conditional on anticipated technology shocks. Hence, the decline (rise) in inventories shown in Figure 3 for the first (second) subsample is consistent with a rise (fall) in their opportunity cost captured by credit spreads.

A vast body of research finds that financial markets are characterized by frictions that lead to credit spreads and hence affect the financing of investment projects.[11] In particular, Görtz and Tsoukalas (2018) and Görtz et al. (2022) emphasize that the empirical relevance of technology news shocks hinges crucially on the shock's transmission being amplified by frictions in financial markets. The responses of investment and the BAA spread shown in Figure 3 are consistent with this finding in so far as the response of the BAA spread indicates a much stronger transmission via financial markets in the second subsample. This and the relaxation of credit frictions, as indicated by the decline of the BAA spread, is consistent with the strong expansion in investment we document for the second subsample.[12] In contrast, the somewhat muted rise of credit spreads in the first subsample is indicative of tighter lending conditions which is consistent with the somewhat less pronounced rise in investment.

[11] See for example Philippon (2009) and Gilchrist and Zakrajsek (2012).

[12] Görtz et al. (2022) stress the importance of movements in credit spreads for the propagation of anticipated technology shocks. They show that such a favorable shock is amplified via financial markets since an endogenous strengthening of banks' balance sheets relaxes lending conditions associated with a decline in credit spreads.

Our empirical results are supported by the fact that the above literature documents a close connection between the same variables which we find to change the sign of their IRFs across subsamples. Changes in the nature of US business cycles during the mid-1980s are a widely documented phenomenon. By considering two separate subsamples we take account of this finding and avoid masking differences in shock transmission across the two subsamples. Estimating the VAR over the entire sample (1954Q2-2019Q4) yields responses that are similar to those of the second subsample. Details are provided in Appendix B.

2.3.2 Conditional Evidence and Unconditional Dynamics in the Data

Our sample split coincides with the end of the Great Inflation and the literature has documented a number of structural changes in the economy that occurred around this time. Interestingly, these structural changes would be reflected in some of those variables that we find to depict the most substantial differences in responses across subsamples, i.e. inventories, hours worked and credit spreads. McCarthy and Zakrajsek (2007) and Kahn et al. (2002) document that significant changes in inventory dynamics occur in the mid-1980s due to improvements in inventory management. Sarte et al. (2015) document that time-series properties of inventories and hours have changed with the onset of the Great Moderation and attribute this, at least partly, to variations in credit market frictions. Adrian et al. (2010) and Jermann and Quadrini (2012) argue that the importance of the financial sector for the determination of credit and asset prices has risen significantly from the mid-1980s. Further, Jermann and Quadrini (2009) discuss a variety of financial innovations that were taking place or intensified in the 1980s — including banking liberalization, and flexibility in debt issuance through the introduction of the Asset Backed Securities market — and stress their role for a slowdown in output volatility. Fuentes-Albero (2019) documents that contemporaneous to the onset of the Great Moderation there was a widespread increase in the volatility of financial variables. This literature studies the unconditional dynamics of inventories, hours and credit spreads in relation to potential sources for the end of the Great Inflation. While our paper does not aspire to speak to the reasons for the onset of the Great Moderation, we note that there might potentially be a link between the sources of structural change — e.g. improvements in inventory management and developments in financial markets — that have been attributed to be potential sources of the Great Moderation and our documented changes in the transmission of technology shocks.[13]

2.3.3 Rolling Windows: Timing the Change

We now shed some more light into the timing of when impulse responses flip sign. For this purpose, we estimate our VAR model over rolling windows of 119 quarters. This choice implies that the first rolling window is consistent with our first subsample and we shift this window forward until its end corresponds to the end of the second subsample. Figure 4 displays the maximum or minimum (whichever is larger in absolute terms) of IRF responses within the first ten quarters.[14] For hours worked, it is evident that six quarters after the rolling window shifts beyond the end of the first subsample, the largest (in absolute terms) median response within the first ten quarters turns positive. Once the end of the rolling estimation window includes the year 2000 the positive response is almost always significant. For inventories the picture is similar, although here the response flips into positive significant territory already for a sample end at around 1994. Also investment moves very quickly from a negative response to an insignificant one before it becomes significant and positive once the sample end includes 1999. A similar picture is evident for the response of the BAA spread. It becomes insignificant very soon once estimation windows move away from the first subsample. The spread response remains insignificant somewhat longer than those of the other variables and flips to be negative and significant once the sample includes observations after the financial crisis.

Overall, Figure 4 shows that as soon as the sample includes observations that are con-

[13] Other factors that have been suggested to contribute to the end of the Great Inflation are changes in monetary policy making and smaller shocks. While this paper does not attempt to speak to this debate on unconditional changes in time series behavior, it is interesting to note that our results suggest that the transmission of technology shocks actually resulted in larger, rather than smaller, fluctuations in macroeconomic aggregates in response to technology shocks in the second subsample.

[14] In Appendix B, we report corresponding statistics for the impact responses of IRFs. Results are consistent with those of Figure 4. The same holds for corresponding figures with a shorter window length, which are also provided in this appendix.

sidered part of the Great Moderation period, the negative response of hours, investment and inventories, and the positive response of the spread become insignificant. Once samples include more post 1984 observations the IRFs flip sign and remain in this territory. This rolling window exercise illustrates that the findings discussed in relation to Figure 1 are not solely related to the two specific subsamples under consideration but reflect a broader feature in the data. It also shows that the transmission of technology shocks has been affected for some variables by significant events — such as the financial crisis for the BAA spread and investment, the Great Moderation for inventories, investment and hours, and the late 1990's technology boom for investment and hours.

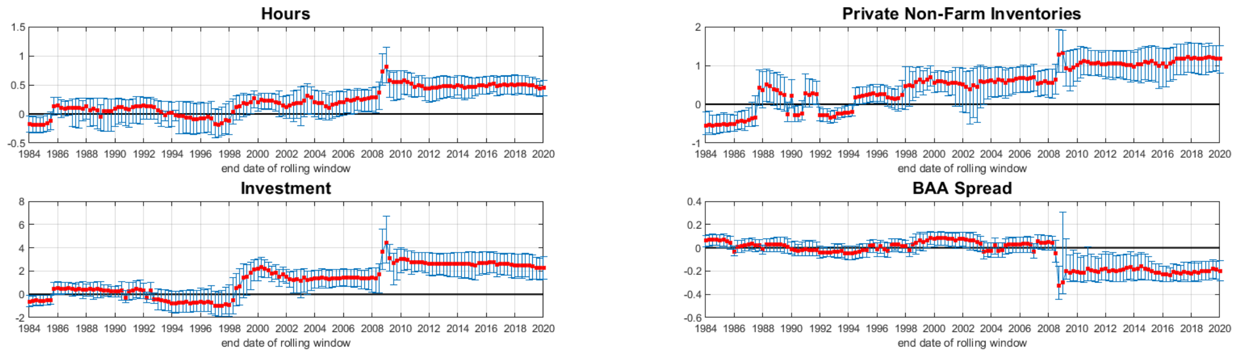


Figure 4: **Maximum/minimum (whichever is largest in absolute terms) IRF response within the first ten quarters to a TFP shock for rolling window.** First rolling window sample is 1954Q2-1983Q4 (119 quarters). The window is shifted up to 2019Q4. We display the median (red dot) and the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations. Subplots are based on a VAR with TFP, GDP, consumption, hours worked, the S&P 500 and one of the plotted variables at a time.

2.4 Exploring the Source of Subsample Differences: Impulse or Propagation?

Our results above suggest that not only have technology shocks played more of a role in accounting for aggregate fluctuations over time, but their impact on the macroeconomy has also changed. While the former effect on its own could simply reflect some change in a feature of the technology shock itself, the latter result however is more suggestive of a change in some underlying feature of the macroeconomy. We now take a first-pass at trying to understand the reason for this change within the context of our econometric setup.

As we show in detail in Appendix A, our econometric approach considers the following vector autoregression (VAR), which describes the joint evolution of an $n \times 1$ vector of variables y_t:

$$y_t = A(L)u_t.$$

$A(L) = I + A_1 L + ... + A_p L^p$ is a lag polynomial of order p over conformable coefficient matrices $\{A_p\}_{i=1}^{p}$. u_t is an error term with $n \times n$ covariance matrix Σ. We assume a linear mapping between the reduced form errors u_t and the structural shocks ε_t:

$$u_t = B_0 \varepsilon_t,$$

where B_0 is an identification matrix. We can then write the structural moving average representation of the VAR:

$$y_t = C(L)\varepsilon_t,$$

where $C(L) = A(L)B_0$, $\varepsilon_t = B_0^{-1} u_t$, and the matrix B_0 satisfies $B_0 B_0' = \Sigma$. B_0 can also be written as $B_0 = \widetilde{B}_0 D$, where $\widetilde{B}_0$ is any arbitrary orthogonalization of Σ and D is an orthonormal matrix such that $DD' = I$.

Thus through the lens of our structural moving-average representation in equation (3), the subsample differences can be driven by: (i) differences in the polynomial lag matrix $A(L)$, (ii) differences in the variance-covariance matrix associated with ε_t, which in turn results from differences in the estimates in the variance-covariance matrix Σ. We test for this as follows: We draw from the posterior coefficient matrix based on the reduced form VAR estimated for each of the two subsamples (we use the same seed for the random number generator). We then identify the TFP shock for the first subsample (as outlined in Section 2.1 and Appendix A.1) using the second-subsample polynomial-lag coefficients and the first-subsample variance-covariance matrix. Similarly, we identify a TFP shock for the second subsample, using the first-subsample polynomial-lag coefficients and the second-subsample variance-covariance matrix.

Figure 5 shows the results of this exercise. The red shaded areas shown in the first row are the IRFs based on the first subsample. The blue shaded areas in the second row are the IRFs based on the second subsample. These shaded areas are congruent with those shown in Figure 1 and are used as a point of reference. The blue dashed and dotted lines in the first row show the median and posterior bands for the second subsample, but the shock is identified using the first-subsample polynomial-lag coefficients and the second-subsample variance co-variance matrix. Similarly, the red lines in the second row of Figure 5 show the responses if the VAR is run on the first subsample and the shock is identified using the second-subsample polynomial-lag coefficients and the first-subsample variance co-variance matrix. It is striking from the first row that if we use subsample two data but identify the shock using polynomial-lag coefficients that are consistent with the first subsample and a second-subsample variance co-variance matrix, the resulting IRFs are extremely similar to the original first subsample responses. In other words, the only difference between the blue shaded areas in the second row and the blue dashed line in the first row is that the latter uses the polynomial lag coefficients implied by the first subsample. This is sufficient for the IRFs to look rather similar to those implied by the first subsample (the red shaded IRFs). The same holds vice versa for the second row. This implies that the documented differences across subsamples are driven to a large extent by differences in the polynomial-lag coefficients, rather than differences in the variance co-variance matrices. This is indicative of a role for differences in the shock's transmission through the economy across the two subsamples.

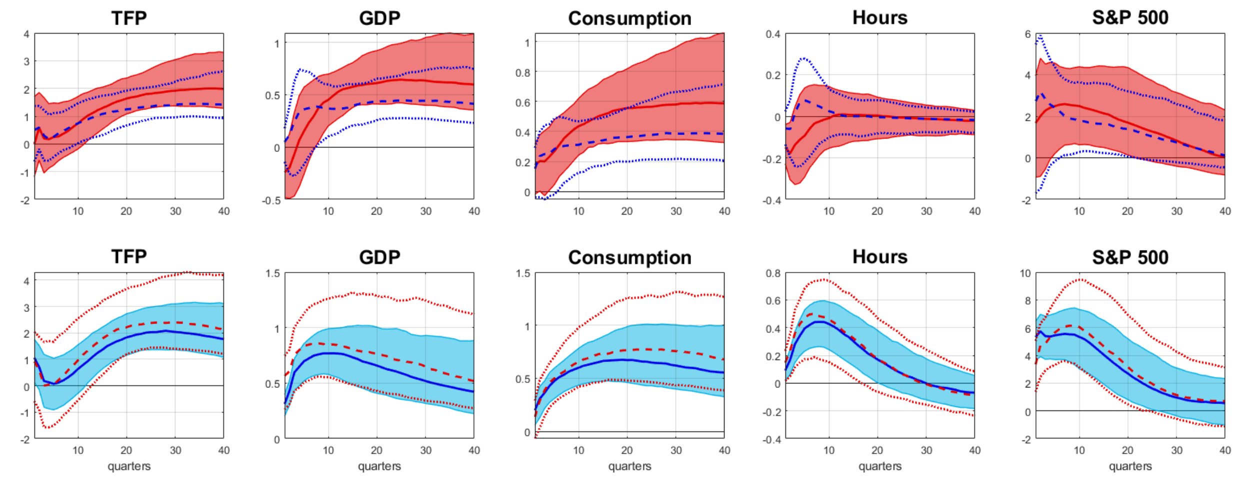


Figure 5: **IRF to TFP shock.** The solid red (blue) line is the median and the shaded red (blue) areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters on the first (second) subsample. First subsample is subsample 1954Q2-1983Q4, second subsample is 1984Q1-2019Q4. The blue (red) dashed and dotted lines in the subplots in row one (two) are the median and posterior bands when running the VAR on the second (first) subsample, but identifying the shock using the polynomial lag coefficients implied by the first (second) subsample and the variance co-variance matrix implied by the second (first) subsample.

3 Differences in Shock Transmission through the Lens of a Structural Model

Our empirical results above document the changes in the response of the economy to technological shocks over time, yet the analysis remains agnostic about the underlying source of these changes. We now use use a structural model to provide some interpretation to potential underlying causes. As we discussed above, the extensive literature studying changes in the structure of the macroeconomy over the 1970's – 1990's have suggested several important changes over this period, including: (1) changes in inventory management (2) changes in labour market rigidities (3) changes in monetary policy (4) emergence of the information and communications technology (ICT) era. Our rich structural model allows us to provide some insight into whether these potential underlying changes in the economy noted in other contexts could also be behind the changing impact of technology.

Our structural framework is a medium scale New Keynesian model of augmented with inventories, a financial sector with financial frictions, and knowledge capital accumulation by firms. We model inventories as in Lubik and Teo (2012), based on the stock-elastic demand model of Bils and Kahn (2000), where finished goods inventories are sales-enhancing. The financial side of the model uses the setup of Gertler and Karadi (2011). Finally, knowledge capital accumulation by firms follows the approach of Gunn and Johri (2011a), Chang et al. (2002) and Cooper and Johri (2002) whereby firms accumulate productivity-enhancing knowledge through an internalized learning-by-doing process in labor.

Our results above focus on the response of the economy to an identified exogenous technology shock, and thus our core analysis in our theoretical model focuses on the conditional response of the model economy to an exogenous non-stationary neutral technological shock. Additionally, our empirical results above suggest that the dominant technological shock in both subsamples is an anticipated or diffused shock where the 16% lower posterior band of TFP impulse response only rises above zero in the range of 12 periods out. Thus, our exogenous technological shock in the structural model takes the form of a "news" or anticipated shock to TFP received 12 periods in advance of the actual change in TFP.

Since we are only interested in anticipated neutral technology shock in the context of our particular question, in our model exposition we do not include the suite of other shocks typical in such models. For balanced growth properties however we do include a non-stationary investment-specific technological shock in addition to the neutral technology shock, such that the model contains stochastic trends owing to both the neutral and investment-specific technology shocks.

In the model description that follows, we describe the key components of the model, leaving the details to Appendix D. Appendix D.2 details the model equilibrium and equilibrium equation system.

3.1 Model Description

The model consists of a large number of identical infinitely-lived households, a competitive intermediate goods-producing firm, a continuum of monopolistically competitive distributors, a competitive final goods producer, a continuum of competitive financial intermediaries, a competitive capital services firm, a competitive capital goods producer, a continuum of monopolistically competitive labour unions, a competitive employment agency and a monetary policy authority. The intermediate goods firm produces a homogeneous good that it sells to distributors. This good is then differentiated by the distributors into distributor-specific varieties that are sold to the final-goods firm. The varieties are aggregated into final output, which then becomes available for consumption or investment. Households are comprised of a fraction $1 - f$ of workers and f of bankers. Workers supply labor, bankers manage financial intermediaries, and both return their earnings to the household. Since our particular decentralization of wage stickiness implies that choices on consumption and hours worked are identical across households, for simplicity we will refer to a stand-in representative household.

3.2 Households

The stand-in household's lifetime utility is defined over sequences of consumption C_t and hours worked N_t and is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(V_t^{1-\sigma} - 1\right)}{1-\sigma}, \tag{1}$$

where $0 < \beta < 1$, $\sigma > 0$. The argument V_t is given by

$$V_t = C_t - bC_{t-1} - \psi N_t^{\xi} F_t, \quad \text{where} \quad F_t = \left(C_t - bC_{t-1}\right)^{\gamma_f} F_{t-1}^{1-\gamma_f}, \tag{2}$$

is a preference component that makes consumption and labor non-time-separable and is consistent with the balanced-growth path in a growing economy. This preference structure, which follows Schmitt-Grohe and Uribe (2012) and is based on Jaimovich and Rebelo (2009), nests the no-income effect structure of Greenwood et al. (1988) in the limit as the parameter $0 < \gamma_f \leq 1$ tends toward zero. The parameter $0 \leq b < 1$ allows for habits in consumption; and $\xi > 1$ is related to the Frisch elasticity of labour supply.

The household enters each period with real financial securities, B_t, which serve as deposits with the financial intermediaries, and nominal bonds, B_t^n, earning risk-free gross real rate of return, R_t, and risk-free gross nominal rate of return, R_t^n, respectively, receiving nominal wage, W_t^h, for supplying hours, N_t^h, to the labour union, and receiving a share of real profits from the various other entities in the model, denoted collectively as Π_t^π. At the end of the period, the household chooses its consumption C_t, its holdings of financial deposits B_{t+1} and nominal bonds B_{t+1}^n. The household's period t budget constraint is given by

$$C_t + B_{t+1} + \frac{B_{t+1}^n}{P_t} + T_t = R_t B_t + R_t^n \frac{B_t^n}{P_t} + \frac{W_t^h}{P_t} N_t^h + \Pi_t^\pi, \tag{3}$$

where P_t is the price of the final good in terms of the nominal unit under the control of the central bank and T_t denotes lump-sum taxes. The household's problem is to choose sequences of C_t, N_t^h, B_{t+1} and B_{t+1}^n to maximize equation (1) subject to equations (2) and (3), resulting in standard first-order conditions.

Revenues from taxation go directly to government spending G_t, where we assume that the budget is always balanced such that $G_t = T_t$. Furthermore, government spending follows the deterministic process $G_t = \varepsilon^g Y_t$, where ε^g is a constant.

3.3 Financial Intermediaries

Our financial intermediary framework follows that of Gertler and Karadi (2011) and so we show only the core elements here. In period t, the jth financial intermediary obtains deposit funds, B_{jt+1}, from households. The intermediary uses those funds and their own net-worth, N_{jt}^b, to make state-contingent loans, S_{jt}^b, to non-financial capital services firms, such that the intermediary's financing satisfies the balance sheet identity

$$q_t^k S_{jt}^b = N_{jt}^b + B_{jt+1},$$

where q_t^k is the price of the state-contingent loan. The intermediary's net-worth then evolves as

$$N_{jt+1}^b = R_{t+1}^k q_t^k S_{jt}^b - R_{t+1} B_{jt+1},$$

where R_{t+1} is the non-contingent rate paid on household deposits (determined in t), and R_{t+1}^k is the state-contingent return on loans.

An intermediary in period t remains to be an intermediary in $t+1$ with exogenous probability θ_b. With probability 1-θ_b they have been deemed to exit, a feature that insures an intermediary will not grow so large as to be able to self-finance all its loans. The intermediary will continue to operate and build wealth until exiting as long as the risk adjusted premium on making loans over borrowing is positive. The intermediary thus maximizes expected terminal wealth, given by

$$V_{jt}^b = \max_{\{S_{jt+i}^b, N_{jt+1+i}^b\}} E_t \sum_{i=0}^{\infty} (1-\theta_b)\theta_b^i \Lambda_{t,t+1+i} N_{jt+1+i}^b,$$

where $\Lambda_{t,t+i} = \beta^i \frac{\lambda_{t+i}}{\lambda_t}$ is the household's stochastic discount factor.

The financial friction takes the form of a moral hazard/cost enforcement problem where each period, the intermediary can divert the fraction λ_b of assets back to the household, at which point the intermediary is forced into bankruptcy and the depositors recover the fraction $1-\lambda_b$. Thus for depositors to be willing to supply funds to the intermediary, the following enforcement constraint

$$V_{jt}^b \geq \lambda_b q_t^k S_{jt}^b$$

must hold, such that the value to the intermediary of continuing to operate is at least as large as the value of absconding funds. Conjecturing and subsequently verifying that the solution is linear in its balance sheets components in the form

$$V_{jt} = \nu_{bt} q_t^k S_{jt} + \eta_{bt} N_{jt},$$

and that the leverage ratio, ϕ_{bt}, defined as

$$\phi_{bt} = \frac{q_t^k S_{jt}}{N_{jt}},$$

is not dependent on intermediary-specific factors, we can then solve for ν_{bt} and η_{bt}. Under the case that the enforcement constraint is binding (as in Gertler and Karadi (2011)),

$$\phi_{bt} = \frac{\eta_t}{\lambda_b - \nu_{bt}},$$

then ν_{bt} and η_{bt} are given by

$$\nu_{bt} = E_t \beta \frac{\lambda_{t+1}}{\lambda_t} \Gamma_{t+1} \delta_{bt+1} \qquad \text{and} \qquad \eta_{bt} = E_t \beta \frac{\lambda_{t+1}}{\lambda_t} \Gamma_{t+1} R_{t+1},$$

where $\Gamma_t = 1 - \theta_b + \theta_b(\nu_{bt}\phi_{bt} + \eta_{bt})$ and $\delta_{bt} = R_t^k - R_t$.

3.4 Employment Unions and Employment Agency

Our sticky-wage framework follows the decentralization of Schmitt-Grohe and Uribe (2012) and Smets and Wouters (2007) with a continuum of monopolistically competitive labor unions on a unit mass indexed by $q \in [0,1]$, and a competitive employment agency. Monopolistic unions buy homogeneous labor from households, transform it into differentiated labor inputs, and sell it to the employment agency who aggregates the differentiated labor into a composite which it then sells to the intermediate goods producer. The unions face Calvo frictions in setting their wages for each labour type — such that each period they can re-optimize wages with probability $1 - \zeta_w$ — and re-set their wage according to an indexation rule when unable to reoptimize.

Since this model component is standard, we relegate the exposition of further details to Appendix D.1. The sticky wage framework results in an endogenous time-varying markup μ_t^w between the wage W_t paid by the intermediate goods firm and the wage W_t^h paid to the household, such that

$$\mu_t^w = \frac{W_t}{W_t^h} = \frac{w_t}{w_t^h}. \tag{4}$$

where $w_t = \frac{W_t}{P_t}$ and $w_t^h = \frac{W_t^h}{P_t}$. The dynamics of μ_t^w is captured by a resulting equilibrium wage Phillips curve derived from imposing equilibrium on the combination of the employment agency and union's problem.

3.5 Intermediate Goods Firm

The competitive intermediate goods firm produces the homogeneous good Y_t with technology

$$Y_t = (\Omega_t N_t)^{\alpha_n} \widetilde{K}_t^{\alpha_k} (\Omega_t H_t)^{1-\alpha_n-\alpha_k},$$

where Ω_t is a non-stationary exogenous stochastic neutral productivity process, and H_t is the stock of intangible capital that resides within the firm and that we refer to as knowledge capital. The growth rate g_t^{Ω} of Ω_t is given by

$$\ln\left(\frac{g_t^{\Omega}}{g^{\Omega}}\right) = \rho_{g^{\Omega}} \ln\left(\frac{g_{t-1}^{\Omega}}{g^{\Omega}}\right) + u_t^{g^{\Omega}}, \qquad \text{with} \qquad u_t^{g^{\Omega}} = \epsilon_{g^{\Omega}t}^{0} + \epsilon_{g^{\Omega}t-12}^{12},$$

where $\epsilon_{g^{\Omega}t}^{0}$ is an unanticipated shock and $\epsilon_{g^{\Omega}t-p}^{p}$ is a news shock that agents receive in period t about the innovation in time $t+p$. The innovations $\epsilon_{g^{\Omega}t}^{0}$ and $\epsilon_{g^{\Omega}t-p}^{p}$ are assumed to be i.i.d. and independent across time and news horizon.

Following Gunn and Johri (2011b), Chang et al. (2002) and Cooper and Johri (2002), we assume that the stock of knowledge capital, H_t, evolves as an internalized learning-by-doing process to capture the idea that agents acquire new technological knowledge through their experiences in engaging labor in the production process.[15] Accordingly, H_t evolves as

$$H_{t+1} = (1-\delta_h)H_t + H_t^{1-\nu_h} N_t^{\nu_h}, \qquad \text{where} \qquad 0 \leq \delta_h \leq 1, \quad 0 \leq \nu_h < 1. \tag{5}$$

The accumulation equation (5) nests a log-linear specification for $\delta_h = 1$, common in the literature such as in Chang et al. (2002), Cooper and Johri (2002) and d'Alessandro et al. (2019), but also allows for a more general linear formulation for $0 < \delta_h < 1$.

Each period the firm acquires labor, N_t, at wage, w_t, from the labor market, and capital services, $\widetilde{K}_t$, at rental rate r_t from the capital services market. It then sells its output, Y_t, at real price, τ_t, to the distributors. Additionally, we find it convenient to define the marginal cost of production for intermediate goods, $mc_t = \frac{w_t}{MPN\,t} = \frac{w_t}{\alpha_n Y_t/N_t}$, where MPN_t is the marginal product of labor. It then follows that the output price, τ_t, is equal to the marginal cost of production, mc_t.

The firm's optimization problem involves choosing N_t, $\widetilde{K_t}$ and H_{t+1} to maximize its stream of profits, $E_0 \sum_{t=0}^{\infty} \frac{\beta^t \lambda_t}{\lambda_0} \Pi_t^y$, subject to the production function and knowledge capital accumulation equation, where $\Pi_t^y = \tau_t Y_t - w_t N_t - r_t \widetilde{K}_t$.

[15] The idea of learning-by-doing, and in particular skill-accumulation through work experience, has a long history in labor economics, where empirical researchers have found a significant effect of past work effort on current wage earnings. Researchers have studied learning-by-doing both as a growth mechanism as in Arrow (1962), as well as a short-run supply-side mechanism that enhances the dynamics of business cycle models, as e.g. in Chang et al. (2002), Cooper and Johri (2002), Gunn and Johri (2011b), d'Alessandro et al. (2019) and Görtz et al. (2022)

3.6 Capital Producer

The competitive capital-goods producer operates a technology that combines existing capital with new investment goods to create new installed capital. At the end of each period it purchases existing capital, K_t^k, from the capital services firms at price $\tilde{q}_t^k$, combining it with investment, I_t, to yield new capital stock, K_t^{nk}, which it sells back to the capital services firm in the same period at price q_t^k. The capital-producer faces capital adjustment costs in the creation of new capital, and incurs depreciation in the process, so that

$$K_t^{nk} = (1-\delta)K_t^k + I_t - S\left(\frac{I_t}{K_t^k}\right)K_t^k. \tag{6}$$

where $S(\cdot)$ is an investment adjustment cost function with the properties that in steady state, $S(\cdot) = 0$, $S'(\cdot) = 0$, and $S''(1) = s'' > 0$, where s'' is a parameter. With this form of adjustment costs, the capital producer's problem is static, whereby each period it chooses I_t and K_t^{nk} to maximize period t profits $\Pi_t^{nk} = q_t^k K_t^{nk} - \bar{q}_t^k K_t^k - \Upsilon_t I_t$ subject to equation (6), and where Υ_t is a non-stationary exogenous stochastic investment-specific productivity process.

The growth rate g_t^Υ of Υ_t is given by

$$\ln\left(\frac{g_t^\Upsilon}{g^\Upsilon}\right) = \rho_{g^\Upsilon} \ln\left(\frac{g_{t-1}^\Upsilon}{g^\Upsilon}\right) + \epsilon_{g^\Upsilon t}^0,$$

where $\epsilon_{g^\Upsilon t}^0$ is an unanticipated shock, i.i.d. and independent across time and news horizon.

3.7 Capital Services Firm

At the end of each period t the competitive capital services firm buys capital, K_{t+1}, from the capital producer at price q_t^k, financing it with loans from the financial intermediaries in the form of state-contingent claims, S_t^b, equal to the number of units of capital, and pricing each claim at the price of a unit of capital. At the beginning of $t+1$, the firm rents services of the capital, $\tilde{K}_{t+1} = u_t K_{t+1}$, to intermediate goods firms at price r_t. At the end of the period, the firm incurs utilization costs of $a(u_{t+1})K_{t+1}\Upsilon_{t+1}$, sells the undepreciated capital back to capital goods producers at price $\tilde{q}_{t+1}^k$, and pays out state-contingent profits Π_{t+1}^k to financial intermediaries, where

$$\Pi^k_{t+1} = q^k_t S^b_t - q^k_t K_{t+1} + r_{t+1}u_{t+1}K_{t+1} - a(u_{t+1})K_{t+1}\Upsilon_{t+1} + \tilde{q}^k_{t+1}K_{t+1}.$$

After observing the aggregate state in $t+1$, the firm the faces the problem to choose u_{t+1} to maximize Π^k_{t+1}, yielding the optimality condition $a'(u_{t+1})\Upsilon_{t+1} = r_{t+1}$. We assume that the function $a(u_t)$ is convex in the rate of utilization, such that $a'(\cdot) > 0, a''(\cdot) > 0$. We also assume that $u_t = 1$ in steady state, and that $a(1) = 0$.

Letting R^k_{t+1} be the state-contingent gross real return on the claims issued in t, then $\Pi^k_{t+1} = R^k_{t+1}q^k_t S^b_t = R^k_{t+1}q^k_t K_{t+1}$, such that using the firm's optimality conditions for u_{t+1}, and $q^k_t S^b_t = q^k_t K_{t+1}$, the state-contingent real return is given by

$$R^k_{t+1} = \frac{r_{t+1}u_{t+1} - a(u_{t+1})\Upsilon_{t+1} + \tilde{q}^k_{t+1}}{q^k_t}.$$

3.8 Final Goods Firm

The competitive final goods firm produces goods for sale, S_t, by combining distributor-specific varieties S_{it}, $i \in [0,1]$, according to the technology

$$S_t = \left[\int_0^1 \nu_{it}^{\frac{1}{\theta}} S_{it}^{\frac{\theta-1}{\theta}} di\right]^{\frac{\theta}{\theta-1}}, \qquad \text{with} \qquad \nu_{it} = \left(\frac{A_{it}}{A_t}\right)^{\zeta}, \qquad \text{and} \qquad \theta > 1,\ \zeta > 0,$$

where ν_{it} is a taste shifter that depends on the stock of goods available for sale A_{it}. The latter is composed of current production and the stock of goods held in inventory.[16] We assume that ν_{it} is taken as given by the final goods producer and A_t is the economy-wide average stock of goods for sale, given by $A_t = \int_0^1 A_{it}di$. The parameters θ and ζ capture, respectively, the elasticity of substitution between differentiated goods and the elasticity of demand with respect to the relative stock of goods.

The firm acquires each variety i from the distributors at relative price $p_{it} = P_{it}/P_t$, where $P_t = \left[\int_0^1 v_{it}P_{it}^{1-\theta}di\right]^{\frac{1}{1-\theta}}$ is the aggregate price index. It sells the final good for use in consumption or as an input into the production of investment goods. The firm maximizes the profit function $\Pi^s_t = S_t - \int_0^1 \frac{P_{it}}{P_t}S_{it}di$ by choosing S_{it}, $\forall i$. This results in demand for S_{it}

[16]This structure follows Bils and Kahn (2000) and is standard in modeling demand for goods drawn from inventories. It also supports a convenient decentralization of production.

for the ith variety

$$S_{it} = \nu_{it} p_{it}^{-\theta} S_t. \tag{7}$$

An increase in ν_{it} shifts the demand for variety i outwards. This preference shift is influenced by the availability of goods for sale of variety i, which thereby provides an incentive for firms to maintain inventory to drive customer demand and avoid stockouts.

3.9 Distributors

We follow Bils and Kahn (2000) in modeling inventories as a mechanism that helps generate sales, while at the same time implying a target inventory-sales ratio that captures the idea of stockout avoidance. Distributors acquire the homogeneous good Y_t from the intermediate goods firms at real price τ_t. They differentiate Y_t into goods variety Y_{it} at zero cost, with a transformation rate of one-to-one. Goods available for sale are the sum of the differentiated output and the previous period's inventories subject to depreciation

$$A_{it} = (1 - \delta_x) X_{it-1} + Y_{it}, \tag{8}$$

where the stock of inventories X_{it} are the goods remaining at the end of the period

$$X_{it} = A_{it} - S_{it}, \tag{9}$$

and $0 < \delta_x < 1$ is the rate of depreciation of the inventory stock.

The distributors have market power over the sales of their differentiated varieties. The ith distributor sets price p_{it} for sales S_{it} of its variety subject to its demand curve (7). Distributors face frictions in setting their prices, and as in Lubik and Teo (2012) , we assume that the ith distributor faces convex adjustments costs in the form $\frac{\kappa}{2}\left[\frac{P_{it+k}}{\pi_{t-1}^{\iota_p}\pi^{1-\iota_p}P_{it+k-1}} - 1\right]^2 S_t$. Each period, a distributor faces the problem of choosing p_{it}, S_{it}, Y_{it}, and A_{it} to maximize profits

$$E_t \sum_{k=0}^{\infty} \beta^k \frac{\lambda_{t+k}}{\lambda_t} \left\{ \frac{P_{it+k}}{P_{t+k}} S_{it+k} - \tau_t Y_{it+k} - \frac{\kappa}{2}\left[\frac{P_{it+k}}{\pi_{t-1}^{\iota_p}\pi^{1-\iota_p}P_{it+k-1}} - 1\right]^2 S_t \right\},$$

subject to the demand curve (7), the law of motion for goods available for sale (8), and the definition of the inventory stock (9), and where λ_t is household's marginal utility of wealth.

3.10 Monetary Policy

We close the model with a standard monetary policy rule where the interest rate, R^n_{t+1}, is set by the monetary authority according to a feedback rule,

$$\frac{R^n_{t+1}}{R^n} = \left(\frac{R^n_t}{R^n}\right)^{\rho_r} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y^*_t}\right)^{\phi_y}\right)^{(1-\rho_r)},$$

where Π_t is the gross inflation rate, Π the corresponding stead state level, Y^*_t is level of output that would preside under flexible wages and prices. The parameter ρ_r governs interest rate smoothing over time; and ϕ_π and ϕ_y control the interest rate response to deviations in inflation and output from their respective reference points.

3.11 Understanding the Response of Hours

The primary qualitative change in the response to a technology shock evidenced in our empirical analysis was the change in the comovement of hours worked with consumption. Moreover, in both subsamples, productivity evolved in a diffused manner, consistent with the interpretation of the technology shock as an anticipated or news shock. Before we confront the model with the data to study these features, we first highlight some key mechanisms of the model to understand the response of hours to such news shocks and frame our subsequent analysis.

We examine the key equations of the labor market equilibrium to develop an expression that characterizes the response of hours worked. We work with the linearizatons of the stationary transformations of the underlying non-stationary system, and introduce wedges into the model as stand-ins for several of the structural mechanisms in the model. The wedges can be interpreted as endogenous equilibrium objects that represent deviations from some reference model. Additionally, in our linearizations we focus on a "news phase" where the model economy has received a news-shock about an increase in future TFP, but where the TFP shock has not yet materialized, and thus the linearized shocks are all zero.

We begin with the labor-supply equation

$$\xi\psi\Gamma_t v_t^{-\sigma} n_t^{\xi-1}\frac{f_t}{\bar{\lambda}_t} = \frac{\bar{w}_t^h}{\phi_t^{ls}}, \tag{10}$$

where we define ϕ_t^{ls} as a labour supply wedge between the marginal rate of substitution on the left-hand side and the real wage. In this model the labour supply wedge is equal to the wage markup term resulting from the presence of sticky wages which we discuss more below.[17] Next, we write the labor demand equation as

$$\bar{w}_t\phi_t^{ld} = \alpha_n\tau_t\frac{y_t}{n_t}, \tag{11}$$

where ϕ_t^{ld} is a labor demand wedge, equal to the knowledge capital markup wedge which we will discuss more below, and τ_t is the relative price of output, which itself acts as a wedge through its link to the inventory stocking equation. Finally, we write the production function as

$$y_t = (n_t)^{\alpha_n}\left(u_t\frac{k_t}{g_t^k}\right)^{\alpha_k}\phi_t^e, \tag{12}$$

where ϕ_t^e is an efficiency wedge, equal to the input of knowledge capital in production, $h_t^{(1-\alpha_n-\alpha_k)}$, and g_t^k is the growth rate of the stochastic trend in capital. Linearizing equations (10), (11) and (12), eliminating the real wage and isolating hours-worked gives

$$\hat{n}_t = \frac{1}{(\xi-\alpha_n)}\left[\hat{\psi}_t^n - \hat{\phi}_t^{ls}\right] + \frac{1}{(\xi-\alpha_n)}\left[\hat{\tau}_t + \hat{\phi}_t^e - \hat{\phi}_t^{ld} + \alpha_k\hat{u}_t + \alpha_k\hat{k}_t\right], \tag{13}$$

where "hat's" denote percent-deviations of the transformed stationary variables from steady state, and $\hat{\psi}_t^n = \hat{\lambda}_t + \sigma\hat{v}_t - \hat{f}_t$ is a stand-in for the preference elements from the Jaimovich-Rebelo class of preferences.

Equation (13) describes the response of hours during the news-phase when no shocks other than the news shock are present. The terms in the first set of square brackets on the right hand side are labor supply shifters, and those in the second set of square brackets are labor demand shifters. Movements in the former and latter that are associated with an increase in the response of hours will tend to lower and raise the real wage, respectively.

[17] Equations in this section are stationarized and lower case variables correspond to their non-stationary upper case counterparts. Also the bar above λ_t and w_t denote the stationarized versions of these variables. See Appendix D.2.1 for details of the model stationarity.

The coefficient term on both sets of brackets is a function of $\xi - \alpha_n$ which contribute to the relative slopes of the linearized labor supply and demand curves. Through the lens of the model, any change in the response of hours over the subsamples must show up somehow in the elements of this equation, and thus we use it to summarize the main possibilities for a change in the response of hours over the two subsamples.

Preference hypothesis. In principle, a change in preferences could account for the change in the response of hours over time, either through the parameter ξ which parameterizes the Frisch elasticity of labor and thus the amount of labour households are willing to supply for a given wage, or through the stand-in variable $\hat{\psi}_t^n$, which itself depends on the "wealth effect" parameter γ_f and consumption habits parameter b. The parameter γ_f is a particularly strong potential channel given the strong link between the wealth effect of expanding technology on consumption and the comovement of hours and consumption. As has been studied extensively in the literature, when γ_f is large, the standard income-effect on leisure means that while consumption rises in response to the increase in lifetime wealth from the increase in technology, leisure also rises, and thus consumption and hours negatively co-move. When γ_f is near zero on the other hand, the income-effect on labor is minimal, such that consumption can increase in response to an increase in wealth without implying a corresponding drop in hours.[18] While changes in preferences over time are possible, we find large changes unlikely. Nevertheless, in our quantitative analysis, we will allow for changes in ξ and γ_f, but we will restrict their range within common values used in the literature to limit the possibility that large jumps in preferences alone explain the change in hours.

Labor market frictions hypothesis. The direct effect of changes in labor market frictions in equation (13) work through the labor supply wedge ϕ_t^{ls}, which equals the wage markup from the wage Phillip's curve. This occurs through the changes in the parameter ω in the model, which measures the Calvo probability of not being able to optimally re-set household wages in a given period. An increase in ω would imply a more sluggish response of

[18]To see this most clearly, note that with $\gamma_f = 0$ and no consumption habits ($b = 0$), the stand-in variable $\hat{\psi}_t^n = 0$ and thus, it drops out of equation (13).

the real wage w_t^h facing the household, and thus a larger drop in ϕ_t^{ls} putting upward pressure on hours worked.

Monetary policy hypothesis. A change in the stand of monetary policy in the model impacts the response of hours through at least two main channels: the first through interaction via sticky wages, and the second through the real interest rate. For the first channel, as discussed extensively by Christiano et al. (2008), under sticky nominal wages, an inflation-targeting central bank directly impacts the real wage markup through the impact of inflation. Like the change in labor market frictions discussed above, this would manifest itself directly in equation (13) through the labor supply wedge ϕ_t^{ls}. The second channel impacts equation (13) indirectly through the general equilibrium impacts of the real interest rate on the variables in this equation, such as the preference term ψ_t^c, capacity utilization u_t, and the marginal cost of output τ_t through the impact of the real interest rate on inventory. For our quantitative analysis we allow for changes in the parameters ρ_r, ϕ_π, and ϕ_y of the monetary policy rule.

Credit market hypothesis. Like the second channel of monetary policy above, changes in credit market frictions in the model manifest themselves in equation (13) indirectly through the general equilibrium impacts of the real interest rate on variables in this equation, as well as the impacts of the credit spread, capacity utilization u_t, and choice of capital k_t. We note however that with capital predetermined on impact and sluggish in subsequent periods relative to the other variables such as capacity utilization, variation in k_t isn't likely to be a dominant factor in the response of hours in the initial few periods. Changes in credit market frictions in the model occur through changes in the parameter λ_b, which captures the proportion of capital a financial intermediary threatens to abscond. For our quantitative analysis, we allow for changes in λ_b by estimating steady-state leverage, ϕ_b, which, based on our model solution and partial calibration, maps directly to λ_b.[19]

Inventory hypothesis. The equilibrium optimal stocking condition in the model im-

[19]Due to non-linearities in the steady-state relations, estimating ϕ_b instead of λ_b reduces computational complexity.

plies that the inventory sales ratio $\frac{X_t}{S_t}$ is given by

$$\frac{X_t}{S_t} = \chi(\tau_t, \mu_t^x), \tag{14}$$

where the partial derivatives $\chi_\tau(t) = \frac{\partial\chi(\tau_t,\mu_t^x)}{\partial\tau_t} < 0$ and $\chi_{\mu^x}(t) = \frac{\partial\chi(\tau_t,\mu_t^x)}{\partial\mu_t^x} < 0$, and where μ_t^x is equal to the expected discounted value of future marginal costs, $\mu_t^x = (1-\delta_x)\,\beta E_t \frac{\lambda_{t+1}}{\lambda_t}\tau_{t+1}$. Faced with an increase in demand for sales triggered by the TFP news shock, distributors can satisfy the demand by some combination of running down inventories or purchasing new output at real price τ_t. The function $\chi(\cdot)$ depends on the parameter ζ, which measures the elasticity of demand for sales with respect to the relative stock of good varieties, and thus changes in ζ will impact the equilibrium response of τ_t and the associated response of hours in equation (13).

We note here also our empirical results suggesting that in both subsamples, hours and inventory co-move positively, no matter how hours and consumption co-move. In terms of equation (13), we see that all else equal, hours varies positively with the real price of output, τ_t. A change in inventory management which implies meeting any increase in sales demand with relatively more new production relative to existing stocks of inventory would drive up the real price of output τ_t and thus hours worked, implying upward force on both hours and inventories.

Knowledge capital hypothesis. The Intermediate Goods Firm's optimal labour choice is given by

$$w_t = \tau_t \alpha \frac{Y_t}{N_t} + \nu_h q_t^h \frac{H_t^{1-\nu_h} N_t^{\nu_h}}{N_t}, \tag{15}$$

where q_t^h as the Lagrange multiplier on equation the knowledge capital accumulation equation (5) and has the interpretation as the marginal value of acquiring new knowledge capital in terms of expected future lifetime profits. q_t^h is in turn given by

$$q_t^h = \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \left\{ (1-\alpha_n-\alpha_h)\tau_{t+1}\frac{Y_{t+1}}{H_{t+1}} + q_{t+1}^h \left(1-\delta_h + (1-\nu_h)\frac{H_{t+1}^{1-\nu_h} N_{t+1}^{\nu_h}}{H_t} \right) \right\}. \tag{16}$$

The presence of internalized knowledge capital in the firm's technology adds an additional term into the firm's hours worked first order condition (15) that shifts labor demand. News about future TFP increases the value of future knowledge through the impact of knowledge in future production according to (16), increasing the value of knowledge today, q_t^h, shifting out the firm's labor demand.

This manifests itself directly in equation (13) as a decrease in the labor demand wedge, ϕ_t^{ld} as the firm increases hours today in order to increase future knowledge capital, thus lowering its markup and current profits in the present in order to increase profits in the future. In our quantitative analysis we study changes in knowledge capital accumulation in the model occur through changes in the parameters δ_h, the depreciation rate of knowledge capital, and ν_h, the elasticity of labor in the production of new knowledge.

Other channels. A change in the steady state elasticity cost of adjusting capacity utilization, $\epsilon_u \frac{a''(u)}{a'(u)} u$, directly impacts equation (13) through its impact on u_t. We can gain additional insight by using the linearized form of the capital services firm's first-order condition for utilization, $\bar{r}_t = \delta'(u_t)$ and the Intermediate Goods Firm's first-order condition for capital services $\bar{r}_t = (1-\alpha)\tau_t \frac{y_t}{u_t \frac{k_t}{g_t^k}}$ to eliminate u_t in equation (13), resulting in

$$\hat{n}_t = \frac{1}{(\xi - \chi_u \alpha_n)} \left[\hat{\psi}_t^n - \hat{\phi}_t^{ls}\right] + \frac{1}{(\xi - \chi_u \alpha_n)} \left[\chi_{\hat{u}} \tau_t + \chi_u \hat{\phi}_t^e - \hat{\phi}_t^{ld} + (1 + \chi_u(\alpha_k - 1))\alpha_k \hat{k}_t\right], \tag{17}$$

where $\chi_u = \frac{1-\epsilon_u}{1-\epsilon_u-\alpha_k}$, where we can see that the primary role of capacity utilization in the model is to increase the elasticity of the other components of labour demand.[20] In addition to the direct effect, a change in the cost of utilizaton can impact equation (17) indirectly through the general equilibrium impacts of the real interest rate due to the influence of the cost of utilization on the return to capital and thus real interest rate.

In additional to the cost of utilization, a change in the cost of adjusting investment or capital, s'', impacts equation (17) indirectly through the general equilibrium impacts of the real interest rate on variables in this equation, working through the credit sector by influencing the price of capital and thus the return on capital.

[20]We note that the relative price of capital, q_{kt} does not play a role here as an independent shift factor for utilization, as in Greenwood et al. (1988) or Jaimovich and Rebelo (2009). Unlike in those models where the cost of utilization is incurred within the capital accumulation equation and this in terms of units of capital, in this model decentralization with separate financial, capital services and production sectors that subdivide this overall capital accumulation process, the utilization cost is incurred in terms of consumption units as in Christiano et al. (2005).

4 Quantitative Approach

We now detail our approach for quantitatively studying how the model might account for the changes in the response to technology shocks that we documented earlier in the empirical section. The approach is a hybrid of calibration, econometric and counterfactual exercises designed to illuminate candidate channels that could explain the changes in response across subsamples.

As in the empirical section, we break the sample data into two subsamples, 1954Q2-1983Q4 and 1984Q1-2019Q4, as an approximation for gradual or more abrupt structural change over that period. We then estimate a subset of the model parameters independently over the two subsamples, allowing the remaining subset of the parameters to remain fixed over both subsamples. Our estimation for each subsample follows the approach of Christiano et al. (2005) such that the parameters are estimated by minimizing a measure of the distance between the model and empirical impulse response functions, conditional on a single structural shock in the model that corresponds to the shock identified in the empirical VAR. We use the results of the estimation over the two subsamples to highlight the key parameter changes, and then perform counterfactual exercises to explore the potential role of each key parameter in the change in impulse responses over the two subsamples.

4.1 Estimated and Fixed Parameters

The parameters that we estimate and that will be the focus of our analysis correspond to the parameters highlighted in our analytical analysis in Section 3.11 as being potentially important for the response of hours worked. Let $\vartheta = (\xi, \gamma_f, \epsilon_u, s'', \zeta, \delta_x, \delta_h, \nu_h, \rho_\Omega, \phi_\pi, \phi_y, \rho_r, \kappa, \zeta_w, \phi_b)$ be the vector of these parameters. Then let $\psi(\vartheta)$ be the mapping from ϑ to the first ten elements of the model impulse response functions for the target variables consumption (C), output (Y), hours worked (N) and investment (I), and $\hat{\psi}$ be the median of the estimated posterior distribution of the corresponding empirical impulse response functions. For each of the two subsamples, we then estimate ϑ as the solution to the problem

$$J_i = \min_{\vartheta_i} \left[\hat{\psi}_i - \psi(\vartheta_i)\right]' V_i^{-1} \left[\hat{\psi}_i - \psi(\vartheta_i)\right], \tag{18}$$

where V_i is a weighting matrix, and $i = 1, 2$ denotes the first or second subsample. We construct V_i using the variances of the posterior distribution of empirical impulse response functions along the diagonal for each subsample.

As discussed above, the estimated parameters in ϑ directly affect the response of hours worked to technology shocks. The remaining model parameters are held fixed at constant values over both subsamples. The calibration is standard and we report the calibrated values in 1 in Appendix E.1.

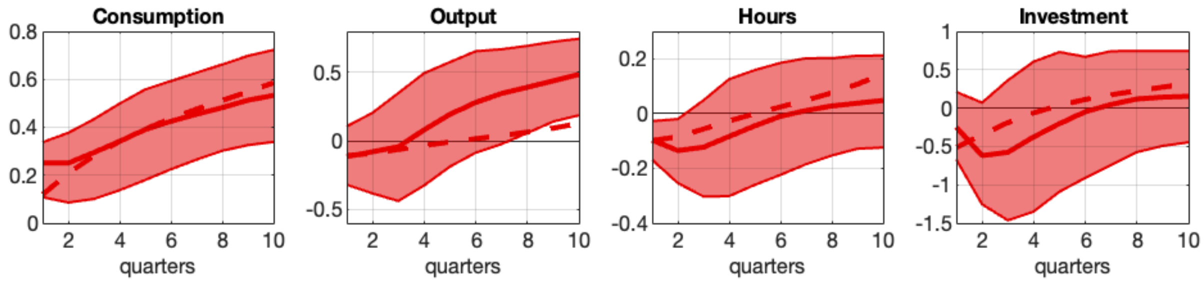
4.2 Impulse Response Functions

We now presents the results of the impulse response function matching as well as a series of counterfactual experiments.

Figure 6 shows the model impulse response functions resulting from the matching exercise above. The first and second rows in the figure show the impulse response functions based on estimates from the first and second subsamples respectively. In the first row (second), the red (blue) solid line and shading indicate the empirical VAR median and 16% and 84% posterior bands respectively for the posterior distribution of VAR parameters for the first (second) subsample. The red (blue) dashed line is the model IRF obtained from the IRF matching procedure over this period.

The figure shows that the estimation procedure over the two subsamples captures the primary nature of the change in the empirical response over the two subsamples: in the model IRFs like in the empirical IRFs, consumption rises in both samples, whereas hours and investment fall in the first subsample and rise in the second. For the vast majority of the periods, the theoretical IRFs lie within the posterior bands of the empirical VAR.

Subsample 1: 1954Q2-1983Q4.



Subsample 2: 1984Q1-2019Q4.

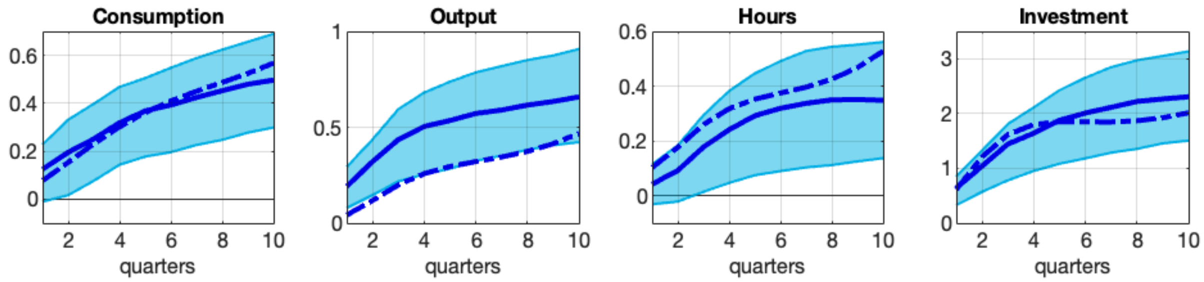


Figure 6: **VAR and model based IRF to permanent productivity shock: IRF match target variables C,Y,N,I.** Red (blue) solid line is the median VAR estimate on the first (second) subsample and the shaded areas are the 16% and 84% posterior bands generated from the posterior distribution of empirical VAR parameters. Red (blue) dashed (dash-dotted) line is model IRF to 12 period ahead news shock using IRF-matching procedure on the first (second) subsample. The units of the vertical axes are percentage deviations.

4.3 Parameter Estimates

Table 2 in Appendix E.2 shows the estimated values from the impulse response function matching exercise. We draw attention to some key insights.

First, the point estimates of the inventory taste shifter curvature ζ, the labor elasticity in knowledge capital parameter ν_h, the Taylor rule output parameter ϕ_y, the Taylor rule smoothing parameter ρ_r, and the wage rigidity parameter ζ_w are constant over the two subsamples. This suggests that a change in these parameters was not likely a factor in the change in the response to technology shocks over the two samples. We will refer to this group of parameters as "*Group A*" parameters.

The point estimates of the remaining parameters change to varying degrees over the two subsamples. Thus any combination of these Group B of parameters could potentially account for the change in the response to technology over the two subsamples. We will refer to this group of parameters as "*Group B*" parameters.

We note that while the change in the point estimate of the "Wealth elasticity parameter" is very modest over the subsamples, models tend to be very sensitive to this parameter, and so we cannot discount its role by magnitude of the change alone. Nevertheless, the point estimates of this parameter are very small in both subsamples, implying nearly "zero income effect" on labour supply, consistent with very small values found in studies applying Bayesian estimation techniques to structural models, as in e.g. Schmitt-Grohe and Uribe (2011) and Görtz et al. (2022). Small values of this parameter are typically relevant in models where comovement of hours worked and consumption is important, as in many news-shock models, which is interesting given that in our empirical results hours-worked and consumption positively co-move in the second sample but negatively co-move in the first.

Whether the change in the estimate of a particular Group B parameter plays a significant role depends on both the magnitude of the change in the estimate as well as the model's sensitivity to changes in that particular parameter. To assess this more, we next study the model's sensitivity to changes in these Group B parameters changes.

4.4 Counterfactual Experiments

The above discussion suggests that changes in all or some subset of the Group B parameters could potentially account for the change in the response to technology shocks over the two subsamples. Was the empirical change in the response of the IRFs due to change in a combination of underlying factors – captured in the model by a change in multiple parameters – or could a few factors (parameters) have been dominant? We now qualitatively explore this question through the lens of the model, examining the role of each of the key parameter changes through counterfactual experiments to determine if one or a small subset of these factors were dominant. To do this, we follow one of two experiments to study the potentially role of each parameter in Group B to individually account for the change in the IRF: (1) we set all Group B parameters to their point estimates obtained from subsample one, and then one-at-a-time we change each parameter value to its subsample two point estimate; or, (2) we set all Group B parameters to their point estimates obtained from subsample two, and then one-at-a-time we change each parameter value to its subsample one point estimate.

Whether we use experiment (1) or (2) for a given parameter depends on the following rule: *use experiment (1), unless the change in the parameter under consideration causes an indeterminacy or instability in the model, in which case, use experiment (2).*

Figure 7 shows the results of this exercise for parameters assigned to experiment 1, and Figure 8 shows the results for parameters assigned to experiment 2. In both figures, in each panel, the blue solid line and shading indicate the median and 16% and 84% posterior bands respectively for the posterior distribution of VAR parameters for the second subsample, and the blue dash-dotted line is the model IRF obtained from the IRF matching procedure over this same period (i.e. the blue shading and blue dash-dotted line in each panel reproduces the blue shading and dash-dotted line of Figure 6). In both figures, the red dashed line in each panel is the model IRF obtained from the IRF matching procedure over the first subsample, and the blue dash-dotted line is the model IRF obtained from the IRF matching procedure over the second subsample (i.e. the red dashed line and blue dash-dotted line correspond to the same in Figure 6). In Figure 7, the black dotted line in each panel is then the counterfactual model IRF using all parameters values obtained from the IRF matching procedure over the *first* subsample, except for the parameter in question where the value is set to the value obtained form the IRF matching procedure over the *second* subsample (i.e. with no counterfactual change in the parameter of question, the black dotted line would coincide exactly with the red dashed line). In other words, the dotted black line shows the extent to which the single parameter change in question can shift the model IRF from the red dashed line to the blue dash-dot line. In contrast in Figure 7, the black dotted line in each panel is the counterfactual model IRF using all parameters values obtained from the IRF matching procedure over the *second* subsample, except for the parameter in question where the value is set to the value obtained form the IRF matching procedure over the *first* subsample.

Beginning with Figure 7, if a given parameter has the potential to account for a significant portion of the change in the response of the IRFs between the two subsamples, we would expect the dotted black line to move the IRF further away from the dashed red line and towards the dash-dotted blue line (in other words, the change in a given parameter from its subsample one to subsample two point estimate moves the IRFs closer to the subsample two matched IRF). First, focusing on the response of hours worked, we can see from Panels 1, 3 and 4 that the change in Frisch elasticity parameter ξ, capital adjust cost parameter s'', and TFP growth process parameter ρ_Ω respectively actually move the black dotted in the wrong direction (i.e. further away from the subsample two matched IRF). We interpret this as suggesting that these three parameters are not likely a factor in the change in the response to technology shocks over the two samples. Next, the change in the price adjustment cost parameter κ, and the steady state leverage parameter ϕ_b move the blacked dotted line in the right direction, however, the magnitude of the change in the response of the IRFs is very small. We thus interpret this as suggesting that these two parameters are not likely important factors in the change in the response to technology shocks over the two samples. The remaining two parameters in this figure – the utilization cost parameter ϵ_u and the Taylor rule inflation parameter ϕ_π – move the response of hours worked substantially and in the right direction, suggesting that both of these parameters may be factors in the change in the response to technology shocks over the two samples.

Turning to Figure 8, if a given parameter in this figure has the potential to account for a significant portion of the change in the response of the IRFs between the two subsamples, we would expect the dotted black line to move the IRF further away from the dash-dotted blue line and towards the dashed red line (in other words, the change in a given parameter from its subsample two to its subsample one point estimate moves the IRFs closer to the subsample one matched IRF). Focusing again on the response of hours worked, both the change in the wealth elasticity parameter, γ_f, and the inventory depreciation parameter, δ_x, move the black dotted line in the wrong direction, away from the red dashed line, suggesting that these two parameters are not likely important factors in the change in the response to technology shocks over the two samples. The change in the knowledge capital depreciation parameter δ_h on the other hand moves the black dotted line substantially in the correct direction towards the red cashed line, suggesting that this parameter may be factor in the change in the response to technology shocks over the two samples. Interestingly, the change in this parameter even causes the response of hours worked to overshoot the matched IRF, attesting to the model sensitivity to changes in this parameter.

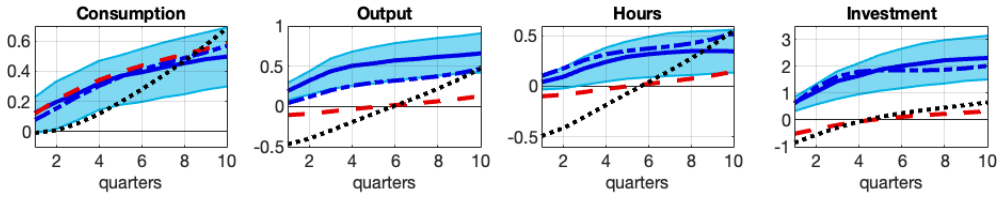
Overall, our results from this exercise suggest that changes in the nature of knowledge capital accumulation through the depreciation parameter δ_h, tighter monetary policy in response to inflation (ϕ_π) and an increase in the cost of utilization (ϵ_u) all potentially contributed to the change in the response of technology shocks over the two subsamples.

5 Re-Visiting the Model-Based Hypotheses

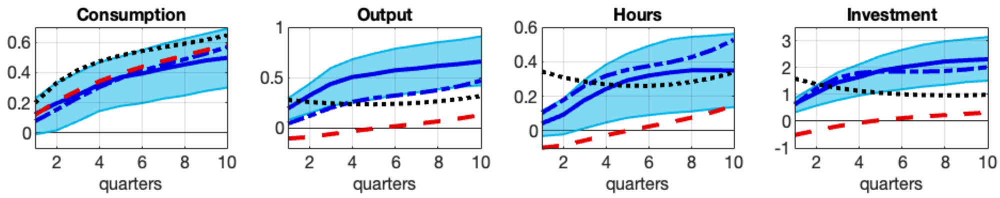
With our evidence in hand from the various model-based exercises above, we can now circle back to the potential model-based hypotheses concerning the sources of the change in the response to technology shocks that we outlined in Section 3.11.

Preference hypothesis. Our estimates suggest that the wealth effect parameter γ_f

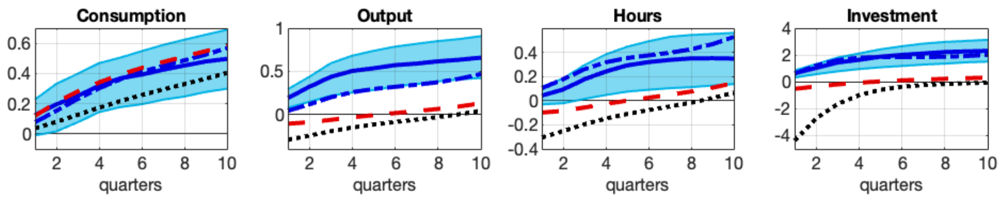
Panel 1: Frisch elasticity parameter, ξ, counterfactual: $1.65 \to 1.33$.



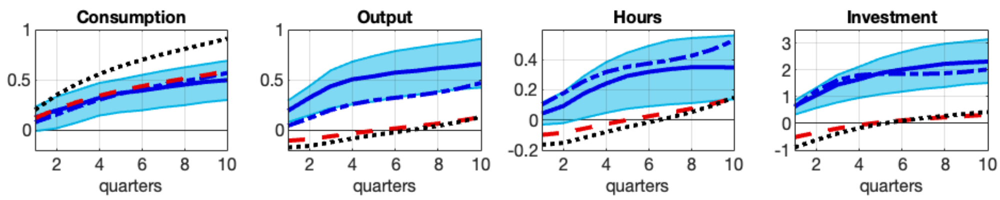
Panel 2: Utilization cost, ϵ_u, counterfactual: $0.067 \to 0.17$.



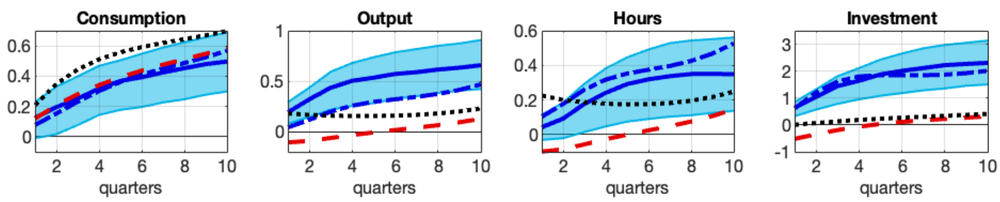
Panel 3: Capital adjustment cost, s'', counterfactual: $0.21 \to 0.067$.



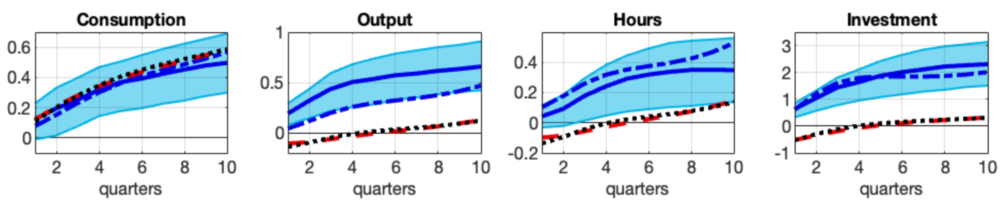
Panel 4: TFP growth process persistence, ρ_Ω, counterfactual: $0.40 \to 0.65$.



Panel 5: Taylor rule inflation, ϕ_π, counterfactual: $1.1 \to 2.42$.



Panel 6: Price adjustment cost, κ, counterfactual: $99.9 \to 42.2$.



Panel 7: Steady state leverage, ϕ_b, counterfactual: $3.5 \to 6.0$.

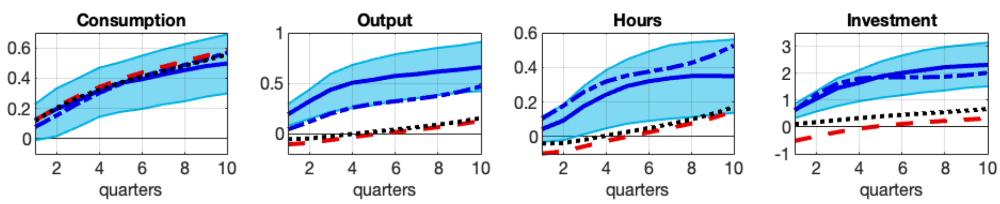
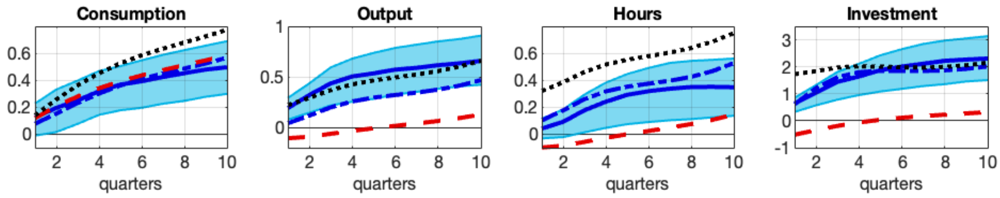
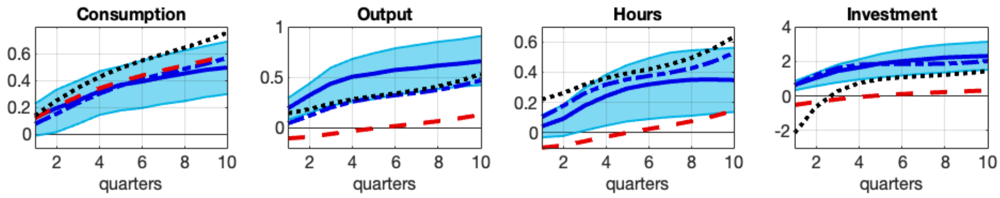


Figure 7: **IRFs to 12 period out permanent TFP news shock.** Blue solid line (shaded blue areas) is the median (the 16% and 84% posterior bands generated from the posterior distribution) of empirical VAR parameters using data on 1984Q1-2019Q4. Blue dash-dotted line is model IRF using IRF-matching procedure on data sample 1984Q1-2019Q4. Red dashed line is model IRF using IRF-matching procedure on data sample 1954Q2-1983Q4. Black dotted line is counterfactual model IRF using all parameter values obtained from IRF matching procedure on **first subsample** except for parameter in question which is set to **second subsample** value. The units of the vertical axes are percentage deviations.

Panel 1: Wealth elasticity parameter, γ_f, counterfactual: $0.0038 \rightarrow 0.0051$.



Panel 2: Inventory depreciation, δ_x, counterfactual: $0.001 \rightarrow 0.0075$



Panel 3: Knowledge capital depreciation, δ_h, counterfactual: $0.3 \rightarrow 0.15$.

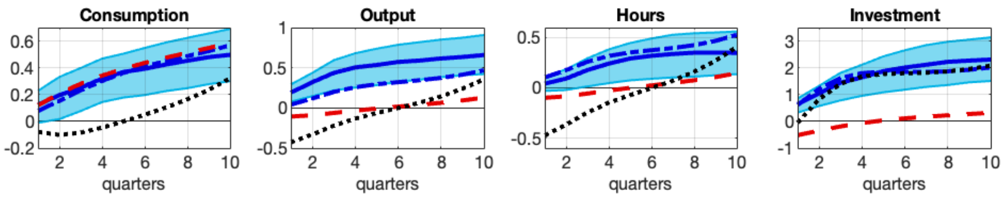


Figure 8: **IRFs to 12 period out permanent TFP news shock.** Blue solid line (shaded blue areas) is the median (the 16% and 84% posterior bands generated from the posterior distribution) of empirical VAR parameters using data on 1984Q1-2019Q4. Blue dash-dotted line is model IRF using IRF-matching procedure on data sample 1984Q1-2019Q4. Red dashed line is model IRF using IRF-matching procedure on data sample 1954Q2-1983Q4. Black dotted line is counterfactual model IRF using all parameter values obtained from IRF matching procedure on **second subsample** except for parameter in question which is set to **first subsample** value. The units of the vertical axes are percentage deviations.

and the disutility of working parameter ξ changed over the subsamples, yet our experiments suggest that changes did not move the IRF responses in the correct direction. Thus our results suggest that a change in preferences was not likely a dominant source of the change.

Labor Market Frictions Hypothesis. Our estimates suggest a high degree of wage rigidities that did not materially change over both subsamples. While this rigidity is a key propagation mechanism, the lack of a change suggests that a change in labor market frictions where likely not a source of the change in the impact of technology.

Monetary Policy Hypothesis. Our results suggest that a change in monetary policy between the two subsamples was a likely contributor to the change in the impact of technology, in the form of tighter monetary policy in response to inflation through the parameter ϕ_π. As outlined in Section 3.11, an inflation targeting central bank can, under sticky nominal wages, impact directly the real wage markup through inflation. The documented increase in ϕ_π in the second subsample implies that, relative to the first subsample, a given positive labor demand shock has a larger impact on hours worked as small jumps in inflation, under sticky nominal wages, imply a lower responsiveness of real wages.

Credit Hypothesis. Our estimates suggest a change in the steady state leverage parameter ϕ_b over the two subsamples, yet our experiments suggest the magnitude of change in the response of the IRFs was not material. Thus a change in credit market frictions over time was not likely a source of the change in the impact of technology.

Inventory Hypothesis. Our estimates suggest the inventory taste shifter curvature, ζ, was constant over the two samples, and while the estimate of the inventory depreciation parameter, δ_x, changed over the subsamples, the magnitude of the change did not transmit into material changes in IRFs. Thus a change in inventory management practices as evidenced through these parameters was not likely a source of the change in the impact of technology.

Knowledge Capital Hypothesis. Our results suggest that changes in the nature of intangible capital accumulation was a likely contributor to the change in the impact of technology over time through the knowledge capital depreciation parameter δ_h. Taking this modeling mechanism literally, one interpretation is a change in the way firms learned about organizing the inputs into production as the processes of production changed rapidly heading into the information and technology revolution of the 1980's and 1990's. Taken more broadly, the effect can be seen to be symptomatic of the emergence of a labor-demand side wedge that feeds into an efficiency wedge in production.

We can link our finding to the discussion of model elements in Section 3.11. In anticipation of higher future TFP, the future and current value of knowledge capital rises which primes firms to build up a higher knowledge capital stock. As knowledge capital is accumulated as a by-product of working, this implies higher labor demand. We estimate the knowledge capital depreciation parameter δ_h to decline from the first to the second subsample. This lower depreciation in the second subsample implies that it is less costly to build up knowledge capital well in advance of the time when the anticipated higher TFP actually materializes, allowing for a larger accumulation of knowledge capital via an expansion in hours worked.

Other channels. Our results suggest that an increase in the cost of utilizing capital, ϵ_u, contributed to the change in the response to technology shocks. While we do not offer a direct intuitive interpretation of this change related to actual real world events that transpired over the period, we note that within the model context, the cost of utilization has a direct impact on the return to capital through the banking sector, which has powerful propagation effects in the model through the interest rate. In this case, the increase in the cost of utilization over the subsamples resulted in a higher steady state return to capital in the second subsample relative to the first, perhaps reflective in a reduced form way of developments within capital and credit markets over the period.

6 Conclusion

Technology shocks play an important role in our understanding of aggregate fluctuations. Dis-satisfaction with the idea and plausibility of unexpected technology shocks, especially negative shocks, led researchers in the early 2000's to study whether technology could still play a role in the absence of surprise shocks and technological regress. Beaudry and Portier (2006) showed how a business cycle boom-bust could result in such an environment when the driving impulse was changes in expectations about future positive shifts in technology rather than surprise changes in technology itself.

In this paper we add to the literature attempting to understand the role and importance of technology shocks. We take an agnostic view of the presence of surprise versus anticipated shocks, using a well-established empirical identification that seeks to best account for the variation in TFP at some far out but finite horizon. Rather than using a single sample as much of the work to date, we split our sample at the onset of the Great Moderation and study each sample independently. Our results suggest that the qualitative response of TFP is consistent with a dominant anticipated or diffusion shock, that the importance of TFP shocks has increased over the sub-samples, and that the transmission of the shocks into the broader economy has changed.

This change in the transmission is manifested most clearly in the response of hours worked: hours falls in the first subsample, but rises in the second, despite consumption and stock prices rising consistently in both subsamples. Moreover, despite its differential response over the two subsamples, hours co-varies in a consistent way with investment, inventories, the real wage, and the credit spread over both subsamples.

We then add to the theoretical literature to study the source of the changes in the response of technology through the lens of a rich structural model. We use both an IRF matching procedure and model experiments to evaluate various different hypotheses for the change. Our results suggest that the change in the response of technology over time was likely some combination of a change in the stance of monetary policy, a change in the nature of intangible capital accumulation, and a change in the cost of utilizing capital.

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Appendix

A Details on the VAR Model

This appendix provides details on the VAR model, shock identification and prior specifications.

A.1 VAR-Based Identification of Technology Shocks

We consider the following vector autoregression (VAR), which describes the joint evolution of an $n \times 1$ vector of variables y_t:

$$y_t = A(L)u_t.$$

$A(L) = I + A_1L + ... + A_pL^p$ is a lag polynomial of order p over conformable coefficient matrices $\{A_p\}_{i=1}^{p}$. u_t is an error term with $n \times n$ covariance matrix Σ. We assume a linear mapping between the reduced form errors u_t and the structural errors ε_t:

$$u_t = B_0\varepsilon_t,$$

where B_0 is an identification matrix. We can then write the structural moving average representation of the VAR:

$$y_t = C(L)\varepsilon_t,$$

where $C(L) = A(L)B_0$, $\varepsilon_t = B_0^{-1}u_t$, and the matrix B_0 satisfies $B_0B_0' = \Sigma$. B_0 can also be written as $B_0 = \widetilde{B}_0D$, where $\widetilde{B}_0$ is any arbitrary orthogonalization of Σ and D is an orthonormal matrix such that $DD' = I$.

We identify the technology shock using the max share methodology as suggested in Francis et al. (2014) who maximize the forecast error variance share of a productivity measure at a long but finite horizon. Following Kurmann and Sims (2021), we use TFP as the measure for productivity. The max share methodology identifies productivity variations in the long run. The absence of any short run restrictions makes our applied identification robust to cyclical measurement issues of technology. Note that the methodology does not make a prior assumption on whether technology reacts to the shock only with a lag or not.

Mechanically, we identify the technology shock by finding a rotation of the identification matrix $\widetilde{B}_0$, which maximizes the forecast error variance of the TFP series at some finite horizon. In this, we follow the max share approach of Francis et al. (2014). Specifically, the h-step ahead forecast error is given by:

$$y_{t+h} - E_{t-1}y_{t+h} = \sum_{\tau=0}^{h} A_\tau \widetilde{B}_0 D \varepsilon_{t+h-\tau}.$$

The share of the forecast error variance of variable i attributable to shock j at horizon h is then:

$$V_{i,j}(h) = \frac{e_i' \left(\sum_{\tau=0}^{h} A_\tau \widetilde{B}_0 D e_j e_j' D' \widetilde{B}_0' A_\tau' \right) e_i}{e_i' \left(\sum_{\tau=0}^{h} A_\tau \Sigma A_\tau' \right) e_i} = \frac{\sum_{\tau=0}^{h} A_{i,\tau} \widetilde{B}_0 \gamma\gamma' \widetilde{B}_0' A_{i,\tau}'}{\sum_{\tau=0}^{h} A_{i,\tau} \Sigma A_{i,\tau}'},$$

where e_i denotes a selection vector with one in the i-th position and zeros everywhere else. The e_j vector picks out the j-th column of D, denoted by γ. $\widetilde{B}_0\gamma$ is therefore an $n \times 1$ vector corresponding to the j-th column of a possible orthogonalization and can be interpreted as an impulse response vector.

The max share approach chooses the elements of $\widetilde{B}_0$ to make this restriction on forecast error variance share hold as closely as possible. This is equivalent to choosing the impact matrix so that contributions to $V_{1,2}(h)$ are maximized. Consequently, we choose the second column of the impact matrix to solve the following optimization problem:[21]

$$\arg\max_{\gamma} V_{1,2}(h) = \frac{\sum_{\tau=0}^{h} A_{i,\tau} \widetilde{B}_0 \gamma\gamma' \widetilde{B}_0' A_{i,\tau}'}{\sum_{\tau=0}^{h} A_{i,\tau} \Sigma A_{i,\tau}'}, \qquad \text{s.t. } \gamma\gamma' = 1.$$

We restrict γ to have unit length to be a column vector of an orthonormal rotation matrix of the Choleski decomposition of the reduced-form variance covariance matrix.

[21] The optimization problem is written in terms of choosing γ conditional on any arbitrary orthogonalization $\widetilde{B}_0$ to guarantee that the resulting identification belongs to the space of possible orthogonalizations of the reduced form.

A.2 Specification for the Minnesota Prior in the VAR

We estimate the VAR using a Bayesian approach. The prior for the VAR coefficients A a standard Minnesota prior as commonly used in the literature. It is of the form

$$vec\,(A) \sim N\left(\underline{\beta}, \underline{V}\right),$$

where $\underline{\beta}$ is one for variables in the baseline specification which are in log-levels, and zero for hours. The prior variance $\underline{V}$ is diagonal with elements,

$$\underline{V}_{i,jj} = \begin{cases} \frac{\underline{a}_1}{p^2} \text{ for coefficients on own lags} \\ \frac{\underline{a}_2 \sigma_{ii}}{p^2 \sigma_{jj}} \text{ for coefficients on lags of variable } j \neq i \\ \underline{a}_3 \sigma_{ii} \text{ for intercepts} \end{cases}$$

where p denotes the number of lags. Here σ_{ii} is the residual variance from the unrestricted p-lag univariate autoregression for variable i. The degree of shrinkage depends on the hyperparameters $\underline{a}_1, \underline{a}_2, \underline{a}_3$. We set $\underline{a}_3 = 1$ and we choose $\underline{a}_1, \underline{a}_2$ by searching on a grid and selecting the prior that maximizes the in-sample fit of the VAR, as measured by the Bayesian Information Criterion.[22]

B Additional VAR Evidence

This section provides some additional empirical evidence that corroborates the results presented in the main body.

Labor Market Responses. Figure 9 shows that the subsample differences in hours worked documented in Section 2.2 are also present if we replace total hours worked with its components, the labor force participation rate and the unemployment rate. Consistent with the decline in hours-worked documented for the first subsample, Figure 9 documents a decline in the labor force participation rate and a rise in the unemployment rate. For

[22]The grid of values we use is: $\underline{a}_1$ = (1e-4:1e-4:9e-4, 0.001:0.001:0.009, 0.01:0.01:0.1, 0.1:0.1:1), $\underline{a}_2$ = (0.01,0.05,0.1,0.5,1,5). We consider all possible pairs of $\underline{a}_1$ and $\underline{a}_2$ in the above grids.

the second subsample, the rise in hours-worked comes along with a rise in the labor force participation rate and a decline in the unemployment rate.

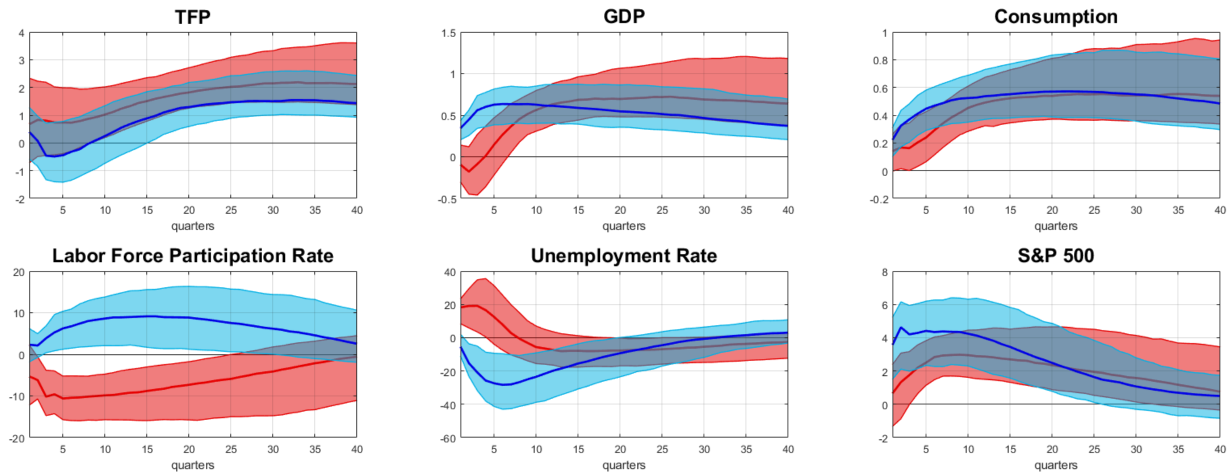

Figure 9: **IRF to TFP shock.** First subsample 1954Q2-1983Q4 (red), second subsample 1984Q1-2019Q4 (blue). The solid line is the median and the shaded colored areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

An Alternative Measure for Technology. Figure 10 shows impulse responses to a shock that maximizes the share of variance explained in labor productivity as in Francis et al. (2014). This shows that responses in Figure 1 are robust to using labor productivity instead of TFP as an alternative measure for productivity. In particular, also when using this measure for productivity we observe an expansion in GDP, consumption and stock prices that is more pronounced in the second subsample. Importantly hours work continue to decline in the first subsample and rise in the second subsample. An important difference between Figures 1 and 10 is that labor productivity responds strongly in the first subsample. This is consistent with findings in Francis et al. (2014) and Kurmann and Sims (2021) who flag this is due to a short-run capital deepening effect: the capital to labor ratio is driven up by the fall in hours-worked which in turn boosts labor productivity on impact relative to the more gradual rise in TFP documented in Figure 1.

Responses to anticipated and unanticipated technology shocks. Figure 11 shows impulse responses to an anticipated (first row) and unanticipated TFP shock. These two

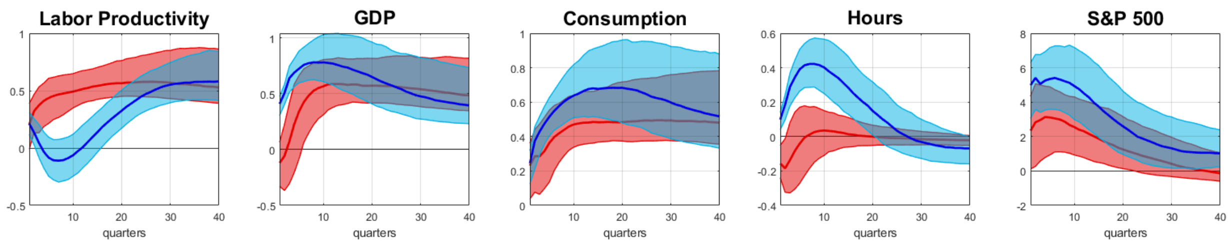

Figure 10: **IRF to shock that maximizes variation in labor productivity.** First subsample 1954Q2-1983Q4 (red), second subsample 1984Q1-2019Q4 (blue). The solid line is the median and the shaded colored areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

shocks are jointly identified as common in the news shock literature (see e.g. Barsky and Sims (2012), Ben Zeev and Khan (2015), Görtz et al. (2022)). Related to our baseline identification, we recover the news shock by maximizing the variance of TFP at the 40 quarter horizon, but impose a zero impact restriction on TFP conditional on the news shock. This scheme identifies the anticipated shock as the one that explains TFP fluctuations in the long run, but doesn't move it on impact. At the same time, the unanticipated shock is identified as the disturbance that can affect TFP on impact and its identification corresponds to a simple Cholesky identification with TFP ordered first.

The anticipated shock shown in the top row, exhibits very similar dynamics to those shown in Figure 1 in the main body. Notably, hours worked decline in the first subsample but rise in the second subsample. The surprise shock shown in the bottom row results for the first subsample in an insignificant response of GDP, consumption and stock prices and a decline in hours worked. In the second subsample the surprise productivity shock triggers an expansion in GDP, consumption and the stock market and a mild decline of hours worked on impact.

The Fernald (2014) series is arguably the best estimate for TFP available. Yet, measuring TFP is notoriously difficult and the Fernald (2014) estimate is only an imperfectly cleansed version of the Solow residual (Kimball et al. (2006)). The literature argues that it is particularly the high frequencies, rather than low frequencies, which may be impaired by measurement error and this hence affects the identification with the zero impact restriction much more than our baseline identification which solely relies on long-run restrictions (see e.g. Kurmann and Sims (2021)).

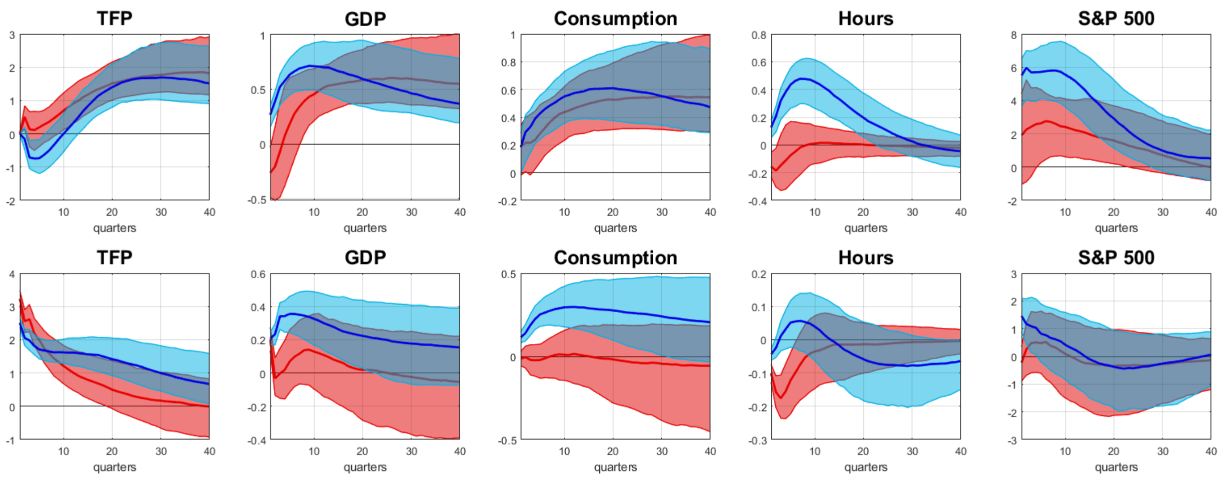

Figure 11: **IRF to jointly identified anticipated (top row) and unanticipated (bottom row) productivity shocks.** First subsample 1954Q2-1983Q4 (red), second subsample 1984Q1-2019Q4 (blue). The solid line is the median and the shaded colored areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Responses over the Entire Sample. Figure 12 shows the responses to a technology shock over the whole sample (1954Q2-2019Q4). All macroeconomic aggregates increase strongly and instantaneously in response to the shock. We also observe a rise in stock prices and a decline in credit spreads, so that these impulse responses resemble those documented in Figures 1 and 3 for the second subsample. Particularly the decline in hours-worked and inventories as well as the rise in credit spreads that we document for the first subsample is not evident when we estimate a VAR over the entire sample.

Robustness for Rolling Window Analysis. Figure 13 shows the median and posterior bands of impact responses for selected variables over different samples. Results are consistent with those in Figure 4 in the main body which shows the most extreme response within the first ten quarters. For hours, inventories and investment, it is evident that impact responses move away from the negative territory over the rolling window analysis. On impact the BAA becomes negative particularly once the window includes the time around

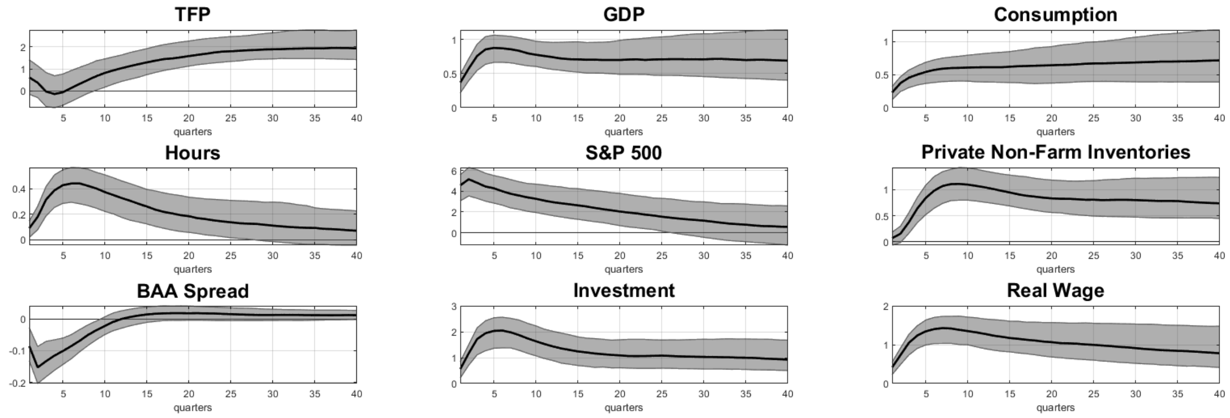

Figure 12: **IRF to TFP shock.** Entire sample 1954Q2-2019Q4 . The solid line is the median and the shaded areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

the financial crisis.

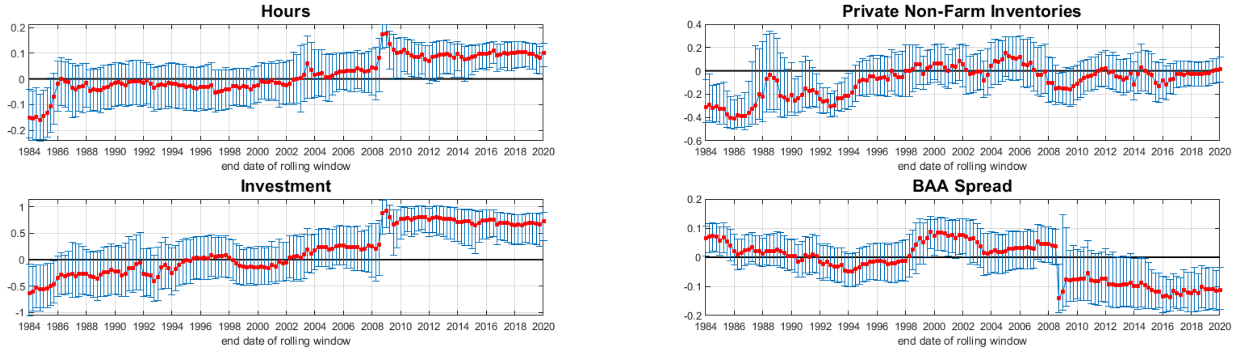

Figure 13: **Impact IRF responses to a TFP shock for rolling windows.** First rolling window sample is 1954Q2-1983Q4. The window is shifted up to 2019Q4. We display the median (red dot) and the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations. Subplots are based on a VAR with TFP, GDP, consumption, hours-worked, the S&P 500 and one of the plotted variables at a time.

Figures 15 and 14 show statistics corresponding to those in Figure 4 in the main body. They show for each rolling window the maximum or minimum IRF (whichever is largest in absolute terms) within the first ten quarters to a TFP shock for rolling window. Figures 15 and 14 differ from the one depicted in the main body in that they consider a shorter rolling window of 90 and 100 quarters, respectively, instead of 119 quarters.

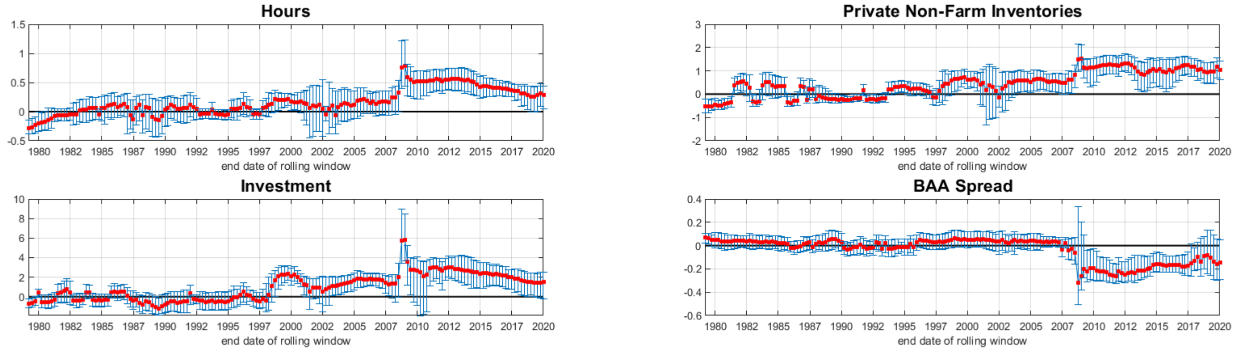

Figure 14: **Maximum/minimum (whichever is largest in absolute terms) IRF response within the first ten quarters to a TFP shock for rolling window.** First rolling window sample is 1954Q2-1979Q1 (100 quarters). The window is shifted up to 2019Q4. We display the median (red dot) and the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations. Subplots are based on a VAR with TFP, GDP, consumption, hours-worked, the S&P 500 and one of the plotted variables at a time.

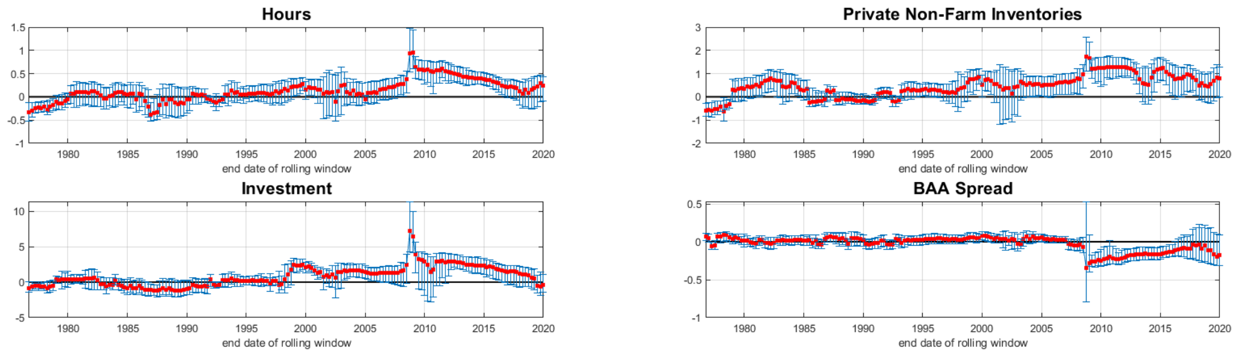

Figure 15: **Maximum/Minimum (whichever is largest in absolute terms) IRF response within the first ten quarters to a TFP shock for rolling window.** First rolling window sample is 1954Q2-1976Q3 (90 quarters). The window is shifted up to 2019Q4. We display the median (red dot) and the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations. Subplots are based on a VAR with TFP, GDP, consumption, hours-worked, the S&P 500 and one of the plotted variables at a time.

C Data Sources and Time Series Construction

This section provides an overview of the data used to construct the observables. All the data transformations we have made in order to construct the dataset used for estimating the various VAR specifications and they enter in levels. The majority of the raw data described below were retrieved from the Federal Reserve of St.Luis FRED database. The exceptions are the TFP and utilization data series which is from Fernald (2014) at the Federal reserve bank of San Francisco, and the data on market yield and the BAA spread which are from the Federal reserve board and Bloomberg.

Data Sources. We describe the exact source of each data series below.

Gross domestic product, current prices: U.S. Bureau of Economic Analysis, Gross Domestic Product [GDP], retrieved from FRED, Federal Reserve Bank of St. Louis; $https://fred.stlouisfed.org/series/GDP$.

Gross Private Domestic Investment, current prices: U.S. Bureau of Economic Analysis, Gross Private Domestic Investment [GPDI], retrieved from FRED, Federal Reserve Bank of St. Louis; $https://fred.stlouisfed.org/series/GPDI$.

Real Gross Private Domestic Investment: U.S. Bureau of Economic Analysis, Real Gross Private Domestic Investment [GPDIC1], retrieved from FRED, Federal Reserve Bank of St. Louis; $https://fred.stlouisfed.org/series/GPDIC1$.

Personal Consumption Exp.: Durable Goods, current prices: U.S. Bureau of Economic Analysis, Personal Consumption Expenditures: Durable Goods [PCEDG], retrieved from FRED, Federal Reserve Bank of St. Louis; $https://fred.stlouisfed.org/series/PCEDG$.

Real Personal Consumption Exp.: Durable Goods: U.S. Bureau of Economic Analysis, Real Personal Consumption Expenditures: Durable Goods [PCEDGC96], retrieved from FRED, Federal Reserve Bank of St. Louis; $https://fred.stlouisfed.org/series/PCEDGC96$.

Personal Consumption Expenditures: Services, current prices: U.S. Bureau of Economic Analysis, Personal Consumption Expenditures: Services [PCES], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/PCES*.

Real Personal Consumption Expenditures: Services: U.S. Bureau of Economic Analysis, Real Personal Consumption Expenditures: Services [PCESC96], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/PCESC96*.

Personal Consumption Exp.: Nondurable Goods, current prices: U.S. Bureau of Economic Analysis, Personal Consumption Expenditures: Nondurable Goods [PCEND], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/PCEND*.

Real Personal Consumption Exp.: Nondurable Goods: U.S. Bureau of Economic Analysis, Real Personal Consumption Expenditures: Nondurable Goods [PCENDC96], retrieved from FRED, Federal Reserve Bank of St. Louis;
https://fred.stlouisfed.org/series/PCENDC96.

Real Private Nonfarm Inventories: U.S. Bureau of Economic Analysis [A373RX1Q020SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis;
https://fred.stlouisfed.org/series/A373RX1Q020SBEA.

Civilian Noninstitutional Population: U.S. Bureau of Labor Statistics, Population Level [CNP16OV], retrieved from FRED, Federal Reserve Bank of St. Louis;
https://fred.stlouisfed.org/series/CNP16OV.

Non-farm Business Sector: Compensation Per Hour: U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Compensation Per Hour [COMPNFB], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/COMPNFB*.

Non-farm Business Sector: Hours of All Persons: U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Hours of All Persons [PRS85006031], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/PRS85006031*.

Effective Federal Funds Rate: Board of Governors of the Federal Reserve System (US), Effective Federal Funds Rate [FEDFUNDS], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/FEDFUNDS*.

Implicit GDP deflator: U.S. Bureau of Economic Analysis, Gross Domestic Product: Implicit Price Deflator [A191RI1Q225SBEA], retrieved from FRED, Federal Reserve Bank of

St. Louis; $https://fred.stlouisfed.org/series/A191RI1Q225SBEA$.
10 year treasury yield: The market yield on U.S. Treasury securities at 10-year constant maturity are available from the Federal Reserve Board H.15 database.
The BAA yield is Moody's Bond Indices Corporate BAA obtained from Bloomberg.
The real S&P 500 index is obtained from Robert Shiller's website:
$http://www.econ.yale.edu/\ shiller/data.htm$.
The utilization adjusted TFP data and the series for capacity utilization can be accessed at $www.frbsf.org/economic-research/economists/jfernald/quarterly\_tfp.xls$.

The raw data are transformed as follows for the analysis. Consumption (in current prices) is defined as the sum of personal consumption expenditures on services and personal consumption expenditures on non-durable goods. The times series for real consumption is constructed as follows. First, we compute the shares of services and non-durable goods in total (current price) consumption. Then, total real consumption growth is obtained as the chained weighted (using the nominal shares above) growth rate of real services and growth rate of real non-durable goods. Using the growth rate of real consumption we construct a series for real consumption.

Real output is GDP derived by dividing current price GDP with the GDP deflator and the Civilian Noninstitutional Population measure. Similarly for hours-worked, consumption, investment and hourly wages (defined as total compensation per hour). All these series, as well as the real inventory measure are expressed in per capita terms using the series of non-institutional population, ages 16 and over. The nominal interest rate is the effective federal funds rate. The BAA spread series is the difference between the BAA yield and the 10 year treasury yield.

D Additional Theoretical Model Details

D.1 Labor Unions and Employment Agency

Labor unions acquire homogeneous labor, N_t^h, from the household at wage W_t^h, differentiate it into labor types N_{qt}, $q \in [0,1]$, where $N_t^h = \int_0^1 N_{qt} dq$, and then sell the differentiated labor to the employment agency for wage, W_{qt}. The unions have market power, and can thus choose the wage for each labor type subject to the labor demand curve for that labor type. In particular, the unions face Calvo frictions in setting their wages, such that each period they can re-optimize wages with probability $1 - \zeta_w$. A union that is unable to re-optimize wages re-sets it according to the indexation rule $W_{qt} = W_{qt-1} \left(\Pi_{t-1} g_{t-1}^y\right)^{\iota_w} \left(\pi g^y\right)^{1-\iota_w}$, $\quad 0 \leq \iota_w \leq 1$, where $\Pi_t = P_t / P_{t-1}$ and Π is its steady state, where $0 \leq \iota_w \leq 1$, and where $g_t^y = \frac{X_t^y}{X_{t-1}^y}$ is the growth rate of the stochastic trend in output, X_t^y. A union that can re-optimize its wage in period t chooses its wage W_{qt}^* to maximize

$$E_t \sum_{s=0}^{\infty} \zeta_w^s \beta^s \frac{\lambda_{t+s} P_t}{\lambda_t P_{t+1}} \left[W_{qt}^* (\Pi_{k=0}^s (\Pi_{t+k-1} g_{t+k-1}^y)^{\iota_w} (\pi g^y)^{1-\iota_w}) - W_{t+s}^h \right] n_{qt+s},$$

subject to the demand curve for N_{qt}.

The employment agency acquires each qth intermediate labor type N_{qt}, $q \in [0,1]$, at wage W_{qt} from the labor unions, and combines the differentiated labor into a composite N_t according to

$$N_t = \left[\int_0^1 N_{qt}^{\nu_w} dq \right]^{\frac{1}{\nu_w}}, \quad 0 < \nu_w \leq 1.$$

The agency sells the composite labor to the intermediate goods producers for wage W_t. The agency chooses N_{qt} $\forall q$ to maximize profits $W_t N_t - \int_0^1 W_{qt} N_{qt} dq$, yielding a demand function n_{qt} for the qth labor type,

$$N_{qt} = \left[\frac{W_{qt}}{W_t} \right]^{\frac{1}{\nu_w - 1}} N_t,$$

and wage index W_t, given respectively by

$$W_t = \left[\int_0^1 W_{qt}^{\nu_w/(\nu_w-1)} dq \right]^{\frac{(\nu_w-1)}{\nu_w}}.$$

D.2 Model Equilibrium, Stationary and Solution Method: Baseline Model

For variables related to the Distributors and the Final Goods Firms, under the Rotemberg style price adjustment costs, in a symmetric equilibrium all firms choose the same price P_t^* every period, and thus, $P_{it} = P_t^* \quad \forall i$, such that

$$P_t = \left[\int_0^1 \nu_{it}(P_t^*)^{1-\theta} di\right]^{\frac{1}{1-\theta}} = P_t^*,$$

and implying that $\frac{P_{it}}{P_t} = 1 \quad \forall i$. Furthermore, $Y_{it} = Y_t^*$, $A_{it} = A_t^*$, $X_{it} = X_t^*$, and $S_{it} = S_t^*$ $\forall i$. It then follows that $Y_t = \int_0^1 Y_t^* di = Y_t^*$, $A_t = \int_0^1 A_t^* di = A_t^*$, $X_t = \int_0^1 X_t^* di = X_t^*$. Integrating over the taste shifter then yields

$$\int_0^1 \nu_{it} di = \int_0^1 \left(\frac{A_{it}}{A_t}\right)^{\zeta} di = \frac{1}{A_t^{\zeta}} \int_0^1 A_t^{\zeta} di = 1,$$

and

$$S_t = \left[\int_0^1 \nu_{it}^{\frac{1}{\theta}} S_t^{*\frac{\theta-1}{\theta}} di\right]^{\frac{\theta}{\theta-1}} = S_t^*.$$

For variables related to the labor sector, the fraction $1-\zeta_w$ of unions given the opportunity to adjust wages through the Calvo mechanism will choose wage $W_{qt} = W_t^*$. The remaining fraction of non-adjusting unions will remain with the previous period's wage, indexed for inflation. The aggregate wage is then given recursively by

$$W_t = \left[(1-\zeta_w) W_t^{*\frac{\nu_w}{\nu_w-1}} + \zeta_w \left(W_{t-1}\left(\pi_{t-1} g_{t-1}^y\right)^{\iota_w} (\pi g^y)^{1-\iota_w}\right)^{\frac{\nu_w}{\nu_w-1}}\right]^{\frac{\nu_w-1}{\nu_w}}.$$

Substituting in the demand function for N_{qt} into $N_t^h = \int_0^1 N_{qt} dq$ yields $N_t^h = \Delta_t^w N_t$, where Δ_t^w is a wage dispersion term, given by

$$\Delta_t^w = \int_0^1 \left(\frac{W_{qt}}{W_t}\right)^{\frac{1}{\nu_w-1}} dq,$$

which can then be expressed without heterogeneity and recursively as

$$\Delta_t^w = W_t^{\frac{1}{1-\nu_w}} \left[(1-\zeta_w) W_t^{*\frac{1}{\nu_w-1}} + \zeta_w \left(W_{t-1}\left(\pi_{t-1} g_{t-1}^y\right)^{\iota_w} (\pi g^y)^{1-\iota_w}\right)^{\frac{1}{\nu_w-1}}\right].$$

For the various asset and credit variables, equilibrium in the capital goods market implies that $K_t^{nk} = K_{t+1}$ and $K_t^k = K_t$, and equilibrium in the deposts market implies that $B_{t+1} =$

$\int_0^1 B_{jt+1}dj$. Nominal bonds are in zero net-supply such that $B_t^n = 0$. Since leverage

$$\phi_{bt} = \frac{q_t^k S_{jt}}{N_{jt}} = \frac{\eta_t}{\lambda_b - \nu_{bt}}$$

is not dependent on intermediary-specific factors, then we can express the aggregate quantity of intermediated assets S_t^b and aggregate net worth N_t^b as $q_t^k S_t^b = \phi_{bt} N_t^b$. Finally, the capital producer's state contingent payment contract implies $S_t^b = K_{t+1}$.

Starting with the representative household budget constraint, and substituting in the various profits that flow to the household, as well as equilibrium labour and asset market flows, we obtain the aggregate resource constraint

$$C_t + \Gamma_t I_t + G_t = S_t - a(u_t) K_t \Upsilon_t - \frac{\kappa}{2} \left[\frac{\pi_t}{\pi_{t-1}^{\iota_p} \pi^{1-\iota_p}} - 1 \right]^2 S_t. \tag{19}$$

The resulting equilibrium model system consists of a symmetric competitive equilibrium as a set of stochastic processes $\{C_t, V_t, I_t, G_t, T_t, S_t, Y_t, N_t, u_t, J_t, K_{t+1}, B_{t+1}, N_{t+1}^b, Z_t^b, \phi_{bt}, \eta_t, \nu_{bt},$ $\Gamma_t, \delta_{bt}, X_t, A_t, \mu_t^x, W_t, W_t^h, W_t^*, r_t, R_{t+1}, R_{t+1}^k, q_t^k, \tilde{q}_t^k, \tau_t, \mu_t^f, \lambda_t, P_t, \Pi_t\}_t^\infty$, given initial conditions and exogenous stochastic processes, and where μ_t^f, and λ_t respectively denote the multipliers on the definition of F_t and the household budget constraint.

In the following, we list these equations and detail how to transform the non-stationary system, which is driven by stochastic trends, into a stationary counterpart amenable to solution and estimation.

The equilibrium system is as follows:

$$V_t = C_t - bC_{t-1} - \psi N_t^{\xi} F_t, \tag{20}$$

$$F_t = \left(C_t - bC_{t-1}\right)^{\gamma_f} F_{t-1}^{1-\gamma_f}, \tag{21}$$

$$\Gamma_t V_t^{\sigma} + \mu_t^f \gamma_f \frac{F_t}{C_t - bC_{t-1}} = \lambda_t + b\beta E_t \left\{ \Gamma_{t+1} V_{t+1}^{-\sigma} + \mu_{t+1}^f \gamma_f \frac{F_{t+1}}{C_{t+1} - bC_t} \right\}, \tag{22}$$

$$\xi \psi \Gamma_t V_t^{-\sigma} N_t^{\xi-1} F_t = \lambda_t \frac{W_t^h}{P_t}, \tag{23}$$

$$\mu_t^f = -\psi \Gamma_t V_t^{-\sigma} N_t^{\xi} + \beta(1-\gamma_f) E_t \mu_{t+1}^f \frac{F_{t+1}}{F_t}, \tag{24}$$

$$\lambda_t = \beta R_{t+1}^n E_t \lambda_{t+1} \frac{1}{\Pi_{t+1}}, \tag{25}$$

$$\lambda_t = \beta R_{t+1} E_t \lambda_{t+1}, \tag{26}$$

$$r_t = a'(u_t) \Upsilon_t, \tag{27}$$

$$R_t^k = \frac{r_t u_t - a(u_t)\Upsilon_t + \tilde{q}_t^k}{q_{t-1}^k}, \tag{28}$$

$$q_t^k = \frac{\Upsilon_t}{1 - S'(\frac{I_t}{K_t})}, \tag{29}$$

$$\tilde{q}_t^k = q_t^k \left[1 - \delta + S'\left(\frac{I_t}{K_t}\right) \frac{I_t}{K_t} - S\left(\frac{I_t}{K_t}\right) \right], \tag{30}$$

$$K_{t+1} = (1-\delta) K_t + I_t - S\left(\frac{I_t}{K_t}\right) K_t, \tag{31}$$

$$Y_t = \left(\Omega_t N_t\right)^{\alpha_n} \widetilde{K}_t^{\alpha_k} \left(\Omega_t H_t\right)^{1-\alpha_n-\alpha_k}, \tag{32}$$

$$H_{t+1} = (1-\delta_h) H_t + H_t^{1-\nu} N_t^{\nu}, \tag{33}$$

$$\frac{W_t}{P_t} = \tau_t \alpha \frac{Y_t}{N_t} + q_t^h \nu \frac{H_t^{1-\nu_h} N_t^{\nu}}{N_t}, \tag{34}$$

$$q_t^h = \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \left\{ (1-\alpha_n-\alpha_h)\tau_{t+1} \frac{Y_{t+1}}{H_{t+1}} + q_{t+1}^h \left(1 - \delta_h + (1-\nu_h)) \frac{H_{t+1}^{1-\nu_h} N_{t+1}^{\nu}}{H_{t+1}} \right) \right\}, \tag{35}$$

$$r_t = (1-\alpha_k)\tau_t \frac{Y_t}{u_t K_t}, \tag{36}$$

$$A_t = (1-\delta_x) X_{t-1} + Y_t, \tag{37}$$

$$X_t = A_t - S_t, \tag{38}$$

$$\tau_t = \zeta \frac{S_t}{A_t} + \mu_t^x \left(1 - \zeta \frac{S_t}{A_t} \right), \tag{39}$$

$$\mu_t^x = \beta(1-\delta_x) E_t \frac{\lambda_{t+1}}{\lambda_t} \tau_{t+1}, \tag{40}$$

$$(1-\theta)S_t - \kappa \Big[\frac{\Pi_t}{\Pi_{t-1}^{\iota_p} \Pi^{1-\iota_p}} - 1 \Big] \frac{\Pi_t S_t}{\Pi_{t-1}^{\iota_p} \Pi^{1-\iota_p}} + \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \kappa \Big[\frac{\Pi_{t+1}}{\Pi_t^{\iota_p} \Pi^{1-\iota_p}} - 1 \Big] \frac{\Pi_{t+1} S_{t+1}}{\Pi_t^{\iota_p} \Pi^{1-\iota_p}} + \mu_t^x \theta S_t = 0, \tag{41}$$

$$W_t = \left[(1-\zeta_w) W_t^{*\frac{\nu_w}{\nu_w - 1}} + \zeta_w \left(W_{t-1}\left(\Pi_{t-1} g_{t-1}^y\right)^{\iota_w} (\Pi g^y)^{1-\iota_w}\right)^{\frac{\nu_w}{\nu_w-1}}\right]^{\frac{\nu_w-1}{\nu_w}}, \tag{42}$$

$$\sum_{s=0}^{\infty} \zeta_w^s \beta^s \frac{\lambda_{t+s}}{\lambda_t} \frac{P_t}{P_{t+s}} \left(\frac{\nu_w}{\nu_w - 1}\right) \left(\Pi_{t,s}^w W_t^* - \frac{1}{\nu_{wt+s}} W_{t+s}^h\right) \tilde{N}_{t+s} = 0, \tag{43}$$

$$\text{where} \quad \tilde{N}_{t+s} = \left[\frac{W_t^* \Pi_{t,s}^w}{W_{t+s}}\right]^{\frac{1}{\nu_{wt+s}-1}} N_{t+s},$$

$$\text{and} \quad \Pi_{t,s}^w = \begin{cases} 1 \quad \text{for} \quad s = 0 \\ \Pi_{k=1}^s \left(\Pi_{t+k-1} g_{t+k-1}^y\right)^{\iota_w} (\Pi g^y)^{1-\iota_w} \quad \text{for} \quad s > 0, \end{cases}$$

$$q_t^k K_{t+1} = N_t^b + B_{t+1}, \tag{44}$$

$$q_t^k K_{t+1} = \phi_t^b N_t^b, \tag{45}$$

$$N_t^b = \theta^b Z_t^b N_{t-1}^b + \omega^b q_t^k K_t, \tag{46}$$

$$Z_{t+1}^b = \delta_{t+1}^b \phi_t^b + R_{t+1}, \tag{47}$$

$$\phi_{bt} = \frac{\eta_t}{\lambda_b - \nu_{bt}}, \tag{48}$$

$$\nu_{bt} = E_t \beta \frac{\lambda_{t+1}}{\lambda_t} \Gamma_{t+1} \delta_{bt+1}, \tag{49}$$

$$\eta_{bt} = E_t \beta \frac{\lambda_{t+1}}{\lambda_t} \Gamma_{t+1} R_{t+1}, \tag{50}$$

$$\Gamma_t = 1 - \theta_b + \theta_b(\nu_{bt}\phi_{bt} + \eta_{bt}), \tag{51}$$

$$\delta_{bt} = R_t^k - R_t, \tag{52}$$

$$G_t = \varepsilon^g Y_t, \tag{53}$$

$$C_t + \Gamma_t I_t + G_t = S_t - a(u_t) K_t \Upsilon_t - \frac{\kappa}{2}\left[\frac{\Pi_t}{\Pi_{t-1}^{\iota_p} \Pi^{1-\iota_p}} - 1\right]^2 S_t, \tag{54}$$

$$\Pi_t = \frac{P_t}{P_{t-1}}, \tag{55}$$

$$\frac{R_{t+1}^n}{R^n} = \left(\frac{R_t^n}{R^n}\right)^{\rho_r} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_t^*}\right)^{\phi_y}\right)^{(1-\rho_r)}, \tag{56}$$

where Y_t^* is the associated level of output under flexible wages and prices.

In addition, we have laws of motion for the exogenous processes $g_t^\Upsilon = \Upsilon_t / \Upsilon_{t-1}$ and $g_t^\Omega =$

Ω_t/Ω_{t-1} as described in the main text.

D.2.1 Stationarity and Solution Method

The model economy inherits stochastic trends from the two non-stationary stochastic processes for Υ_t and Ω_t. Our solution method focuses on isolating fluctuations around these stochastic trends. We divide non-stationary variables by their stochastic trend component to derive a stationary version of the model. We then take a linear approximation of the dynamics around the steady state of the stationary system.

The stochastic trend components of output and capital are given by $X_t^y = \Upsilon_t^{\frac{\alpha^*-1}{\alpha^*}}\Omega_t$ and $X_t^k = \Upsilon^{\frac{-1}{\alpha^*}}\Omega_t$, respectively, where $\alpha^* = 1-\alpha_k$. The stochastic trend components of all other non-stationary variables can be expressed as some function of X_t^y and X_t^k. In particular, define the following stationary variables as transformations of the above 18 endogenous variables: $c_t = \frac{C_t}{X_t^y}$, $v_t = \frac{V_t}{X_t^y}$, $i_t = \frac{I_t}{X_t^k}$, $g_t = \frac{G_t}{X_t^y}$, $s_t = \frac{S_t}{X_t^y}$, $y_t = \frac{Y_t}{X_t^y}$, $n_t = N_t$, $u_t = u_t$, $f_t = \frac{F_t}{X_t^y}$, $k_t = \frac{K_t}{X_{t-1}^k}$, $x_t = \frac{X_t}{X_t^y}$, $a_t = \frac{A_t}{X_t^y}$, $\bar{w}_t = \frac{w_t}{X_t^y}$, $\bar{r}_t = \frac{X_t^k}{X_t^y}r_t$, $\tau_t = \tau_t$, $\bar{\mu}_t^f = (X_t^y)^\sigma \mu_t^f$, $\bar{q}_t^k = \frac{X_t^k}{X_t^y}$, $\bar{\bar{q}}_t^k = \frac{X_t^k}{X_t^y}$, $\bar{\lambda}_t = (X_t^y)^\sigma \lambda_t$, $n_t^b = \frac{N_t^b}{X_t^y}$, $b_t^b = \frac{B_t^b}{X_{t-1}^y}$. In addition, define the two additional stationary variables, $g_t^y = \frac{X_t^y}{X_{t-1}^y}$ and $g_t^k = \frac{X_t^k}{X_{t-1}^k}$ as the growth-rates of the stochastic trends in output and capital.

The stationary system is then given by:

$$v_t = c_t - b\frac{c_{t-1}}{g_t^y} - \psi N_t^{\xi} j_t, \tag{57}$$

$$f_t = \left(c_t - b\frac{c_{t-1}}{g_t^y}\right)^{\gamma_f}\left(\frac{f_{t-1}}{g_t^y}\right)^{1-\gamma_f}, \tag{58}$$

$$\Gamma_t v_t^{\sigma} + \bar{\mu}_t^j \gamma_j \frac{f_t}{c_t - b\frac{c_{t-1}}{g_t^y}} = \bar{\lambda}_t + b\beta E_t\left(g_{t+1}^y\right)^{-\sigma}\left\{\Gamma_{t+1} v_{t+1}^{-\sigma} + \bar{\mu}_{t+1}^j \gamma_f \frac{f_{t+1}}{c_{t+1} - b\frac{c_t}{g_t^y}}\right\}, \tag{59}$$

$$\xi\psi\Gamma_t v_t^{-\sigma} n_t^{\xi-1}\frac{f_t}{\bar{\lambda}_t} = \bar{w}_t^h, \tag{60}$$

$$\bar{\mu}_t^f = -\psi\Gamma_t v_t^{-\sigma} n_t^{\xi} + \beta(1-\gamma_f)E_t\left(g_{t+1}^y\right)^{1-\sigma}\bar{\mu}_{t+1}^f \frac{f_{t+1}}{f_t}, \tag{61}$$

$$\lambda_t = \beta R_{t+1}^n E_t \lambda_{t+1}\frac{1}{\Pi_{t+1}}, \tag{62}$$

$$\lambda_t = \beta R_{t+1} E_t \lambda_{t+1}, \tag{63}$$

$$\bar{r}_t = a'(u_t), \tag{64}$$

$$R_t^k = \frac{\bar{r}_t u_t - a(u_t) + \bar{\bar{q}}_t^k}{\bar{q}_{t-1}^k}, \tag{65}$$

$$q_t^k = \frac{1}{1 - S'(\frac{i_t}{k_t} g_t^k)}, \tag{66}$$

$$\bar{\bar{q}}_t^k = \bar{q}_t^k\left[1 - \delta + S'\left(\frac{i_t}{k_t} g_t^k\right)\frac{i_t}{k_t} g_t^k - S\left(\frac{i_t}{k_t} g_t^k\right)\right], \tag{67}$$

$$k_{t+1} = (1-\delta)\frac{k_t}{g_t^k} + i_t - S\left(\frac{i_t}{k_t} g_t^k\right)\frac{k_g}{g_t^k}, \tag{68}$$

$$y_t = n_t^{\alpha_n}(\widetilde{k}_t/g_t^k)^{\alpha_k}\left(h_t\right)^{1-\alpha_n-\alpha_k}, \tag{69}$$

$$h_{t+1} = (1-\delta_h)h_t + h_t^{1-\nu} n_t^{\nu}, \tag{70}$$

$$\bar{w}_t = \tau_t \alpha \frac{y_t}{n_t} + \bar{q}_t^h \nu \frac{h_t^{1-\nu_h} n_t^{\nu}}{n_t}, \tag{71}$$

$$\bar{q}_t^h = \beta E_t \frac{\bar{\lambda}_{t+1}}{\bar{\lambda}_t}(g_{t+1}^y)^{1-\sigma}\left\{(1-\alpha_n-\alpha_h)\tau_{t+1}\frac{y_{t+1}}{h_{t+1}} + \bar{q}_{t+1}^h\left(1 - \delta_h + (1-\nu_h))\frac{h_{t+1}^{1-\nu_h} n_{t+1}^{\nu}}{h_{t+1}}\right)\right\}, \tag{72}$$

$$\bar{r}_t = (1-\alpha_k)\tau_t \frac{y_t}{u_t k_t/g_t^k}, \tag{73}$$

$$a_t = (1-\delta_x)\frac{x_{t-1}}{g_t^y} + y_t, \tag{74}$$

$$x_t = a_t - s_t, \tag{75}$$

$$\tau_t = \zeta\frac{s_t}{a_t} + \mu_t^x\left(1 - \zeta\frac{s_t}{a_t}\right), \tag{76}$$

$$\mu_t^x = \beta(1-\delta_x)E_t\frac{\bar{\lambda}_{t+1}}{\bar{\lambda}_t}(g_{t+1}^y)^{-\sigma}\tau_{t+1}, \tag{77}$$

$$(1-\theta)s_t - \kappa\left[\frac{\Pi_t}{\Pi_{t-1}^{\iota_p}\Pi^{1-\iota_p}} - 1\right]\frac{\Pi_t s_t}{\Pi_{t-1}^{\iota_p}\Pi^{1-\iota_p}} + \beta E_t\frac{\bar{\lambda}_{t+1}}{\bar{\lambda}_t}(g_{t+1}^y)^{-\sigma}\kappa\left[\frac{\Pi_{t+1}}{\Pi_t^{\iota_p}\Pi^{1-\iota_p}} - 1\right]\frac{\Pi_{t+1}s_{t+1}}{\Pi_t^{\iota_p}\Pi^{1-\iota_p}} + \mu_t^x\theta s_t = 0, \tag{78}$$

$$w_t = \left[(1-\zeta_w) w_t^{*\,\frac{\nu_w}{\nu_w - 1}} + \zeta_w \left(w_{t-1} \left(\frac{\Pi_{t-1} g_{t-1}^y}{\Pi g_y} \right)^{\iota_w} \left(\frac{\Pi_t g_t^y}{\Pi g^y} \right)^{1-\iota_w} \right)^{\frac{\nu_w}{\nu_w - 1}} \right]^{\frac{\nu_w - 1}{\nu_w}}, \tag{79}$$

$$\sum_{s=0}^{\infty} \zeta_w^s \beta^s \bar{\lambda}_{t+s} \left(\Pi_{k=1}^s (g_{t+k}^y)^{1-\sigma} \right) \left(\frac{\nu_w}{\nu_w - 1} \right) \left(\tilde{\Pi}_{t,s}^w w_t^* - \frac{1}{\nu_{wt+s}} w_{t+s}^h \right) \tilde{n}_{t+s} = 0, \tag{80}$$

$$\text{where} \quad \tilde{n}_{t+s} = \left[\frac{w_t^* \tilde{\Pi}_{t,s}^w}{w_{t+s}} \right]^{\frac{1}{\nu_{wt+s} - 1}} n_{t+s},$$

$$\text{and} \quad \tilde{\Pi}_{t,s}^w = \begin{cases} 1 \quad \text{for} \quad s = 0 \\ \Pi_{k=1}^s \left(\frac{\Pi_{t+k-1} g_{t+k-1}^y}{\Pi g^y} \right)^{\iota_w} \left(\frac{\Pi_{t+k} g_{t+k}^y}{\Pi g^y} \right)^{-1} \quad \text{for} \quad s > 0, \end{cases}$$

$$\bar{q}_t^k k_{t+1} = n_t^b + b_{t+1}, \tag{81}$$

$$\bar{q}_t^k k_{t+1} = \phi_t^b n_t^b, \tag{82}$$

$$n_t^b = \theta^b z_t^b \frac{n_{t-1}^b}{g_t^y} + \omega^b \bar{q}_t^k \frac{k_t}{g_t^k}, \tag{83}$$

$$z_{t+1}^b = \delta_{t+1}^b \phi_t^b + R_{t+1}, \tag{84}$$

$$\phi_{bt} = \frac{\eta_t}{\lambda_b - \nu_{bt}}, \tag{85}$$

$$\nu_{bt} = E_t \beta \frac{\bar{\lambda}_{t+1}}{\bar{\lambda}_t} \left(g_{t+1}^y \right)^{-\sigma} \Gamma_{t+1} \delta_{bt+1}, \tag{86}$$

$$\eta_{bt} = E_t \beta \frac{\bar{\lambda}_{t+1}}{\bar{\lambda}_t} \left(g_{t+1}^y \right),^{-\sigma} \Gamma_{t+1} R_{t+1} \tag{87}$$

$$\Gamma_t = 1 - \theta_b + \theta_b (\nu_{bt} \phi_{bt} + \eta_{bt}), \tag{88}$$

$$\delta_{bt} = R_t^k - R_t, \tag{89}$$

$$g_t = \varepsilon^g y_t, \tag{90}$$

$$c_t + i_t + g_t = s_t - a(u_t) k_t / g_t^k - \frac{\kappa}{2} \left[\frac{\Pi_t}{\Pi_{t-1}^{\iota_p} \Pi^{1-\iota_p}} - 1 \right]^2 s_t, \tag{91}$$

$$\Pi_t = \frac{P_t}{P_{t-1}}, \tag{92}$$

$$\frac{R_{t+1}^n}{R^n} = \left(\frac{R_t^n}{R^n} \right)^{\rho_r} \left(\left(\frac{1+\Pi_t}{1+\Pi} \right)^{\phi_\pi} \left(\frac{y_t}{y_t^*} \right)^{\phi_y} \right)^{(1-\rho_r)}, \tag{93}$$

where y_t^* is the associated level of output under flexible wages and prices,

$$g_t^y = g_t^\Omega \left(g_t^\Upsilon \right)^{(\alpha-1)/\alpha}, \tag{94}$$

$$g_t^k = g_t^y / g_t^\Omega, \tag{95}$$

in addition to the exogenous processes g_t^{Υ} and g_t^{Ω}.

E Additional Model Results

E.1 Parameter Calibration

The parameters that we hold fixed at calibrated value over both subsamples are detailed in Table 1 along with their calibrated values. Our choice values for this subset of parameters is guided by the existing literature, where we maintain comparability with Jaimovich and Rebelo (2009) and Schmitt-Grohe and Uribe (2012) for the aspects of the news shock mechanism and Lubik and Teo (2012) for the inventory component.

We set the household's discount factor β to 0.9957, which is implied by the real interest rate computed from average inflation and the federal funds rate over our sample period. We set the elasticity of intertemporal substitution as in Jaimovich and Rebelo (2009), $\sigma = 1$, and the consumption habits parameter b to 0.7.

On the firm side, we set the elasticity parameter in the production function to $\alpha = 0.64$ as in Jaimovich and Rebelo (2009), and the degree of decreasing-returns-to-scale (DRS) to labor and capital in production, $1 - \alpha_n - \alpha_k$, to 0.1, following Jaimovich and Rebelo (2009) and Schmitt-Grohe and Uribe (2012). For the parameters related to physical capital, we fix steady-state physical capital depreciation at $\delta = 0.025$.

The parameters related to inventories are based on the empirical estimates in Lubik and Teo (2012). The goods aggregator curvature parameter θ is set to 6.8, which results in a steady-state goods markup of 10%.

For the parameters related to the banking sector, following Gertler and Karadi (2011), we set θ_b, the determinant of a banker's life horizon, to 0.972. We then set w_b, the proportional transfer to enter bankers to 0.0038, such that for a steady-state leverage ratio of 4 (which we will estimate), the annualized steady state credit spread is about 100 basis points.

For the parameters related to the nominal side of the economy, we choose values consistent with the literature, setting the steady state wage markup to 10%, and wage and price indexation to 0.5.

Finally, a number of steady-state parameter values are implied by average values in the data, such as the (quarterly) steady-state growth rates of GDP g^y and the relative price of investment (RPI) g^{RPI}, which we find to be 0.43 and -0.58, respectively. We also set the steady-state government-spending ratio to output to $g/y = \varepsilon^g = 0.18$ following Smets and Wouters (2007) and target a level of hours in steady state of 0.2, while steady-state capacity utilization is targeted at one.

Table 1: Calibrated model parameters

Description	Parameter	Value
Subjective discount factor	β	0.9975
Household elasticity of intertemporal substitution	σ	1
Habit persistence in consumption	b	0.70
DRS to N and K in production	$1-\alpha_n-\alpha_k$	0.1
Labor elasticity in production	α_n	0.64
Capital depreciation	δ_k	0.025
Goods aggregator curvature	θ	6.8
Price indexation	ι_p	0.5
Wage indexation	ι_w	0.5
Proportional transfers to entering bankers	w_b	0.0038
Survival rate of bankers	θ_b	0.972
Steady state government spending over output	$\varepsilon^g(=g/y)$	0.18
Steady state hours	n	0.2
Steady state capacity utilization	u	1
Steady state wage markup	λ_w	1.1
Steady state GDP growth rate (in %)	g^y	0.42545
Steady state RPI growth rate (in %)	g^{rpi}	-.58203

E.2 Parameter Estimates

Table 2 shows the estimated values from the impulse response function matching exercise. Column 3 shows the search domain for each parameter of the minimization procedure, and columns 4 and 5 show the estimated values for the first and second subsamples respectively.

Table 2: Estimated model parameters

Description	Parameter	Match Search Bounds	1954-1983 Point (CI)	1984-2019 Point (CI)
Determinant of Frisch elasticity of labor supply	ξ	$[1.2, 6]$	1.65 (1.2,1.7)	1.33 (1.24,1.57)
Wealth elasticity parameter (GHH/KPR pref)	γ_f	$[0.001, 0.999]$	0.0038 (0.0017,0.040)	0.0051 (0.0049,0.019)
Elasticity of capacity utilization	ϵ_u	$[0.01, 1]$	0.067 (0.050,0.22)	0.17 (0.11, 0.34)
Capital adjustment cost	s''	$[0.01, 0.5]$	0.21 (0.019,0.26)	0.067 (0.021,0.13)
Inventory taste shifter curvature	ζ	$[0.55, 0.7]$	0.70 (0.55,0.70)	0.70 (0.55,0.70)
Inventory depreciation	δ_x	$[0.001, 0.05]$	0.001 (0.0010,0.05)	0.0075 (0.0010, 0.0028)
Knowledge capital depreciation	δ_h	$[0.001, 0.3]$	0.3 (0.096,0.30)	0.15 (.092,0.30)
Labor elasticity in knowledge capital	ν_h	$[0.001, 0.3]$	0.3 (0.25,0.30)	0.3 (0.094,0.30)
TFP growth process persistence	ρ_Ω	$[0.001, 0.999]$	0.40 (0.0010,0.53)	0.65 (0.0010,0.79)
Taylor rule inflation	ϕ_π	$[1.1, 2.5]$	1.1 (1.1,2.5)	2.42 (1.1,2.5)
Taylor rule output	ϕ_y	$[0.05, 0.1]$	0.1 (0.050,0.10)	0.1 (0.050, 0.10)
Taylor rule smoothing	ρ_r	$[0.5, 0.95]$	0.95 (0.5,0.95)	0.95 (0.88,0.95)
Price adjustment costs	κ	$[25, 300]$	99.9 (25,60.9)	42.2 (25,62.8)
Calvo wage parameter	ζ_w	$[0.5, 0.95]$	0.95 (0.5,0.95)	0.95 (0.95,0.95)
Steady state leverage	ϕ_b	$[3.5, 6]$	3.5 (3.5,6)	6 (3.5,6)